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Integration of Market Risk, Natural Hazard Risk and Ecosystem Services in the Analysis of Land Use Portfolios

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To the loving memory of my father

This work is also dedicated to my grandfather José Cabra, a farmer who lost everything due to environmental risks

Abstract

The need to provide food for an ever-growing human population has generated enormous pressure on resources resulting in a significant expansion of agricultural land at the expense of forest cover. This is particularly relevant in several South American countries where, until recently, farmers could only maintain their land tenure rights if they kept their land free of forest. In spite of this apparent low value that developing countries place on forests, scientific evidence has shown that forest plays a critical role in limiting and slowing-down the impact of global warming. The international community has therefore created mechanisms that compensate farmers who actively stop deforesting their land. These compensations are mostly regular payments, the amount of which is a current research topic. To date the scientific discussion has mostly focused on obtaining fair compensation payments that will motivate farmers to enter forest protection contracts that may last decades.

As an initial approach, financial models developed for other economic areas have been used to compute fair compensations. Although relevant as a first step, such models need further adaptation to truly represent the current conditions in agricultural economies of developing countries. For example, most models assume that the prices of commodities are Gaussian distributed, an assumption that is seldom fulfilled in agricultural economies due to the high volatility of food prices. A further drawback is that such models do not usually account for the impact of environmental risks on farm productivity and thus may generate overly optimistic results. This is particularly relevant in South American countries where agricultural techniques like slash-and-burn and intentional use of fires to deforest areas are the rule and not the exception. Afforestation and reforestation projects located in such areas, although well intended, may suffer from vast and uncontrolled fires. Thus, if farmers are willing to enter such compensation contracts a thorough environmental risk assessment, especially for fire, is extremely important because the post-fire recovery processes in a forest can be extremely slow and may take several decades, which puts the sustainability and success of such projects at

high risk.

The goal of this PhD research is to improve current methodologies used to compute fair compensations to ensure the sustainability of projects where farmers stop deforestation in the long term. For this, a new model to generate spatial-temporal information of productivity changes generated by fire damages has been developed. The information generated is then fed into an adapted version of an existing model that computes necessary financial compensations within Gaussian and non-Gaussian distribution contexts. The results of the modeling approach show how a fair compensation value is subject to the location of the project and indicate the locations where such projects may be viable and sustainable or where they may become prohibitively expensive due to high risks. Further, the most popular international methodology used to compute the environmental risks of forest projects is compared against the PhD modeling approach showing where such methodology could be improved. Three of the most forested countries in South America were used as the study area. Two of the countries studied also suffer from the most frequent and most devastating damages caused by forest fires in the region, but at the same time are among the most productive in terms of agriculture output.

The need to stop deforestation has generated a compensation mechanism that needs constant adaptation and improvement. This has triggered an open discussion among policy makers and the scientific community leading to the creation of the first projects that actively protect forests in developing countries. As all projects are intended to obtain long-lasting results, the continuous improvement of current techniques will help achieve project sustainability and hopefully halt deforestation.

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Last but not least, the constant love and support of my wife and family have motivated me to give my best, I thank you all. With all my love to Grete, Himeldita, Nes, Patty, Mayis, Canela and Julieta.

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Chapter 1

Introduction

Agriculture is one of the riskiest sectors of economic activity, and effective risk-reducing instruments are severely lacking in rural areas (World Bank, 2008, p89). With respect to market risk farmers are subject to low prices that threaten their long term viability, when income is too low to provide for the operational needs of the farm (IFAD *et al.* 2011). Farmers are also subject to high food-price variability; out of all non-fuel commodities, food prices show the highest ever historical volatility over a decade (1971-1980), (IMF, 2006, p4), with the second highest peak between 2008 and 2009 (IMF, 2011, p39). Land-use related activities are also exposed to operational risk, mostly in the form of environmental hazards (fires, droughts, floods, frosts, plagues, *etc.*), which are among the most frequent, costly and strongest causes of the kinds of shock that can cause people to become poor in the first place, and that make the escape from poverty so difficult (Evans, 2010, p6). Yet, about 75% of the world's poor people live in rural areas, and most of them are involved in farming (Kwadwo *et al.* 2008), also known as family-farming.

Family-farmers also face constraints that halt them from transferring risks, this results in fewer possibilities to increase their production and revenues. Limited access to financial and insurance services, dislocation from markets, poor access to inputs, lack of advisory services or information, and poor infrastructure (World Bank, 2011, p1.) are common constraints of farm economies, especially in developing countries due to low government investment at rural level. The main problem is that such constraints, see Table 1.1, leave rural households more exposed to uninsured risks, forcing them to adopt low-risk and low-return farming activities, thus reducing the farmers' likelihood of accumulating the assets needed to escape poverty through savings and investment (Barnett *et al.* 2008). Losses in agriculture, associated with such types of risk exposure, are not exclusive to farmers, but to

agribusiness entities, financial and insurance providers, governments and all actors involved throughout the supply chain.
As an additional constraint to agricultural activities, the World Trade Organization (WTO) regulations generally forbid governments from subsidizing agriculture directly (FAO, 2005, p.11). The WTO does, however, permit the subsidization of agricultural insurance premiums. In face of WTO regulations, and to protect small traditional and commercial farmers, the public sector in several Latin American countries has recently begun to purchase private agricultural insurance coverage, see Fig. 1.1, to transfer the costs

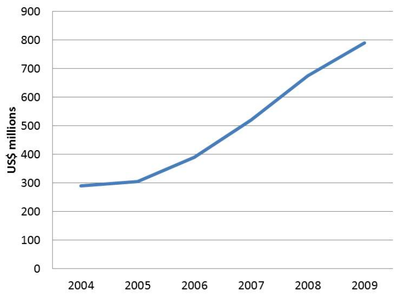

Figure 1.1: Fiscal expenditures on agricultural insurance in Latin America. Source: The World Bank (2010 p.55)

of catastrophic agricultural risks to international markets (The World Bank, 2010, p.19). According to Herbold (2013), these so called public-private partnerships are the most promising and sustainable approach for crop insurance. However, these partnerships have historically favored larger investment projects (commercial agriculture) rather than family-farmers (Streck and Zurek, 2013, p.18).

Table 1.1: Constraints faced by family-farmer agriculture in developing countries (Streck *et al.* 2012)

Investment Barriers	**Social/Institutional Barriers**	**Technological Barriers**
Lack of assets and savings	Poorly functioning markets	Lack of technical expertise
No or little access to credit or extension services	No or limited market access	Existing resource degradation (for example soil/water)
No or little access to insurance	Limited market information and understanding	Lack of baseline data (for example forest or soil carbon) content
Lack of infrastructure and equipment	Weak land tenure security	

In spite of the aforementioned risks and constraints, the amount of land available for agricultural purposes has been increasing in the last decades. Commercial agriculture and, to a lesser extent, family-farming have benefited from weak tenure land rights and specific national policies fostering deforestation; until recently in several Latin American countries farmers could only maintain their land use rights if they kept the land forest-free (Streck and Zurek, 2013, p.7). As a result, and also because commercial agriculture has better access to insurance and financial services to transfer risks, land used for commercial agriculture has expanded significantly in recent decades. Typical products of large-scale agriculture like soybeans, palm oil and sugarcane have altogether shown an annual growth of arable land of 12% between 1990 and 2010 (Pacheco, 2012, p.1 and 4). According to Kissinger *et al.* (2012, p5.), commercial agriculture has become the most important driver of deforestation in Latin America, representing around 66% of the total deforested area, followed by agriculture of subsistence (family-farming) with almost 27%, see Fig. 1.2.

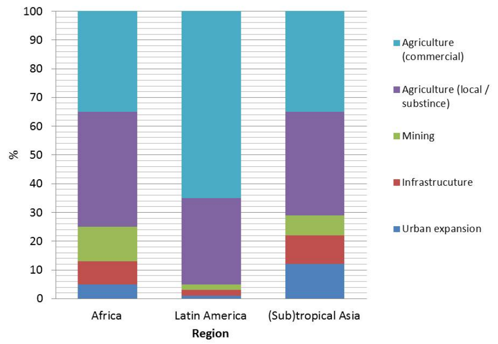

Figure 1.2: Total deforested area (in %) and direct drivers of deforestation and forest degradation. Source: Kissinger et al. (2012)

According to the State of the World's Forests report (FAO, 2011, p118), South America had an estimated 864 million hectares covered by forest, which represented almost half of its total land cover by 2011. These abundant forest resources account for 21% of the world's forest areas and 57% of its primary forests. Yet South America lost more than 164 million hectares of its total forest area between 1990 and 2010 (8,2 million hectares per year), at a rate three times higher than the rate of global forest loss during the same period (FAO, 2011, p.118). Due to higher returns on investments of some highly productive agricultural commodities, the conversion of forest land to agriculture has become the leading cause of the regional deforestation (FAO, 2011), which is performed mainly through illegal logging and intentionally-ignited fires. According to Uriarte *et al.* (2012) this effect is magnified in regions with severe droughts, that are close to roads and rivers, and that have extensive use of pastures and agricultural crops. The authors further argue that policies to promote low-fire land use systems and access to education, as well as the improvement of early warning systems and other mechanisms, could reduce fire in the region (Uriarte *et al.* 2012). Recently, mechanisms like "payment for ecosystem services" have been used as a means to stop deforestation, by generating additional value to forests, with promising results.

1.1 Payments for ecosystem services to avoid deforestation

In broad terms ecosystem services (ES) are the benefits that people derive from ecosystems (WWF, 2010). The Millennium Ecosystems Assessment (2005) identified 24 specific ecosystem services that can be divided in four categories: provisioning, supporting, regulating and cultural services, see Fig. 1.3. To compensate and encourage individuals or groups engaged in activities

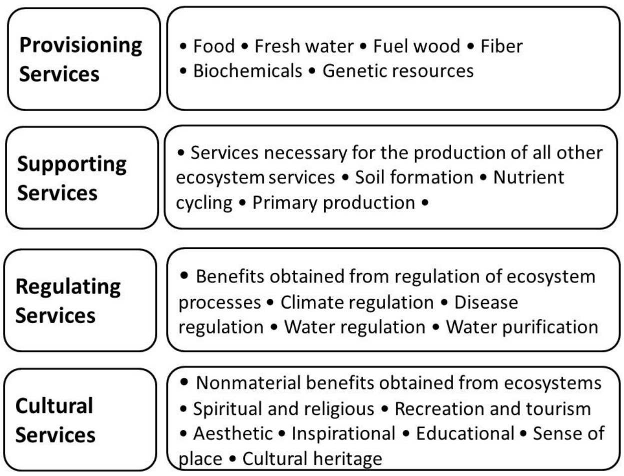

Figure 1.3: Ecosystem services defined by the Millennium Ecosystem Assessment (2005)

that support the provision of such services (WWF, 2010), financial transfers known as payments for ecosystem services (PES) are made by individuals, institutions, governments or entities that benefit directly or indirectly of such services. Wunder (2005) provides an often cited definition for a PES as "a voluntary transaction where a well-defined environmental service or a land use likely to secure that service is being 'bought' by a (minimum of one) service buyer from a (minimum of one) service provider if, and only if, the service provider secures service provision (providing conditionality)." Not all services listed in the Millennium Ecosystem Assessment are appropriate for a PES scheme (Jindal *et al.* 2007). Appropriate services are those that are under-valued or not valued, thus threatening their supply. The most common ES delivered through PES schemes are carbon sequestration and storage, biodiversity conservation, watersheds and landscape beauty (WWF, 2010).

Although PES studies and literature have increased massively in recent years, PES or PES-like schemes are not a new phenomenon. In the 1880s, PES is thought to have been first introduced in the form of conservation easements in the US (WWF, 2010). In Latin America the earliest formal PES programs began in Colombia's Cauca Valley in the mid-1990s (Echavarria, 2002), but PES really took off after Costa Rica instituted its Programa de Pagos por Servicios Ambientales (PPSA) program in 1997 (Pagiola, 2013). Costa Rica's example led many other countries, as well as other actors concerned with natural resource management at many scales, to consider PES (Pagiola, 2013). By the end of the decade, there were over 150 PES and PES-like programs operating in Latin America, conserving about 2.5 million hectares including national, government-financed programs in Costa Rica, Mexico and Ecuador, and local user-financed programs in most countries (Camhi and Pagiola, 2009). In Costa Rica alone, nearly one million hectares of forest have been part of the PES program at one time or another since 1997, and forest cover has now returned to over 50% of the country's land area, from a low of just 20% in the 1980s (Porras *et al.* 2013).

According to Greiber (2009), PES involve the obligation to manage land in a particular manner for a particular period of time in exchange for compensation, and therefore the parties must enter into an agreement of some kind. Some risks arising from such exchanges can be explicitly addressed by mechanisms for risk allocation (*e.g.* contracts, risk buffer zones, insurance, etc.). The most significant risks in PES agreements are market risk, innocent loss and party risk (Greiber, 2009). The author further argues that for market risk there is a danger that the price of a certain market good will rise or fall unexpectedly, thus if a long-term relationship between both parties of the agreement is an objective, ensuring that the contract remains fair over time will be a priority. Thus, fair payments must be provided to benefit all actors involved in PES and to ensure sustainability. Risk of innocent loss, also known as *force majeure* is the failure to fulfill contract conditions in the face of an uncontrollable event such as fire or flood. With party risk, the concern is that one of the parties will fail to perform its obligations (Greiber, 2009). Arguably, the most advanced agreements have been the contracts developed for carbon sequestration and storage, because abundant scientific literature has dealt with the analysis of fair prices to be paid to farmers willing to stop deforestation. Current carbon sequestration contracts also involve analyzing risks and generating risk buffer zones that are used in case natural hazards affect the area generating ES. However, as will be shown in the following sections of this study, current mathematical models used to determine fair financial compensations tend to underestimate market risk and methodologies used to assess natural hazards seriously underestimate their risk, and are therefore overly optimistic about the real damages to which projects involved in PES are subject and thus overestimate the returns of the investments. While all PES programs worldwide monitor compliance of participants with contract conditions, few adequately monitor actual environmental benefits. Given the incipient experience with PES in countries like Brazil and the innovative nature of many of the programs, it is unfortunate that few programs—not even those which are explicitly intended as pilots—have put in place arrangements for rigorous impact evaluation (Pagiola *et al.* 2013). If in the near future such projects suffer damages that could have been avoided or mitigated, the reputation and sustainability of PES may also be at risk.

Proambiente was an early example of a program modeled after a PES scheme with the aim of controlling deforestation in Brazil (Fortmann, 2014). The program was incorporated in the 2004-07 Plan of Action sponsored by the federal government and involved 11 Pioneer Centres in six states across the Brazilian Amazon. The program was created to promote integrated rural development[1], and its targeted beneficiaries were small-scale farmers (Greiber, 2009). The goal of Proambiente was to encourage the replacement of slash-and-burn agriculture and extensive pasture by rural communities with more environmentally sustainable livelihood practices. The goal of the project was to reduce deforestation and forest degradation generated by fires, conserve soil and protect biodiversity (Fortmann, 2014). In practice, Proam-

[1]Official subsidies for settling the Amazon historically promoted deforestation rather than conservation. PES is one possible solution to altering this pattern (Hall 2008:1926), and this was the original intent of Proambiente.

biente did not have a monitoring system that allowed for verifying results (Greiber, 2009). The large turnover of the extension agents working in the field and the lack of a monitoring procedure made it very difficult for the program management to monitor the progress of the project and identify difficulties occurring in the field (Ferreira 2008: p.86).

1.2 Carbon PES and REDD programs in Latin America

There are two basic kinds of PES programs (Pagiola and Platais, 2007; Engel *et al.* 2008): user financed PES programs in which service providers are paid by service users, and government-financed PES programs in which providers are paid by a third party, typically a government. User-financed PES programs have most commonly been established for water services, where users are easy to identify and receive well-defined benefits (Pagiola and Platais, 2007). Carbon projects are a smaller but rapidly growing group of PES programs (Pagiola, 2013). Attention has particularly focused on forestry projects because a significant proportion of carbon emissions worldwide come from deforestation (17% according to IPCC, 2007). Research has shown that reducing emissions from deforestation and forest degradation (REDD) is a potentially effective way to reduce net emissions through increased carbon sequestration (Fortmann, 2014). Thus, activities such as planting trees, changing agricultural tillage and cropping practices, or re-establishing grasslands help to increase carbon sinks by sequestering carbon (Pearson, 2005). The Voluntary Carbon Standard (VCS, 2010) presents some examples of land management activities for carbon sequestration and/or emissions reduction that can form the basis of PES schemes, see Fig. 1.4. The resulting emissions reductions are then sold either in regulated carbon markets, such as that established under the Kyoto Protocol's Clean Development Mechanism (CDM), or in voluntary markets (Pagiola, 2013). According to Diaz *et al.* (2011), about 75 million metric tonnes of CO_2 have contracted in projects covering 8 million ha in 49 countries. From these, voluntary markets dominate accounting for about 83 % of total carbon transacted (Diaz *et al.* 2011).

Wunder et al. (2008) looked at payment structures across PES programs including the payment schedules, amounts paid and duration of contracts. Programs that do not require extensive physical changes on the land tend to have lower payments that are similar to the opportunity cost of alternative

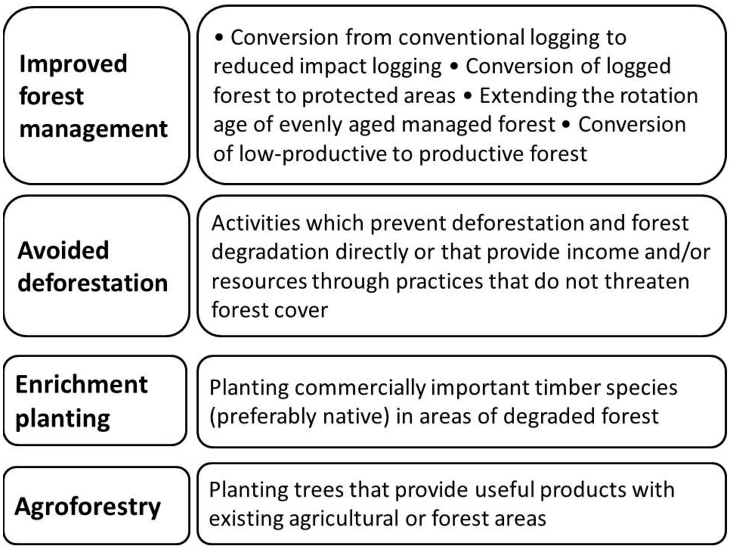

Figure 1.4: Examples of land management activities for carbon sequestration and/or emissions reduction. Sources VCS, 2010 and WWF, 2010

land-use activities, *e.g.* in Costa Rica PES projects pay from US$45/ha/yr to US$64/ha/yr for forest conservation (Wunder et al. 2008; Porras *et al.* 2013). Projects where providers are required to plant trees or change management activities increase the payments to compensate the provider for the costs of planting trees along with the opportunity cost of using the land for other purposes (Fortmann, 2014). Depending of the type of project (protection, reforestation, regeneration, etc.) programs presented in the literature made cash payments ranging from a low of US$1.50/ha/yr in Bolivia to US$294/ha/yr in Costa Rica (Wunder et al., 2008; Porras *et al.* 2013, Pagiola *et al.* 2013). According to Pagiola *et al.* (2013), almost all PES mechanisms in Latin America use flat payments per hectare, at most distinguishing different land uses with different flat payments. Most payments were made annually, some after compliance checks. Most of the contracts spanned from one to 20 years (Fortmann, 2014). Mexico has over 2.2 million hectare paying about US$ 36/ha/yr (Munoz-Piña *et al.* 2008), and in Brazil several programs have started, for example Bolsa Floresta has been implemented in 14 Conservation Units (Unidades de Conservação, UCs) covering over 10 million hectare. The program currently pays over 7,000 households for ES (Pagiola *et al.* 2013) and PES range from about US$ 45/ha/yr to about US$ 112/ha/yr.

According to Garcia-Fernandez *et al.* (2008) PES projects should target sites to ensure maximum efficiency and PES finances should be targeted where they can make a difference. The authors argue that projects are most desirable in locations with high deforestation pressure and high remaining forest cover (i.e. high threat, high benefit), yet most feasible where deforestation has not yet reached a serious level (WWF, 2010). However, areas that put PES investments at high risk and areas where significant carbon loss is very likely should be avoided, as per the risk rating system of the VCS, where projects located in regions with catastrophic fires are classified as unacceptable high/fail (VCS, 2008, 2012).

Countries' efforts to reduce emissions from deforestation and forest degradation, and foster conservation, sustainable management of forest, and enhancement of forest carbon stocks is called REDD+ and is still a relatively new mechanism. A review of initial outcomes of 41 REDD+ projects in 22 countries of Africa, Asia, and Latin America (Lawlor *et al.* 2013) revealed that PES is the most common strategy intervention, with 39% of projects using this method, see Fig. 1.5; from those projects that so far have transferred payments to individuals or households, up to $134 per project per year was paid.

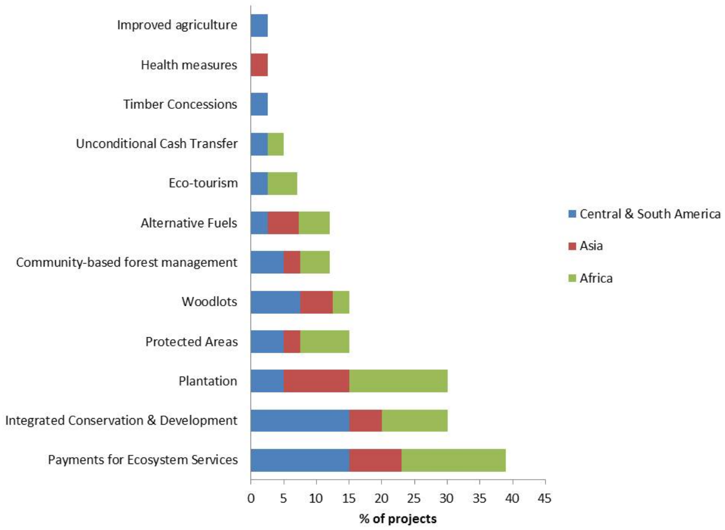

Figure 1.5: Intervention strategies of 41 REDD+ projects in Africa, Asia, and Latin America (Lawlor *et al.* 2013)

A recent study by Knoke *et al.* (2014) has shown that PES can not only help to stop/slow deforestation but can also be used as an incentive to restore abandoned land either for afforestation purposes with native or exotic species or to use the land for high input pasture. The authors conclude that to reduce pressure on biodiverse natural forests to a sustainable level, a compensation amount of up to US$180 per hectare per year may be necessary. However, such compensations are susceptible to volatile food prices (Knoke *et al.* 2013); an increase in food prices of only 10% (producer price index 1.1) could reduce the long-term cover of natural forests by 4% in the same study region.

1.3 Forests and climate change mitigation

According to Stern (2006, p.537), to reverse emissions from land use change, compensation from the international community should be provided and the opportunity costs of alternative uses of the land should be taken into account. This is perhaps the greatest challenge that mechanisms such as REDD+ face. Indeed, Fisher *et al.* (2011) and Pacheco *et al.* (2012) argue that such incentives to keep forests standing cannot compete with palm oil and other crops of commercial agriculture. Butler *et al.* (2009) show that converting a hectare of forest for palm oil production is more profitable (net present values of US$3,835 - $9,630 per hectare) to land owners than preserving it for carbon credits (US$614 - $994 per hectare).

It is clear that PES can hardly compete for land use with commercial agriculture. In such case alternative strategies may be much more effective. Indeed, Brickell and Elias (2013, p.19) present a very interesting example of how international publicity campaigns from environmentalists exposing wrongdoing of multinational companies linked to the soybean supply, have helped reduce deforestation rates in some regions of Brazil. In the particular case of Cargill, a multinational corporation trading agricultural commodities, Greenpeace International reported that the establishment of Cargills exporting port in Santarém (Brazilian Amazon region), dramatically increased regional soya production, which is the major driver of deforestation in the region (Greenpeace. 2006, p.2). Using satellite imagery (Landsat 5 and 7), Cohenca (2005) estimated that between 2002 and 2004, annual deforestation rates jumped from 15,000 to 28,000 hectares in Santarém due to the expansion of the agriculture frontier. Using the analysis of Cohenca (2005), Greenpeace campaigned to major food retailers and won agreement from McDonalds to stop selling chicken fed on soya grown in newly deforested areas of the Amazon rainforest (Greenpeace, 2006b). The main achievement is that McDonald's and other fast food retailers are committed to develop a zero deforestation plan and to put pressure on companies like Cargill to prove that their soya was not grown on recently deforested areas (Greenpeace, 2006a).

Publicity campaigns have surely had an impact on governmental policy makers too. For example, the Brazilian Federal Government publicly committed to significant reductions in deforestation (Boucher et al, 2011) by passing a law in January 2010, which requires all rural properties to be mapped and registered in the Brazilian Rural Environmental Registry (Brickell and Elias, 2013) to enable better monitoring of land use and land use changes. Another important achievement was the creation in 2004 of a public-private partnership between The Nature Conservancy (TNC) and the Cargill company, to help farmers improve their land management practices and address forest loss due to expansion of soybean production. According to Cargill (2012), in Santarém almost all farms participating in the partnership have reported achieving zero net deforestation, while in Pará (Brazil) deforestation in 2012 was less than a third of what it was in 2004 (INPE, 2013; Brickell and Elias, 2013 p.11). According to Kissinger *et al.* (2012) since 2004, which was a peak year of deforestation, the rate of forest clearing in Brazil has fallen by almost 75% attributed to: sanctions on illegal loggers, stronger monitoring and enforcement capabilities, and the Bank of Brazil's veto of agricultural credit for soy farmers seeking to plant in newly cleared forest. While soybean profitability has returned to pre-2006 levels over the past four years, rates of deforestation continued to decline, suggesting that policy interventions and incentives have influenced the agricultural sector (Macedo et al. 2012).

The use of public-private partnerships and law reinforcement has also shown also examples of social, market and environmental improvements of some agricultural commodities like soya in Brazil, palm oil in Malaysia, coffee in Peru and tea in Kenya. To date the major funding for private sector actions has focused on commodity supply chain efforts (Brickell and Elias, 2013) in commercial agriculture. The TNC-Cargill public-private partnership, for example, started with 205 farmers with an average size farm of 644 hectares (Brickell and Elias, 2013, p.11). This is because soybean production depends primarily on large-scale capital-intensive and mechanised agriculture linked to a processing industry (Pacheco, 2012) making it suitable only for commercial agriculture.

1.4 Family-farming

Despite the fact that PES may have a rather limited influence on commercial agriculture, they may be very relevant to family-farmers as a means to ameliorate their poverty and to reduce deforestation and forest degradation. After all, family-farming is the second most relevant driver of deforestation in Latin America, being responsible for an estimated 27% of the total deforested area (Kissinger *et al.* 2012, p5) see Fig. 1.2. According to Schejtman (2008), family-farmers also play an important role in producing staple food and dairy products for national consumption in many Latin American countries. Thus, policies and mechanisms sponsoring forest-friendly activities of family-farmers may also reduce poverty and food scarcity in developing countries. For these reasons REDD+ has sparked renewed hope in the ability of conservation programs to deliver win-win situations by saving the environment and reducing rural poverty (Lawlor et al., 2013). In their study, Lawlor *et al.* (2013) found that many early REDD+ projects are delivering measurable socio-economic benefits by enhancing populations' tenure security and facilitating their empowerment, through meaningful participation in REDD+ project design and implementation. However, to date, projects have produced only modest opportunity benefits (income) for local populations.

In spite of typical land uses (pasture, forest, crops, etc.) of family-farmers being subject to a range of hazards like commodity price vulnerability, environmental risks, change in agricultural or forestry policies, etc., most authors have studied the fairness of compensation under REDD+ or PES mechanisms from a market risk perspective only, *i.e.* the economic vulnerabilities and risk concerning cost-effective compensations under the REDD+ program (Knoke et al. 2011, Hildebrandt and Knoke, 2011, Castro et al. 2013). However, environmental hazards like fires can have enormous economic consequences, as demonstrated in an analysis of social capital and fire spread by Simmons *et al.* (2004). Therefore, a thorough understanding not only of market risk but also of environmental risks affecting family-farmers' land use, is of particular importance for the sustainability of mechanisms such as REDD+ (Román-Cuesta *et al.* 2011) or for any forest-related investment because of the long term impact of fires in forest.

For this study, the case of family-farming in South America is analyzed within the ES perspective of fair payments for avoided deforestation, also considering how to integrate environmental risk analysis to monetarily quantify the potential impact of fire in potential REDD+ projects. The study is divided as follows: first, environmental risk affecting land use is explored and assessed using an original semi-parametric spatial approach that captures hazard, vulnerability and spatio-temporal exposure. The model is presented in section 3.3 using fires as an environmental hazard. Other environmental hazards such as floods, droughts or wind-throw may be integrated as long as they can be recognized with remote sensing techniques (*e.g.* satellites, manned or unmanned aerial vehicles). Second, market risk affecting land use investments is assessed using a methodology adapted to commodity returns departing from symmetric distributions *e.g.* Gaussian. The method used is the expected utility under higher-order moments, which is explained in section (3.4) for the case of three South American representative countries. Third, a model that integrates both market and environmental risk, is presented in section 3.5. Chapter 5 discusses the potential use of such approaches to understand and classify farmers investments with respect to the environmental risk associated with their farms geographical location, and with respect to the market risk at the place where the commodities are traded, in this particular case the national markets.

Chapter 2

State of the art

Risk assessment of land use activities

Several mechanisms can be employed to manage land-use related risks and, more often than not, all available approaches need to be applied within an overall risk management framework at regional and national levels. Yet all too often, the apparent management of one major risk leaves stakeholders with the impression that the overall risk profile has been managed, which is often not the case (World Bank, 2011. p2). Thus, before considering managing risk at the rural-level, a thorough assessment of risk must be completed to address the problems related to agricultural and forestry activities.

According to the Agriculture and Rural Development Department (ARDD) of the World Bank (2011), risk assessments must quantify at least three main variables: hazard, vulnerability and exposure. Hazard is the categorization of the type of risk being considered and should assess its frequency and spatial extent. Vulnerability is an estimation of what the impact of the realized risk would be given the assets affected by the event. Exposure is the identification of the locations that may be directly impacted by the hazard (World Bank, 2011. p2). Several approaches can be employed to manage agriculture- and forestry-related risks, each with different impacts and levels of success. The Agricultural Risk Management Team of the World Bank classifies them (World Bank, 2011. p4) as risk: mitigation, transfer, coping and avoidance.

Due to the aforementioned constraints to which family-farmers are subject, the most common approach in developing countries to deal with various hazards is risk mitigation, which is limited to some technical approaches such as: on-farm crop diversification, using risk reducing inputs (e.g., irrigation, pest control), production of lower risk outputs (*e.g.* cassava instead of maize), share of tenancy, household migration, relocation of range-fed livestock to better pasture (off-farm diversification), *etc.* (Barret *et al.* 2008). However, the implied risk premium for such mitigation strategies is the opportunity cost (Barret *et al.* 2008) that is usually paid exclusively by farmers with little or no governmental support in developing countries. Especially for the case of risk mitigation in forests, Griess *et al.* (2012) and Neuner *et al.* (2015) present interesting studies where mix-stands forests show greater resistance to natural hazards and greater survival rates than mono-culture forests. According to Castro *et al.* (2015), crop diversification thus can be used as a passive, but efficient, risk mitigation strategy. In this study an economical analysis of on-farm crop diversification including costs of risk reducing inputs and off-farm diversification, which are among the most common risk mitigation techniques in family-farming (Mahul and Stutley (2010), is presented in the following chapters.

Risk coping refers to improving the management of the event in the aftermath, usually through disaster relief techniques coordinated by national and international government and non-government agencies. However, mobilizing resources in response to emergencies has largely proved ineffective (Barret *et al.* 2008). Former UN Secretary General Kofi Annan reported in October 2005 that flash appeals generated on average only 16% of the requested funds (Barret *et al.* 2008). Due to the high costs involved in emergency response, many governments in developing countries facilitate the use of market-based risk-transfer approaches, because they can reduce the need and scope for government interventions and thereby decrease the costs incurred by government in ex-post coping activities. The coverage of such approaches is still limited, as they usually cover the most affected ones and not all affected actors (Barret *et al.* 2008).

Risk avoidance, also known as risk prevention, is the fourth approach named by the Agricultural Risk Management Team (World Bank, 2011. p.4), however the discussion is limited to alternative sources of rural employment, which in the case of developing countries is almost non-existant. Perhaps active relocation of farmers producing in risky areas has potential as a risk management technique and would arguably incur less costs than the risk coping techniques mentioned above. Thus, thorough spatial tools assessing agricultural risk might play a role as decision-support-systems for policy makers considering relocation of farmers as a management option. Section 3.3 presents a spatial and temporal statistical approach, which uses remote sensing information on land use and environmental hazards as inputs, to economically quantify the impact of environmental damage at different geographical locations.

Protecting rural households against uninsured risks is an area in need of greater policy attention (World Bank, 2008 p90). In farm economic sectors, there is a strong case for public policy support to search for and test technological and institutional innovations that reduce the costs and risks of doing business (World Bank, 2008 p145). Due to the potentially high benefits that risk transfer and risk avoidance have if implemented effectively, compared to the benefits of risk coping or risk mitigation techniques, the focus of this chapter is to explore current techniques that intend to improve directly or indirectly our knowledge of risk transfer and risk avoidance. In reality, however, all available techniques to assess and manage risk should be implemented to reach a more efficient use of resources that will hopefully lead to improving the livelihood of rural households and halt deforestation.

Risk transfer, commonly used in non-farm economic sectors, shifts potential financial consequences of particular risks from one party to another with mechanisms such as financial and insurance contracts. Their use in subsistence agriculture, unfortunately, is much less widespread because family-farmers are typically asset-poor landholders who rarely have documented credit histories (CGAP, 2006), and who can have difficultly pledging assets or future cash flows to obtain loans or appropriated insurance coverage. When other factors inherent to agricultural production are considered, such as greater geographical dispersion of production, lower population densities, the generally lower quality of infrastructure and the seasonality and often high variability of rural production activities (World Bank, 2008, p143), then the potential financial and insurance contracts with family-farmers become even less interesting to financial and insurance service providers due to higher transaction costs and risks. Therefore, access to traditional transfer mechanisms at the rural-level tends only to be available to commercial agriculture - larger landholders and non-family farming corporations (Deininger and Byerlee, 2011).

Within this framework, microfinance has emerged as a realistic alternative to traditional mechanisms, because the requirements for lending/covering are better tailored to the possibilities of family-farmers. For example, microfinance may ease lending requirements in the absence of a borrower's credit history (CGAP, 2006). Still, microfinance institutions (MFIs) must charge relatively high interest rates to cover the administrative costs of handling small transactions for dispersed populations (MBB, 2005), and thus many traditional financial service providers still view microfinance as unprofitable (Das, 2010). In spite of this, the World Bank (2008, p145) argues that innovation will permit the microfinance movement to partially fill the agricultural void. For example, innovation in information technologies like mobile banking could be one of the major breakthroughs in extending outreach to poor customers (CGAP, 2006), and could make financial inclusion through microfinance profitable for formal financial institutions (Das, 2010).

Another technique which allows users to transfer risk to international markets is insurance. Similar to microfinance, agricultural micro-insurance has shown greater flexibility and accessibility than traditional crop insurance, because the latter is difficult to deliver in rural smallholder economies due to the huge administrative costs of yield estimation surveys (Roy, 2010; GFDRR, 2011). In regions prone to floods or droughts, micro-insurance has shown considerable success with the weather-index approach, which involves lower administrative costs and is technically less complex than traditional crop insurance. Still, the approach might mismatch actual loss and insurance indemnity, because it requires reliable, timely, and high quality data from weather station networks (GFDRR, 2011), which is not always available in developing countries. Although micro-insurance has already proved to have advantages over traditional crop insurance, the approach is still under development and so far has only been applied to droughts, floods and extreme temperatures (World Bank, 2011. p.6). Other increasing damages like fires or plagues are not yet considered. However, approaches developed to understand the spatial and temporal impact of fires may help to better understand the hazard and develop insurance policies intended to protect fire-affected family-farmers.

2.1 Current mathematical approaches to quantify risks in PES and REDD projects

Many REDD+ projects are modeled after PES schemes (Fortmann, 2014). Since its initial introduction to the agenda of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992 REDD has gained increasing recognition, although concerns about ensuring that real and additional reductions in emissions are made remain an issue. To assist developing countries to implement REDD activities, the Forest Carbon Partnership Facility (FCPF) was launched through the World Bank in 2008 to engage countries and direct funds to successfully initiate REDD projects (Fortmann, 2014).

While the discussion about REDD has been driven mainly by the UNFCCC, the World Bank created the FCPF to implement REDD activities mainly in tropical countries. It is funded by 16 financial contributors, including various countries and environmental organizations, who have pledged an estimated US$447 million. Of this, approximately US$230 million goes towards the Readiness Fund and US$205 million to the Carbon Fund (FCPF, 2012). The Carbon Fund, which became operational in May 2011, is the main mechanism for payments for verified emissions reductions in REDD countries (Fortmann, 2014).
At present, there are essentially no ongoing annual financial streams from countries or the private sector for payments to avoid deforestation. Some countries have provided funds to the World Bank FCPF, or other institutions, but these resources are typically one-time donations, not annual funding (Fortmann, 2014). However, there are already examples of private voluntary initiatives for carbon sequestration that allow the purchase of carbon credits generated through REDD activities (UNEP 2011), such as the Verified Carbon Standard (VCS) or the efforts of individual Non-Governmental Organizations (NGOs), like The Nature Conservancy. It is worth noting that efforts to operationalize REDD accounting, such as those by the Verified Carbon Standard, may ultimately enable REDD credits to be included in compliance schemes (Fortmann, 2014).

Since the early days of the Kyoto Protocol there has been debate about the permanence of forest carbon related emission reductions and greenhouse gas GHG removals (Trines 2008, Murray *et al.*, 2007). Forest carbon is considered particularly vulnerable because emission reductions and removals could be reversed, either by natural events (fires, droughts, floods) or due to failure of a project or policy to control the drivers, underlying causes and agents of deforestation (Seifert-Granzin, 2011). The discussion has led to a situation in which GHG removals due to afforestation and reforestation (AR) activities under the CDM can only generate temporary credits or are excluded from compliance markets altogether (as in the case of the European Union Emissions Trading System). However, voluntary carbon markets accept REDD+ and AR credits generated within a comprehensive risk accounting and monitoring framework (Seifert-Granzin, 2011). In Cancun in 2010, the UNFCCC decided that developing countries should develop and provide “robust and transparent national forest monitoring systems for the monitoring and reporting of REDD+ activities” (FONAFIFO *et al.* 2012; UNFCCC, 2011).

A very interesting example of how risk analysis of forest carbon projects is carried out is the popular[1] Voluntary Carbon Standard (VCS), which was used for more than a third of all credits traded in the voluntary market in 2009 (Hamilton *et al.* 2010, Jagger *et al.* 2010) and is used to compute "non-permanence risk[2] and monitoring analysis" of potential projects. The methodology is used to determine which AFOLU project proposals fulfill the minimum risk assessment/mitigation requirements and to compute the number of buffer credits to be set aside to cover such risks (VCS, 2008, 2010). AFOLU projects considered by VCS are: afforestation, reforestation and revegetation (ARR); agricultural land management (ALM); improved forest management (IFM) and reducing emissions from deforestation (RED). In general, the VCS non-permanence risk assessment of all AFOLU projects must be conducted in two steps:

- Risk factor analysis (project, economic, regulatory, social and natural disturbance risks, see Fig. 2.1). Each factor is classified as either unacceptably high/fail, high, medium or low.
- Overall non-permanence risk rating and buffer determination.

Calculating the natural disturbance risk in VCS is based on likelihood[3], *i.e.* the inverse of the average historical number of events occurring in the project area over the past (VCS, 2012 p.14), and significance (*i.e.* the average loss of carbon stocks of such events). All project proposals with evidence of significant natural risks, *i.e.* risk affecting more than 5% of the project area occurring over the past, are considered for further overall Non-Permanence Risk Analysis, except for those proposals with evidence of catastrophic loss (70% to 100% loss of carbon stocks) with a time interval of one destructive event in less than 10 years (see VCS, 2012, classification Table 2.1), which would be classified as unacceptably high/fail. However, if the time interval of such a catastrophic event was greater than 10 years, the project could still be considered for further risk analysis (VCS, 2008, 2012). In the original

[1]Recent market surveys clearly point to a preference among buyers and investors for projects validated under the VCS, as it offers the most comprehensive standard, covering all relevant Agriculture, Forestry and Other Land Use (AFOLU) activities, and is based on the Intergovernmental Panel on Climate Change (IPCC) guidelines (Seifert-Granzin, 2011; Merger *et al.* 2011)

[2]In AFOLU projects, the permanence of emission reductions can be at risk due to various factors. These factors determine the level of buffer credits needed to be set aside to mitigate risks (WCS, 2012)

[3]The likelihood and significance of events is estimated based on historical records, probabilities, remote sensing data, peer-reviewed scientific literature, and/or documented local knowledge, such as survey data from the project (VCS, 2012; Shoch *et al.* 2011)

Table 2.1: Non-Permanence Risk Rating Table for all AFOLU Projects. Source: VCS (2012, p.14)

Natural Risks					
	$< 10yr$	$10yr \leq TI < 25yr$	$25yr \leq TI < 50yr$	$50yr \leq TI < 100yr$	$100yr \leq$
Significance	Score				
Catastrophic 70% $\leq$ loss of carbon stocks	F	30	20	5	0
Devastating 50% $\leq$ loss of carbon stocks $<$ 70%	30	20	5	2	0
Major 25% $\leq$ loss of carbon stocks $<$ 50%	20	5	2	1	0
Minor 5% $\leq$ loss of carbon stocks $<$ 25%	5	2	1	1	0
Insignificant loss of carbon stocks $<$ 5%	2	1	1	0	0
No loss	0	0	0	0	0
LS Score					
Mitigation (M)					
Prevention measures applicable to the risk factor are implemented					0.50
Project proponent has proven history of effectively containing natural risk					0.50
Both of the above = 0.50 x 0.50					0.25
None of the above					1
Score for each natural risk applicable to the project = LS x M					
Fire (F)					
Pest and disease outbreaks (PD)					
Extreme weather (W)					
Geological risk (G)					
Other natural risks (ON)					
Total Natural Risk Score = F + PD + W + G + ON					

Where yr means year, TI is time interval between damaging events and F means that the project has an unacceptable high risk and therefore fails, see section 2.1.

*Instead of *time interval between events*, the word *Likelihood* is used by VCS (2012. Table 10) although likelihood should not have units of time as it is a probability value.

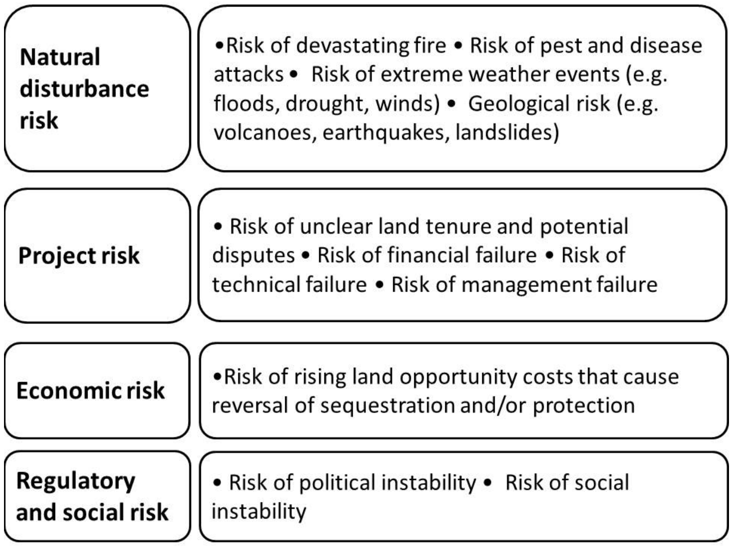

Figure 2.1: Non-permanence risk factors that shall be assessed for all AFOLU project types. Source: VCS (2008)

VCS document the word *likelihood* (VCS, 2012. Table 10) is used instead of the here used *time interval between events*. The term *likelihood* is misleading because it is defined by VCS as the historical average number of times the event has occurred in the project area VCS (2012 p.14), so according to their own terminology likelihood should not be expressed in units of years as it is done in their Table 10. Additionally, in risk analysis the likelihood is usually defined as the hypothetical probability that an event that has already occurred would yield a specific outcome (Weisstein, E.W. 2015), so likelihood has no units. Therefore, for this study, the term *time interval between events* is used instead of *likelihood*, and the later is only used when a probability outcome is discussed.

As already mentioned, validation and verification of non-permanence risk are almost totally absent in PES and conservation incentive programs (FONAFIFO *et al.* p.36, 2012). Therefore, a deeper analysis of the VCS non-permanence risk classification methodology becomes relevant because it is popular, *i.e.* it was used by more than a third of all credits traded in the voluntary market in 2009 (Hamilton *et al.* 2010, Jagger *et al.* 2010), and because other programs may use VCS methodology as a reference starting point to make their own analyses. Thus, potential changes proposed in the following chapters of this study may hopefully improve VCS and other methodologies as well.

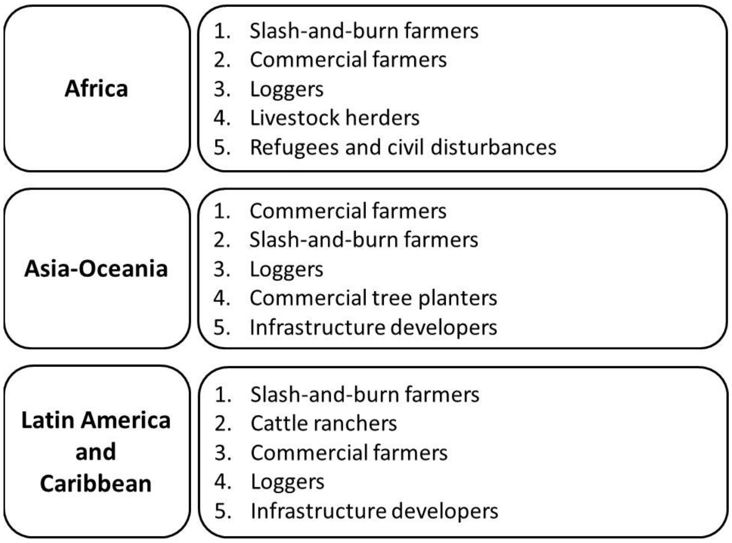

Figure 2.2: Most important agents of deforestation, degradation and fragmentation. Source; FAO Forestry Department, 2007.

Although the VCS classification in Table 2.1 offers a structured classification of risks, it misses valuable information (like the probability of occurrence). Because it is clearly not the same to have a risk of 70% farm damage from fire in the next 25 years, with a 1% probability of occurrence than to have a risk of the same level of damage in the same time-frame with 95% occurrence probability. Although not included in the VCS non-permanence risk methodology of AFOLU projects, fat-tailed risks (Extreme Value Analysis) are also important to consider, particularly for cases with forest fires where the occurrence of a low probability but highly destructive event might result in more forest area being destroyed in one event, than in the previous hundred events (Fortmann *et al.* 2014). Because these types of risks are not usually accounted for, Cooley et al. (2012) claim that non-permanence risks of such projects maybe be substantially underestimated. Although several distribution functions may be used to compute the occurrence probability, such as the Generalized Extreme Value or the Generalized Pareto (Klüppelberg *et al.* 2014b), binomial and Poisson distribution are the basis for extreme value statistics (Fasen *et al.* 2014). Without loss of generality let us use the binomial probability as an example to compute occurrence probability due to its simple and intuitive approach.

To compute the occurrence probability of damages caused by fires in farms, let D be the percentage of farm damage due to fire, and X be a Bernoulli random variable which takes value 1 with success probability p (if the next fire damage is $\geq D$) and value 0 with failure probability $q = 1 - p$ (if the damage is $< D$). Thus its probability function can be expressed as

$$P(X = k) = f(k; p) = p^k (1 - p)^{1-k}, \quad k \in \{0, 1\}$$

If $X_1, ..., X_n$ are independent and identically distributed Bernoulli random variables with success probability p, then $Y = \sum_{i=1}^{n} X_i$ follows a Binomial distribution $\sim B(n, p)$. In this case, the probability of getting exactly k successes in n trials is given by the probability of occurrence:

$$P(Y = k) = f(k; n, p) = \binom{n}{k} p^k (1 - p)^{n-k}, \tag{2.1}$$

where $k = 0, 1, 2, ..., n$ and $\binom{n}{k} = \frac{n!}{k!(n-k)!}$.

Following the VCS' classification in Table 2.1 to determine the risk of, for example, an AFOLU project in a farm that in the last 100 years had 10 catastrophic fires, each with 70% or more loss of carbon stocks *i.e.* $70 \leq D$, we find that the project is viable and it is classified as having a total risk of 30 if no mitigation strategy is put in place. However, in the VCS' table and in their methodology the occurrence of catastrophic events is not mentioned. Let us suppose that we want our farm to be part of an AFOLU project for the next 10 years. Therefore we can compute the probability of occurrence of a catastrophic fire damaging more than 70% of our farm within the next 10 years by using eq. 2.1 and computing out of the historical records that $p = 10/100 = 0.1$:

$$P(Y = 1) = f(1; 10, 0.1) = \binom{10}{1} 0.1^1 (0.9)^9 = 0.387 \approx 39\%,$$

Thus, there is a 39% probability that before the projects ends an area of 70% or more has irreparable damage[4] and even the buffer risk zone might be damaged[5] due to fire. For further analysis, let us consider a complete example of proposed AFOLU project located in Brazil, in a region with a recent history of fire events, *e.g.* at the border of the Amazonas rain forest. Historically, this region shows evidence of low fire activity, but in recent years due

[4]For destructive events, the carbon benefits generated by the destroyed part of the project are assumed to be completely lost. In this case, the number of years that loss continues equates to the remaining lifespan of the project (VCS, 2008).

[5]VCS certified projects have a lifespan between 10 to 100 years (VSC, 2008; Fortmann *et al.* 2014).

to the conversion of forests to more profitable land uses and the extended use of agricultural techniques like slash-and-burn, see Fig. 2.2, the region shows signs of deforestation and forest degradation (FAO Forestry Department, 2007). Statistical evidence obtained from satellite imagery (Acevedo *et al.* 2014) shows that there is a high likelihood of finding areas in this region having up to 8 devastating fires, each having burned approx 60% of the area within the last 12 years. Following the VCS risk rating system and terminology, the project has an average number of events $\frac{8\ events}{12\ years} = 0.66$ and a likelihood of $\frac{1}{0.66} = 1.5$ years between events. According to the VCS rating table, see Table 2.1, the project is classified as having a likelihood-and-significance LS of 30. Let us further assume that the project has no mitigation strategy at all (*i.e.* Mitigation M = 1). Thus, the score for fire risk applicable to the project (determined by LS $\times$ M) is 30. Without loss of generality, let us further assume that other natural risks (pest, extreme weather, geological risk, etc) present "no loss". Therefore the project has a "Total Natural Risk" of 30, which is still acceptable within the VCS framework because the single Total Natural Risk is less than 35 (VCS p.15-17, 2012).

Fat-tailed risks are also important to consider, particularly for cases with forest fires where the occurrence of a low probability but highly destructive event might result in more forest area being destroyed in one event, than in the previous hundred events (Fortmann *et al.* 2014). Because these types of risks are not usually accounted for, Cooley et al. (2012) claim that non-permanence risks of such projects maybe be substantially underestimated.
In case of *force majeure*[6] in REDD projects, additional rules for adjusting the baseline and the risk buffer apply, forcing the project to compensate the risks and losses caused by force majeure (Seifert-Granzin, 2011). However, as in the example above of catastrophic events (60% loss of carbon stocks) not only the project but also the buffer credits set aside to mitigate hazards may easily be at risk of total loss. In case of force majeure in PES projects, typically the agreement will be terminated and neither party is liable to the other party for non-performance (FONAFIFO *et al.* 2012). Thus, in the best case, the landowner (or whoever is responsible for the project) will be left with a terminated contract, the partial or non-covered project costs and serious natural-hazard damages to deal with. Moreover, not only the project may suffer irreparable damage, according to FAO Forestry Department (2007) it

[6]A force majeure event, also known as "an act of God" or "risk of innocent loss", is something that is out of the control of either party, such as a storm, wildfire, or war (Greiber, 2009; FONAFIFO *et al.* 2012)

is thought that about 25% of the total global carbon dioxide emissions result from deforestation and forest fires. Such fires are a key threat that could undermine attempts to implement restoration initiatives underway in the world's deforested or degraded forest regions (WWF, 2004). Even worse, the reputation of such projects is at risk and the low effectiveness of forest carbon sequestration could force the international community to avoid financing forest carbon projects at all.

When mitigation strategies (*e.g.* best-practice fire prevention measures) such as fuel removal, suppression systems, prescribed-fires, fire breaks, fire detection systems and fire fighting equipment are implemented in the project, (VCS, 2010, 2012), VCS penalizes less strongly the "Natural Risk", see Table 2.1. In the above mentioned example, the score for fire risk applicable to the project will be reduced from 30 to $0.50 \times 30 = 15$ if such measures are implemented, increasing thus the overall chances for the project proposal to be accepted.
While mitigation strategies such as fire detection technology (aerial spotting, satellites, communication technology) and fuel removal techniques have shown to improve early detection and effective mitigation (Moghaddas and Craggs 2007), fire suppression techniques have had mixed results and have been accused of leading to greater fire outbreaks in Europe (Moreira *et al.*. 2011) and USA (Stephens and Ruth 2005; Keane *et al.* 2008). Moreover, planed or unplanned fires especially under extreme weather conditions (Gould *et al.* 2007; Moritz *et al.*. 2010) can reach substantial sizes despite sophisticated suppression systems (Gill *et al.* 2013). If fire crews are available, fire-fighters may arrive when fire is already too intense, the perimeter too extensive, and its rate of growth too great for immediate containment (Gill 2008: chapter 1). Other common technique is the use of prescribed-fires, but this technique is largely debated because of the interactions between prescribed burns and unplanned fires. Thus, prescribed burning is forbidden in Greece (Williams *et al.*. 2011) and Namibia (Goldammer *et al.* 2002) while Gillon (1983) discussed choosing the most adequate burning regime in tropical savannas. Therefore, the effectiveness of prescribed burning in minimizing wildfire is contingent on land use. For example, it would be inappropriate in a farmer's improved pastures or crops, useful in some forests for protecting wood products and biodiversity and impossible to carry out in some environments (Gill, 2005; Gill *et al.* 2013). Another popular technique to mitigate forest fires is the use of fuel-free breaks (fire breaks), however determination of effective width is a serious question given that spot fires from lofted firebrands can be a problem (Gill and Stephens 2009).

Biodiversity is another mitigation strategy that has shown a hedge effect against natural hazards (Griess *et al.* 2012; Gill *et al.* 2013). Griess *et al.* (2012) present statistical evidence supporting the theory that short-term benefits achieved by the homogenization of ecosystems, as in mono-culture plantations, and the resulting loss of biodiversity are overshadowed by the consequent reduction in the ability of forest stands to cope with natural risks. Although biodiversity is not included in the VCS rating system of "Natural risks", it is contemplated indirectly in the risk of management failure ("project risk factor", see Table 2.1) if the project manager decides to afforest or reforest with tree species not resistant to regional natural hazards. Some project guidelines establish that a maximum of 25% of the tree varieties can be foreign. In many cases, managers could opt for fast-growing and highly productive (and therefore high takers of carbon emissions) foreign species like *Pinus radiata* and *Eucalyptus*. The establishment of fast-growing non-native tree species is an often-cited example, because they might not only replace more biodiversity-rich habitat but could also have implications for the water table, thus increasing the sensitivity of the system to drought and contribute to wider problems such as acidification, disease transmission or fire risk (Van de Sand, 2012; Smith *et al.* 2013). The experience of Chile with such species is negative, as fires have increased in such plantations since their introduction and currently devastating fires are the rule and not the exception (Acevedo and Knoke, 2011). According to Pena-Fernandez and Valenzuela-Palma (2005) the occurrence of forest fires has increased almost exponentially in Chile from 1973 to present. This increase is closely related to the increase in surface area planted with highly flammable species: Pinus radiata and Eucalyptus globulus. Indeed, the National Forestry Corporation of Chile (CONAF) has detailed statistics of wildfires greater than 200 hectares since 1973 until today (CONAF, 2014), analysis of the data shows that 25% of all historical devastating forest fires (including natural forest and plantations) were in Pinus and Eucalyptus plantations, despite the total area of such monoculture plantations representing less than 10% of the total forest cover in Chile. It is not rare for Eucalyptus plantations to be registered in PES schemes (Rival, 2013), which must be adequately addressed to avoid greater ecological damage.

Our knowledge of the wildfires and how to minimize them is growing, but is also limited. Scientifically, the ability to predict fire properties and their interrelationships is partial; quantifying the probability of asset-negative events and regimes is still very difficult, yet critical, and assessing the efficacy of minimizing actions is usually relative rather than absolute (Gill *et al.* 2013). Furthermore, there is a residual probability of disastrous fire events even after a variety of measures have been introduced to counter it. Thus, even if best-practice fire prevention measures are included in AFOLU projects, the scientific evidence shows that a high risk of devastating forest fires may remain high, contrary to what VCS assesses in its risk ranking system (VCS, 2008, 2010).

Although the example mentioned above highlights weak points of the VCS risk system that could be improved, at least the system involves rigorous validation and verification according to Kyoto (CDM standards). This is unfortunately not the case for national PES and conservation incentive programs, where such validation and verification is almost totally absent (FONAFIFO *et al.* p.36, 2012). Therefore, based on the results of this study a proposed improvement for the VCS risk rating system in Table 2.1 is presented and discussed in chapter 5.

Apart from buffer credits to counteract the damage generated by natural hazards in REDD, risk pooling and insurance are also popular techniques in PES and REDD projects (Angelsen, 2008; Fortmann *et al.* 2014). Risk pooling is a variation of project credit buffers where several projects maintain a joint credit buffer, thus minimizing the risk of damages occurring simultaneously. The individual project buffers can be smaller than non-pooled project credit buffers (Angelsen, 2008). For family-farmers joining PES or REDD projects, risk pooling could become very significant. Insurance could be considered as is an advanced version of risk pooling, where a third-party insurer selects a portfolio of insured projects in a way that several growth regions and ecosystems are covered (Subak 2003). However, as discussed above, insurance for family-farmers is not typical in Latin America and other developing regions due to high transactions costs.

2.1.1 Relevance of fire in environmental risk assessment of PES and REDD projects

Recent decades have been marked by rapid changes in fire regimes as a result of significant shifts in the human population (Pausas and Keeley, 2009). The most common socioeconomic factors contributing to fire regime changes are activities related to agriculture and fire suppression (Pausas and Keeley, 2009). The latter is particularly relevant in the western US due to a combination of fire-suppression policies, fire conductive weather conditions and low ecosystem resilience (Moritz, 2005). The former is currently more relevant in tropical areas due to policies that promote the conversion of original forest cover to other land uses (Aragão and Shimabukuro, 2010).

Most of the area of Brazil, Colombia and Ecuador is labelled by Pivello (2011) as "fire-sensitive". The Cerrado area of Brazil is notable in that it is considered to be "fire-dependent and/or fire-influenced" (Pivello, 2011). This region has been prone to natural fires caused by lightning strikes. The combination of a marked dry season and highly flammable vegetation biomass has contributed to the system's co-evolution with fire (Miranda *et al.* 2002; Simon *et al.* 2009). The presence of fire in the three countries is also closely tied to anthropogenic activity (Pausas and Keeley, 2009). Paleontological evidence shows that indigenous people used fire throughout this region as a regular part of their agricultural practice (Bush *et al.* 2008). The Amazonian rain forest, in contrast, generally does not burn naturally owing to the moist climate. However, in a broad literature review, Pivello (2011) showed that wildfires can occur in the Amazon, mostly due to a mix of drought conditions and human activities. Dry conditions are often correlated with El Niño events, and humans have burned the Amazon as part of slash-and-burn agriculture practices for millennia (Fearnside 2005).

Ecologically, natural wildfires in the Cerrado serve to maintain the savannah system and have influenced the species composition to favour those that re-grow quickly following fires or have a high proportion of below-ground biomass (see Pivello 2011 and references therein). In the Amazonian forests, traditional slash-and-burn practices by indigenous groups resulted in soils with a high charcoal content. The newly-opened plots were cultivated for a number of years, and then left to regrow (Pivello, 2011). Although modern slash-and-burn practices have been shown to result in net deforestation, traditional burning activities were highly controlled and planned carefully to ensure the continued regeneration of forest resources (Pivello, 2011). In present times, low-intensity fires in El Niño years have been shown to contribute up to 5% of annual anthropogenic carbon emissions (Nepstad *et al.* 1999), although this may be higher when delayed tree mortality up to three years post-fire is taken into account (Barlow *et al.* 2003).

Recently fire frequency and intensity increased in South America. The chief culprit is suspected to be climate change. As dry seasons get longer and drier, drought conditions and low humidity create opportunities for natural fire ignitions or for fires lit intentionally as part of agricultural management practices to more easily burn out of control (Nepstad *et al.* 1999).
The effects of fires depend very much on their intensity and the interval

between subsequent fires (Hoffmann *et al.* 2009; Balch *et al.* 2008). Experimental work, based on inventory measurements of 50-hectare treatment plots that manipulated fire frequency and intensity along the forest-savanna boundary in the southeastern Amazon, showed that cumulative tree and liana mortality rates increased with consecutive annual fires. Results showed that three annual 50-hectare burns resulted in moderate increases in mortality compared with once-burned plots (Balch *et al.* 2008; 2011). Balch *et al.* (2008; 2011) showed that repeated fires can reduce soil nutrients and affect tree growth, which is important for land owners whose livelihoods depend on soil fertility, either for crops or plantations. Fires can have enormous economic consequences, as demonstrated in an analysis of social capital and fire contagion by Simmons *et al.* (2004).

In tropical forests, once an area is deforested it is highly likely that highly frequent management fires will follow, particularly in pastures (Balch *et al.* 2010). Thus, repeated fires, including slash-and-burn fires, take place over a several-year period after forest felling (Balch *et al.* 2010). Although fires ignited for management techniques are not intended to be spread further than the area under management, some may become uncontrolled and spread over thousands of hectares due to severe weather conditions or lack of proper mechanisms to suppress them.

2.1.2 Current methodologies for assessing fire risk

A thorough classification of existing spatial simulation models of fire and vegetation dynamics was presented in Keane *et al.* (2004). Using the 44 best known models, the classification was based on what was modeled: vegetation succession, fire ignition, fire spread and fire effects. However, none of the models presented included the spatial detail needed to accurately model the potential effects of fire on highly valued resources (Calkin *et al.* 2011, p. 53). Moreover, the outputs of these models were difficult to downscale to address forest- and project-scale issues (Calkin *et al.* 2011, p. 53).

Other authors have focused on developing summaries of wildfire activity rather than simulating the events (see for example Malamud *et al.* 2005, Moritz *et al.* 2005, Keeley *et al.* 2009). Unfortunately, temporal summaries that involve the separate description and/or modeling of each spatial subregion often depend heavily on the rather arbitrarily chosen boundaries of the spatial regions, and parametric summaries suffer the further disadvantage of reliance on model assumptions (Nichols *et al.*, 2011). To assess the US Burning Index (BI), an index used by fire departments in 90% of all US counties, Peng *et al.* (2005) used a space-time conditional-intensity point process based on kernel smoothers and found that in the case of Los Angeles county wildfires BI does not perform substantially better than the space-time process. Using prototype point processes, Nichols *et al.* (2011) presented an approach that summarized and described wildfires using prototype point processes, which provided useful and easily interpretable summaries of central tendency. Particular advantages of prototypes are that they are entirely non-parametric and do not require that the underlying process be stationary or isotropic (Nichols *et al.* 2011). The selection of the prototype, however, does depend to some extent on the rather arbitrary choice of penalties in a multi-dimensional spike time distance function (Schoenberg and Tranbarger, 2008). Another disadvantage is that prototyping in multiple dimensions is computationally expensive, especially if there are several thousand data points to consider (Nichols *et al.* 2011).

To assess fire risk a semi-parametric model that uses kernel smoothing to assess the spatial intensity (number of events per km) is proposed and presented in section 3.3. Kernel smoothing shares most of the advantages of prototype point processes, such as the ability to work with highly non-stationary events, both in space and time, and does not require that the underlying process be isotropic (Baddeley *et al.* 2008, 2011). This is a major convenience in the case of wildfires in tropical regions, where certain locations and months are more prone to be ignited than others, and fires are strongly non-isotropic, since wildfires are more likely to spread in certain directions (for example, in the direction of prevailing winds (Pyne *et al.* 1996). The semi-parametric approach further explores a spatiotemporal dependence, found in all three tropical countries studied: Brazil, Colombia and Ecuador, to analyze the average time between events and their relationship to damage. Finally, a geographical representation of the damage per hectare at particular locations obtained using binomial proportions of the historical data.

2.2 Underestimation of market risks in land-use portfolio analysis

Traditional insurance and finance (also micro-insurance and micro-finance) have as a common denominator the need for borrowers to repay their loans to achieve a sustainable system where all actors may benefit. Yet, many current techniques to compute potential borrowers' returns or credit-quality still use methodologies not adapted to sectors having strong price volatility, asymmetrical information and fat-tails. Graham and Campbell (2001 and 2002), surveyed Chief Executive Officers (CEOs) of the largest U.S. corporations to determine how they estimate their cost of capital and what tools they use to make their financial decisions, and found that 74% used the Capital Asset Pricing Model (CAPM), a model that assumes symmetrical distribution of returns and uses variance as measurement of risk. Bancel and Mittoo (2004) performed a similar survey in 16 European countries finding that 75% CEOs have a target debt-to-equity ratio computed with either the CAPM (60%) or similar models (Mandelbrot and Hudson, 2004). Even after the 2007-2008 global financial crisis, where critics argued that credit rating agencies and investors failed to accurately price the risk involved with financial products (The White House, 2008), many firms' credit-quality is still being evaluated using cash flow's variance as a measure of leverage's risk (Mittoo and Zhang, Z. 2010).

These approaches may generate overoptimism about the investor's return or credit risk and, in the case of agriculture, might motivate farmers to borrow money that they would not be able to repay as family-farmers difficultly pledge assets or future cash flows as collaterals to obtain loans and insurance coverage. The situation only worsens when environmental risks are not properly addressed to measure their potential impact on the investment. An approach to integrate market and environmental risks to optimize farmers income is discussed in section 3.5.

Computing returns of farmers is also a necessary step within the REDD+ framework, as fair prices of PES must be paid to achieve a sustainable system where first, family-farmers do not have the need to quit a contract due to low income and, second, where deforestation is achieved, *i.e.* the amount of financial compensation necessary to avoid conversion of forest to agricultural use. Therefore, halting global deforestation is inherently linked to economic considerations at both the national and household levels, because most endangered primary forests are located in developing countries where the forest is an important economic commodity (Mertz *et al.* 2005; Knoke *et al.* 2009). In this context, forests represent both a source of income for companies in the primary sector and potential agricultural land for rural households. This naturally works counter to recommendations from studies such as the widely known Stern Report which concluded that reducing deforestation is one of the most powerful pathways to slowing global climate change (Stern, 2008). From a macroeconomic perspective, the immediate reduction of carbon emissions achieved by halting deforestation is highly cost-effective (Eliasch, 2008).

One relevant question that emerges from this discussion is whether adequate international financing mechanisms are in place to provide the necessary economic incentives to convince landowners and farmers to leave their forest-land intact (Peskett *et al.* 2011). With the aim of avoiding deforestation, two types of regimes have emerged: a policy and a voluntary-driven one. The former is currently being established under the United Nations Framework Convention on Climate Change (UNFCC). Up to now, it is unclear whether only Green Climate Funds will be a source for financing this regime or if a link to international carbon markets will be established (Pettenella and Brotto, 2012; Isenberg and Potvin, 2010). The second regime is a market for the voluntary compensation of carbon footprints, for example, carbon credits generated by companies via various project types (Diaz *et al.* 2011). Among the possible project types are forest-related activities in different countries which are aimed at REDD+ (Reducing Emissions from Degradation and Deforestation). According to the FAO (2011), over the last few years, forestry has become a critical part of the international climate change agenda. Several countries recognize the potential impact of REDD+ and have provided financial resources to establish pilot activities (4 out of 16 projects are located in Latin America). Yet, the sustainability of such projects is dependent not only on stable financial sources (notwithstanding whether they are carbon market-based or fund-based) but also on effective forest governance, secure forest carbon tenure and equitable benefit sharing, among other things (FAO, 2011), and must also consider food production (Knoke *et al.* 2012).

2.2.1 Land-use portfolio under market risk

When considering the risks of land-use investments, farmers are most concerned with low prices, when income is too low to provide for the operational needs of the farm (IFAD *et al.* 2011). Another source of risk for producers is the high food-price variability that, out of all non-fuel commodities, shows the highest ever historical volatility over a decade (1971-1980) (IMF, 2006), with the second highest peak between 2008 and 2009 (IMF, 2011). Those peaks from the last forty years benefited neither consumers, nor small to medium producers, as input prices for agriculture increased at the same time, thus canceling out any potential for higher returns for producers (FAO, 2009). Final consumers, however, have an advantage thanks to a greater geographical diversification of production which has reduced the sensitivity of consumer prices to supply shocks (FAO, 2004). Although more limited, family-farmers can partially hedge their investments against market risk through land-use diversification. The first authors to study the diversification effects when using commodities were Mills and Hoover (1982), who used portfolio theory to explain the use of forest as a risk diversifier in spite of its comparatively low economic-yield. Other authors (Benítez, 2006; Knoke *et al.* 2009, Knoke *et al.* 2011) have also studied the benefits of land-use diversification in developing economies. In this section, the approach of choosing land-use portfolio weights that maximize returns and minimize risk is followed, but using a model that departs from previous ones by capturing asymmetry and heavy tails in the distribution of commodity prices, *i.e.* a model that represents more accurately the real market risk situation of developing countries.

Let us consider n risky commodities that a family-farmer is considering to produce, every commodity return is defined as

$$r_{i,t} = \frac{price_{i,t}}{ton} \times prod_{i,t} - \frac{cost_{i,t}}{ha}, \tag{2.2}$$

where $prod_{i,t}$ is the productivity of the commodity in $\frac{ton}{ha}$ and $cost_{i,t}$ its production costs. Thus, the return column vector of all commodities considered is $\mathbf{r_t} = (r_{1,t}, ..., r_{n,t})'$ and it is assumed to be governed by a joint continuous cumulative, although not necessarily Gaussian, probability distribution function $F(\cdot)$. Further, let the column vector $\boldsymbol{\alpha_t} = (\alpha_{1,t}, ..., \alpha_{n,t})'$ be defined as the farmer's land proportions (portfolio weights) allocated to the considered commodities, with the constraint that the weights at any moment sum to one. As an additional constraint we consider the case where a commodity can be produced only in a limited portion of the land due to environmental or soil constraints, this is the case for instance of some crops that need specific soil nutrients and/or water regimes not available over the whole farm and rather restricted to some limited area. Thus for example $\sum_{i=1}^{n} \alpha_{i,t} = 1$ and $\alpha_{1,t} \leq C_{LU_1}$, where C_{LU_1} is the area constrain that the land use 1 has.

The concept of ordinal utility has been widely used as the basis on which portfolio theory is built, thus an investment can be ordered by an individual as better than, equal to, or worse than other alternative. To reflect this behavior several authors have used the approach of stochastic dominance, where a probability distribution over possible outcomes of an investment can be ranked as superior to the distribution of another investment. Moments are used to compare probability distributions to determine “dominance” and thus rank investments. Although portfolio theory has widely used the first two moments (mean and variance) several authors argue about the advantages of using the first fourth moments, such as capturing asymmetry and heavy tails in the distribution of returns. Therefore, conditional on the assumption that higher moments exist, the expected utility can then be represented as an increasing function of the mean and the skewness, and a decreasing function of the variance and the kurtosis of the portfolio return distribution (Jurczenko and Maillet, 2006).

Let W_t be the initial wealth of a family-farmer who is willing to allocate his land-use portfolio. Denote by $U(\cdot)$ a von Neumann-Morgenstern utility function, defined over his next-period wealth W_{t+1}, and assume it belongs to the family of fourth-order stochastic dominance D_4 (Jurczenko and Maillet, 2006) satisfying[7]:

$$D_4 = \{U | U^{(1)}(\cdot) > 0, U^{(2)}(\cdot) < 0, U^{(3)}(\cdot) > 0, U^{(4)}(\cdot) < 0\}$$

where $U^{(i)}(\cdot)$ is a derivative of order i of $U(\cdot)$. Without loss of generality, the beginning-of-period wealth W_t is set equal to one (Jondeau *et al.* 2007) and the next-period family-farmer's wealth is defined as $W_{t+1} := (\boldsymbol{\alpha}_t' \mathbf{r_{t+1}}) W_t = \boldsymbol{\alpha}_t' \mathbf{r_{t+1}}$, where, in the most general case, a utility function is used as a proxy for an investor's expected payoff preferences $E[U(W_{t+1})] = \int_{-\infty}^{\infty} U(W_{t+1})\, dF(W_{t+1})$. Specifically, a family-farmer allocates his next period portfolio by maximizing the expected utility of his wealth return:

$$\begin{aligned} \max_{\boldsymbol{\alpha}} \quad & E[U(\boldsymbol{\alpha}_\mathbf{t}' \mathbf{r_{t+1}})] \\ s.t. \quad & \boldsymbol{\alpha' e} = 1 \end{aligned} \tag{2.3}$$

Where e is a $(n, 1)$ vector of ones. Finally, the return of the farmer's optimal land-use portfolio is determined by

$$\mathbf{r_{p,t+1}}(\boldsymbol{\alpha}_\mathbf{t}) = \boldsymbol{\alpha}_\mathbf{t}' \mathbf{r_{t+1}}. \tag{2.4}$$

2.2.2 Mean-Variance (MV) approach

Based on stochastic dominance of second order, the utility in MV starts with an exponential transformation of wealth, also known as Constant Absolute Risk Aversion (CARA):

$$U(W_{t+1}) = 1 - e^{-\lambda W_{t+1}} = 1 - e^{-\lambda (\boldsymbol{\alpha}_\mathbf{t}' \mathbf{r_{t+1}})}, \tag{2.5}$$

[7]There is no clear economic justification concerning the link between the expected utility function and moments higher than the fourth-order of the investment return distribution, that is using D_5 or higher (Jurczenko and Maillet, 2006)

where $\lambda \geq 0$ is the coefficient of absolute risk aversion and W_{t+1}, therefore $U(W_{t+1})$, is the value that the decision-maker wants to maximize. Risk-neutral investors are usually assumed to have a $\lambda \approx 0$, whereas risk-averse investors have $\lambda > 0$. Whenever a random variable X follows a normal distribution with mean m and variance v^2, the transformation e^X follows a log-normal distribution with expected value $E[e^X] = \int_{-\infty}^{\infty} e^X \, dF(X) = e^{m+\frac{1}{2}v^2}$. Hence, if the returns $\mathbf{r_t}$ are assumed to be normally distributed, equation (2.5) can be rewritten[8] as

$$E[-e^{-\lambda(\boldsymbol{\alpha}_{\mathbf{t}}'\mathbf{r}_{\mathbf{t+1}})}] = -e^{-\lambda(\mu_{p,t+1}-\frac{1}{2}\lambda\sigma^2_{p,t+1})}. \tag{2.6}$$

where $\mu_{p,t+1} = E[\mathbf{r_{p,t+1}}(\boldsymbol{\alpha}_\mathbf{t})] = E[\boldsymbol{\alpha}_{\mathbf{t}}'\mathbf{r}_{\mathbf{t+1}}] = \boldsymbol{\alpha}_{\mathbf{t}}'E[\mathbf{r}_{\mathbf{t+1}}] = \boldsymbol{\alpha}_{\boldsymbol{t}}'\boldsymbol{\mu}_{\boldsymbol{t+1}}$ is the land-use portfolio's expected return and the covariance $\sigma^2_{p,t+1} = E\big[\boldsymbol{\alpha}_{\boldsymbol{t}}'\boldsymbol{r}_{\boldsymbol{t+1}} - E[\boldsymbol{\alpha}_{\boldsymbol{t}}'\boldsymbol{r}_{\boldsymbol{t+1}}]\big]^2 = E\big[\boldsymbol{\alpha}_{\boldsymbol{t}}'(\mathbf{r}_{\mathbf{t+1}} - \boldsymbol{\mu}_{\boldsymbol{t+1}})\big]^2 = \boldsymbol{\alpha}_{\boldsymbol{t}}'E\big[\mathbf{r}_{\mathbf{t+1}} - \boldsymbol{\mu}_{\boldsymbol{t+1}}\big]^2\boldsymbol{\alpha}_{\boldsymbol{t}} = \boldsymbol{\alpha}_{\boldsymbol{t}}'cov_{t+1}\big(\mathbf{r}_{\mathbf{t+1}}, \mathbf{r}_{\mathbf{t+1}}\big) = \boldsymbol{\alpha}_{\boldsymbol{t}}' \cdot \boldsymbol{Cov}_{\boldsymbol{t+1}} \cdot \boldsymbol{\alpha}_{\boldsymbol{t}}$ is used as a measure of the commodities' market risk. Thus, maximizing $E[U(W_{t+1})]$ is equivalent to the optimization problem (Jondeau *et al.* 2007)

$$\begin{array}{ll} \max\limits_{\boldsymbol{\alpha}} & \boldsymbol{\alpha}_{\boldsymbol{t}}' \cdot \boldsymbol{\mu}_{\boldsymbol{t+1}} - \dfrac{1}{2}\lambda\big[\boldsymbol{\alpha}_{\boldsymbol{t}}' \cdot \boldsymbol{Cov}_{\boldsymbol{t+1}} \cdot \boldsymbol{\alpha}_{\boldsymbol{t}}\big] \\ s.t. & \boldsymbol{\alpha}'\boldsymbol{e} = 1 \end{array} \tag{2.7}$$

However, Mandelbrot (1963) showed that the frequency distribution of prices of typical commodities, hence of returns, does not follow a normal distribution. In addition to this, Fama (1965) demonstrated that variance is not an appropriate measure of risk, because it penalizes profits and losses symmetrically, and in the case of heavy tails or skewed distributions, undervalues market risk. Thus, in cases where prices are not normally distributed, wrong portfolio selection may occur when using the MV approach (Mandelbrot and Hudson, 2004).

2.2.3 Alternative market risk measures

Market, credit and operational risk are three measures nowadays acknowledged by the Basel Committee on Banking Supervision (BCBS). With respect

[8] Notice that maximizing the expected value of eq.(2.5) gives the same result as maximizing the expected value of $U(W_{t+1}) = -e^{-\lambda W_{t+1}}$ since the expected values of utility, contrary to the utility function itself, are to be interpreted as ordinal utility instead of cardinal utility. Thus, the sign of the expected utility values are of no significance

to market risk, the BCBS (1996) encourages financial institutions to use the comprehensive *Value-at-Risk (VaR)* measure. VaR is defined as the minimum potential loss that an investment portfolio could obtain over a given time horizon with a preset probability level α. One popular parametric approach for computing the next period VaR is presented by J.P. Morgan's *RiskMetrics* Group (1996), it applies to a multivariate portfolio under the assumption of normality (Garman, 1997) and uses historical return data for computation:

$$VaR_{\theta,t+1} = \mu_{p,t+1} - z_\theta \times \sigma_{p,t+1},$$

where $\mu_{p,t+1}$ is the land-use portfolio's expected gross return, $\sigma^2_{p,t+1}$ is the variance used as a measure of the commodities' market risk, and where $z_\theta = \Phi^{-1}(\theta)$ is the quantile for a probability of loss equal to θ. A common criticism is that VaR is not subadditive (Dowd, 2005), meaning that the VaR of a multivariate portfolio can be larger than the sum of the VaRs of its components (Klüppelberg and Stelzer, 2014). Moreover, in spite of VaR being a BCBS standard measure, some authors (BIS, 2000; Basak and Shapiro, 2001) argue that it fails to account for the risk of extreme losses. After all, VaR defines only the spread "to the left" of the mean as a measure of risk (Heusser, 2009), and most practitioners use either the historical simulation approach or the normal distribution function to compute VaR (Boudt *et al.* 2008). However, the huge and non-expected losses of financial institutions during the 2007-2008 global crisis provided first-hand evidence that standard VaR calculations seriously underestimate true market risk. In response, the BCBS (2009, 2011) supplemented the measure with a new requirement, the *Stressed VaR*, computed using a one-year observation period containing the worst-ever recorded losses. The Stressed VaR is now provided in addition to the most recent one-year observation period VaR. Although no particular approach for computing the VaR is favored, the BCBS requests model validation and backtesting to demonstrate that any assumptions made do not underestimate risk (BCBS, 2011), such us the assumption that returns follow symmetric distributions without heavy tails.

Out of several approaches for computing VaR, three categories are recognized as the most representative: historical simulation, semi-parametric and parametric models (Jondeau *et al.* 2007). Historical simulation is perhaps the simplest and most common approach for calculating VaR. As it makes no particular assumption about the distribution of returns, it is considered non-parametric, its extension for multivariate assets requires minimal additional work. Because a step function is used as an empirical distribution, its main drawback is that it may cause biased results, particularly in the tails of the distribution. As risk management is especially concerned with extreme observations, these limitations might be serious (Goorbergh and Vlaar, 1999; Boudt *et al.* 2008).

The leading alternative to historical simulation makes assumptions about how returns are distributed. The best known semi-parametric approach is based on Extreme Value Theory (EVT) and involves modeling the lower tail of the return's distribution (Embrechts and Klüppelberg, 1997). The method is more accurate than historical simulation, but requires large sample sizes, high-frequency data and filtering to obtain independent and identically distributed observations (Coles, 2001). It is also highly sensitive to the chosen threshold; selection of an optimal one remains a current research topic (Brodin and Klüppelberg, 2008). Extension to the multivariate case is much more complex, (Brodin and Klüppelberg, 2008), making it less popular than other methods.

With respect to parametric approaches, the most popular are *Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH).* GARCH comprise time series analyses that have been extensively studied and from which several models have been developed (Bollerslev, 1986). For the univariate case it is assumed that returns might be autocorrelated, that volatility follows a GARCH(1,1) model and that standardized returns $z_t = \frac{r_t - \mu_t(\theta)}{\sigma_t(\theta)}$ are governed by $g(z_t \mid \eta)$, where the shape vector η captures asymmetry and heavy tails of z_t (Jondeau and Rockinger, 2006). If g is not normal, a Student-t or a variation of it may be used instead (McNeil and Frey, 2000). For multivariate portfolios where a normal distribution is suitable, variations including Factor-GARCH, Orthogonal-GARCH and Flexible-GARCH apply. Outside of the normality assumption, however, several difficulties arise (Ledoit *et al.* 2003).

To cope with the shortcomings of MV and VaR, while at the same time maintaining their intuitive optimization framework, the model of higher moments proposed by Jurczenko and Maillet (2006) and further developed by Jondeau *et al.* (2007) and Heusser (2009) was used. In next chapter the model is presented and adapted for land use portfolios of developing countries. The main advantages of such an approach are that the model relaxes the normality assumption of returns and it is relatively easy to work with multivariate portfolios. Another advantage is that when returns are normally distributed the model converges to the MV, making it thus easier to compare between results from the MV and the higher moments. Although the model is not new it has not yet been applied in the literature to understand land use portfolios, making it an ideal candidate to improve upon the analysis of land use investments.

Chapter 3

Materials and methods

3.1 Study area: South America

According to The World Bank (2012), South America showed a growth in average GDP per capita from US$ 3258 in year 2000 to US$ 7483 in 2010, and the region is expected to growth more than 4% during the next years (IMF, 2011). The past growth is partially attributable to additional agricultural output during the period, which increased 35% in the case of industrial roundwood, 43% in cow milk production; and 66%, 92% and 132% in production of maize, sugar cane and soybeans respectively (table 3.1).

Table 3.1: Most productive agricultural commodities

Top crops	**Ecuador**		**Colombia**		**Brazil**		**S.America**	
	$\times 10^6$ton	(%)	$\times 10^6$ton	(%)	$\times 10^6$ton	(%)	$\times 10^6$ton	(%)
Sugar cane	8,3	(55)	20,3	(-42)	717,5	(119)	811,7	(97)
Soybeans	$\otimes$	$\otimes$	0,04	(40)	68,8	(110)	132,3	(131)
Maize	1,0	(61)	1,5	(27)	56,0	(76)	92,2	(66)
Oil Palm fruit	1.8	(34)	3,2	(30)	1,3	(>200)	$\otimes$	$\otimes$
Top livestock product								
Cow milk	5,7	(184)	7,5	(22)	31,6	(55)	64,4	(43)
Top forest product	$\times 10^6$ m^3	(%)	$\times 10^6$ m^3	(%)	$\times 10^6$ m^3	(%)	$\times 10^6$ton	(%)
Ind. Roundwood	1,8	(8)	2,4	(10)	128,4	(25)	196,1	(35)

Source: FAOSTAT 2010. Production in year 2010, along with change in % compared to year 2000. $\otimes$ means that the commodity is not a top productive one for the particular country or region.

3.1.1 Study subject: family-farmer

In developing countries with abundance of land, the most relevant stakeholders are family-farmers and non-family-farming corporations (Deininger *et al.,* 2011). In the case of Latin America, the FAO/BID (2007) conducted a survey in Brazil, Chile, Colombia, Ecuador, México and Nicaragua, and found that, on average, family-farmers hold 12 hectares per family, while the average farm held by non-family-farming (corporations) is 141 hectares. In the case of Brazil, however, some of these companies control over 300.000 hectares of soybeans or sugarcane (Deininger and Byerlee, 2011). In spite of the relatively small share of agricultural land they hold, South American family-farmers produce large shares of the national consumption totals for many staple food products in the region, *e.g.*, 49% of maize and 52% of milk in Brazil, 70% of maize in Ecuador, and more than 40% of maize and milk in Chile (FAO/BID, 2007; Schejtman, 2008).

Notwithstanding their substantial involvement in national markets, the number of rural households decreased in recent years due mostly to rural-urban migration. Currently only 21% of the Latin American population lives in rural areas (The World Bank, 2012), and a large proportion of these declare family-farming as their main economic activity, with figures ranging from 49% in Chile to 71% in Perú (Modrego *et al.,* 2006; Berdegué and Fuentealba, 2011). Arguably one of the principal reasons that forces families to migrate to the cities is that 53% of rural households in the region live below the poverty line (ECLAC, 2010), with an estimated income of US $1,25 per day per capita (IFAD *et al.,* 2011).

The World Bank (2007), Lipton (2009) and Loayza and Raddatz (2010) argue about the potential impact that family-farming growth has on poverty reduction, and the important role that governments have on generating policies addressing this issue. Because of the high rates of forest conversion to agriculture, in order to improve returns (section 3.1.2), and because small farmers are often the first to expand the agricultural frontier (Deininger and Byerlee, 2011), family-farmers become an interesting target for any financial incentives intended to maintain current land uses, halt further deforestation and reduce rural household poverty. For the analysis, and for the purposes of comparison with previous studies, only family-farmers will be considered.

3.1.2 Selected South American countries

As mentioned in the chapter 1 South America has 21% of the world's forest areas and 57% of its primary forests (FAO, 2011, p118). At the same time the region lost 10% of its total forest area between 1990 and 2010 - a value well above the world's forest loss of 3% for the same period (FAO, 2011, p118). Due to higher returns on investments of some agricultural commodities, the conversion of forest land to agriculture has become the leading cause of regional deforestation, (FAO, 2011). This is reflected in the higher contribution of agriculture to the regional GDP (8,5%) relative to that of forestry, which has a modest 2,1% (table 3.3), in a region where agriculture (crop and pasture) covers only 33% of total area while forest covers 48% (table 3.2).

Some of the most heavily forested countries in South America are Brazil (520 mill ha), Colombia (60 mill ha) and Ecuador (10 mill ha), which combined represent 70% of the total South American forest (FAO, 2010). In terms of GDP (nominal), the three countries rank in a similar fashion, where Brazil is the largest South American economy, Colombia the third biggest, and Ecuador one of the smallest economies (The World Bank, 2012). Thus, South America's abundant forest resources and its above-average deforestation rates make the region a natural target for any international policy intended to halt deforestation. At the same time, the differences in productivity and economic sizes among them make them ideal candidates to study compensation scenarios of large, medium and small South American economies. For this study, data from Brazil and Colombia were used to analyze necessary financial compensations to stop deforestation at the family-farm level.

Uriarte *et al.* (2012) argue that policies to promote low-fire land use systems and access to education, as well as the improvement of early warning systems and other mechanisms, could help towards reducing fire in the region.

3.1.3 Selected agricultural and forest products

In terms of agricultural output, South America's top crops are sugar cane, soybeans and maize (table 3.1); the top livestock product is cow milk; and industrial roundwood is the main forest product. This ranking of commodities is observed as well when looking only at the countries with the most abundant forest resources, with the exception that soybean in Colombia is not a top crop and it is replaced by oil palm fruit.

According to the FAO/BID (2007, p22-25), "sensitive crops" are products thought by regional policy makers to have a higher potential impact on family-farmers due to frequent changes in productivity and prices, or because they are considered relevant as staple foods. Example of staple foods include livestock products: cattle (dairy and meat) and grains, such as maize, wheat, beans and rice. When compared with the list of the most productive agricultural commodities in South America (table 3.1) only maize and cow milk become relevant at national and South American levels. Therefore, in the portfolio analysis of family-farmers the commodities included were: maize as representative commodity of croplands, cow milk as representative of pasture land use and tropical industrial timber as representative of natural forest. Other commodities with higher agricultural output like sugarcane, soybeans or oil palm fruits are typical products of non-family farming corporations (section 3.1.1) and therefore not within the scope of the family-farmer portfolio analysis.

3.1.4 Financial compensation in exchange for avoided deforestation

According to Schejtman (2008 p28), family-farmers would be willing to make changes in a particular land-use if the proposed change in activity meets some of the following conditions:

1. A market exists where the new product can be exchanged at a preset price and guaranteed volume.

2. The new alternative allows a better use of family-farmer manpower in comparison to the traditional land-use.

Table 3.2: Land cover proportions in year 2010

	Ecuador	**Colombia**	**Brazil**	**S.America**
	%	%	%	%
Forest	39,0	55,0	62,0	48,0
Pasture*	19,4	35,0	23,0	27,0
Crop**	5,5	3,0	8,0	6,0
Others	36,1	7,0	7,0	19,0

Source: FAOSTAT 2010.

*Pastures and permanent meadows.

*Permanent

3. The new alternative represents an increment of the return on investment.
4. There is better access to financial resources than under traditional alternatives.
5. It provides access to modern technology or knowledge that the farmer would not otherwise have.

Thus, a clear financial compensation in exchange for every ton of CO_2 sequestered by a farmer's forest, and supported by the international community *e.g.* REDD+, would have good chances to prevail as a competitive alternative within the family-farmer community if it covers most of the requirements that farmers need in order to avoid deforestation.

3.2 Data

3.2.1 Satellite Imagery for environmental risk assessment

Earth observations are collected by artificial satellites within military, commercial or research programs. The gathered imagery must be processed in order to be used for particular purposes like navigation, communications, meteorology, mapping, environmental monitoring, forestry, agriculture etc. Digital maps, for instance, generated with a combination of satellite imagery, processing techniques and calibration methods, can be used to assess the recurrence and spatial extension of land-cover change generated by environmental processes like fires, floods, droughts, etc. For the particular case of fires, for example, satellite remote sensing provides the only means of monitoring vegetation burning at regional to global scale (Roy *et al.*, 2005).

The oldest, and still in operation, provider of continuous space-based observations of earth is the Landsat Program, which has been monitoring with

Table 3.3: Contribution to Gross Domestic Product

	Ecuador %	**Colombia** %	**Brazil** %	**S.America** %
Agriculture	11,3	7,4	2,6	8,5
Forest	2,7	0,7	2,8	2,1

Source: FAO, State of World Forest 2011 and The World Bank 2012

a series of relay satellites since 1972 (NASA, 2013). Other providers include Terra and Aqua satellites monitoring since 1999 (NASA 2012), or commercial programs like RapidEye (2008).
In order to study the temporal and spatial behavior of environmental processes, some variables and costs, inherent to satellite imagery, must be taken into account when considering the purpose of the data analysis; for example the *spatial resolution* of an image determines whether the environmental assessment, to be developed upon it, is suitable for local, regional or national scale. For this purpose, the Ground Sample Distance (GSD) is a measure of the spatial resolution limitations due to sampling of an image of the ground (Leachtenauer and Driggers, 2001). GSD is the smallest unit that maps to a single pixel within an image, thus the lower its value, the better a pixel represents the reality on the ground, requiring as well more storage capacity than images with higher GSD values when the same surface area is compared. Another relevant variable is the *temporal resolution*, which Cambell (2002) defines as the amount of time (days) that passes between imagery collection periods for a given location on the ground, while the *operational period* is the time span (usually years) from the first to the last image collected by a satellite. Thus, the shorter the *temporal resolution* and the larger the *operational period*, the larger will result the total sample size to analyze. According to Evans *et al.* (2000), larger samples increase the chance of finding significant parameters, because they more reliably reflect the sample space, *i.e.* the set of all possible values the events may assume.
Acquisition cost is as well a relevant variable to be considered as it constraints the sampling size. Fortunately, programs like Landsat and MODIS have a policy of no restrictions on subsequent use, sale, or redistribution (Landsat, 2008; NASA, 2013b). Commercial programs on the other hand charge usually per square kilometer. For the purposes of this PhD research the Table 3.4 was used in order to determine the provider to be used:

Although MODIS has a spatial resolution of 500m, *i.e.* a pixel represents 25ha on the ground, its data has no suffered damage like Landsat 7, where a faulty scan line corrector spoiled an estimated 22% of any given scene obtained from years 2003 to 2013 (Landsat, 2013). When considering the area to be analyzed, approximately 10^6 km^2, corresponding to Brazil, Colombia and Ecuador; and in addition to this, the *temporal resolution* and the *operational period* which would require several images of every pixel per year in order to generate the sample size, then the costs of using commercial imagery like RapidEye (3325€/km^2) would be untenable. For the purposes of this research only data of MODIS will be used to assess the environmental impact of fires.

3.2.2 MODIS data and ArcGIS classification of burned areas

Satellite remote sensing provides the only practical means of monitoring biomass burning over large areas (Roy *et al.* 2005). Yet, the timing and spatial extent of actual fires cannot be estimated reliably as the satellite may not pass over when burning occurs and because clouds may preclude active fire detection. Burned area mapping algorithms that examine spectral changes on the landscape, rather than relying on hotspot detection, are generally insensitive to these effects as spectral changes induced by burning persist through time (Roy *et al.* 2002). The Moderate Resolution Imaging Spectroradiometer (MODIS), onboard the Terra satellite from NASA, provides valuable information on long-term observations of the Earth's land, oceans and atmosphere. In order to detect burned areas the *MODIS Burned Area product* (hereafter just: MODIS) uses the *generic change algorithm* (Roy *et al.* 2005), the output is free to download as geotiff. The data comprise a daily 500x500m grids, from the year 2000 onwards, containing per-pixel information on approximate burn date and confidence of detection. For these purposes data from MODIS window 5, corresponding to the northern part of South America was used, this includes Colombia, Ecuador and the northern part of Brazil. The data was converted using ArcGIS from raster to polygons, and used to compute polygon areas, coordinates of centroids and dates of occurrence for every burned area recognized from 2000 to 2012.

3.2.3 Market risk data for portfolio analysis of family-farmers

Costs of production and productivity were obtained from existing studies or from own estimations (Table 3.5). In order to model the financial yield of family-farmers' land-use investments, single commodities were chosen as representative for each of the most popular land-uses in South America: forest, pasture and cropland (Table 3.2). Maize was used as representative for cropland, production of cow-milk for pasture and tropical industrial timber for natural forest. Although this might be considered an oversimplification, it can be justified by the fact that only the top commodities - in terms of both productivity and financial yield - typically produced by family-farmers were used (Table 3.1), and therefore the most likely land-uses that these farmers would choose to replace forest with in the absence of financial compensations. Commodities with higher productivity and financial returns like sugarcane, soybeans or oil palm fruits (Table 3.1) were not considered on the grounds that they are not typically produced by family-farmers, due to prohibitively high costs, and thus not within the scope of this portfolio analysis of family-farmers. In order to compare financial compensation with Mean Variance and Higher-Order Moments methodologies, equations (2.5) and (3.12) were optimized with the constraint that the minimum weight for forest was the current forest area (Table 3.2).

In order to determine the necessary amount of financial compensation under various levels of risk-aversion time series data for product prices and marketed product quantities within the time frame (1990-2007) for Colombia and Brazil were obtained from "FAOSTAT" (FAO Statistic Division web page, 2011). Price and quantity data to represent forest land use were scarce and only data on exported timber, based on data from Knoke *et al.,* (2011), was used.

3.3 Environmental risk assessment modeling approach

In order to assess fire risk, a semi-parametric model that uses kernel smoothing to assess the spatial intensity is proposed, that is, the number of events per km^2. Kernel smoothing shares most of the advantages of prototype point processes, such as the ability to work with highly non-stationary events, both in space and time, and does not require that the underlying process be isotropic (Baddeley *et al.*, 2008, 2011). This is a major convenience in the case of wildfires in tropical regions, where certain locations and months are more prone to be ignited than others, and fires are strongly non-isotropic since wildfires are more likely to spread in certain directions, for example in the direction of prevailing winds (Pyne *et al.*, 1996).
The semi-parametric approach further explores a spatiotemporal dependence, found in all three tropical countries studied: Brazil, Colombia and Ecuador, in order to analyze the average time between events and their relationship to damage. Finally, a geographical representation of the damage per hectare at particular locations is obtained using binomial proportions of the historical data.

The statistical model uses historical remote sensing information, which shows burned areas (Terra satellite, MODIS sensor) from year 2000 onwards, in order to determine the potential damage at chosen locations where land-use investment may take place, and to determine the land-use productivity change per year until 2012. The methodology can be used as a decision

Table 3.4: Satellite image providers information

Provider	Spatial Resolution GSD (m)	Temporal resolution	Operational period (years)	Data Quality	Costs €/km^2
RapidEye	5	daily	2009 - today	good	0.95*
Landsat	30	16 days	1972 - 2002 2003 - today	good 22% loss**	for free for free
MODIS	500	daily***	2000 - today	good	for free

*Minimum order of 3500 km^2 (3325€), RapidEye (2014). ** Since 2003, due to a faulty scan line corrector, an estimated 22% of any given scene obtained with Landsat 7 is lost (Landsat, 2013). ***MODIS has a temporal resolution of 16 days, however it uses a *global algorithm* (Roy *et al.*, 2002, 2005) that maps the approximate day of burning.

Table 3.5: Productivity and cost data for the land-uses and commodities investigated

Land-use	Commodity	Land	Productivity† $\frac{ton}{ha \cdot yr}$	Efficiency* $\frac{animal}{ha \cdot yr}$	Costs* $\frac{US\$}{ha \cdot yr}$	Sources (for *)
Cropland	Maize	Ecuador	2,0	—	217,4	El Día (2010)
		Brazil	3,0	—	232,0	Correia *et al.* (2002 p6)
						Richetti and Melo (2004 p2)
		Colombia	2,0	—	255,0	Campuzano (2005 p7)
						Suaza (2009 p69)
Pasture	Cow milk	Ecuador	1,10	0,56	142,9	Vaca (2003 p29)
						MACA (2004)
		Brazil	0,95	0,86	118,2	IBGE (2006)
						Benedetti (2001)
						Dalponte (2011)
		Colombia	1,02	0,97	153,0	Hoz (2003), DANE (2011)
Nat.Forest	Ind.Timber	All	0,7 $\frac{m^3}{ha \cdot yr}$	—	27,5	Benítez *et al.*(2006)
						Knoke *et al.*(2011)

† Productivity values are taken from FAOSTAT.

support system to determine local and regional changes in productivity per hectare that could be expected due to the environmental hazard of fire. It could be easily adapted to other world regions, to different environmental hazards like floods, windbreak, windthrow, or related land-use changes, or to integrate various environmental hazards simultaneously, as long as they can be monitored via remote sensing (*e.g.* satellite imagery, aerial photographs, etc).

3.3.1 Burned areas from controlled and uncontrolled fires

There has been an important augment of fires in South America between the years 2000 and 2012, see Fig. 3.1. One important distinction for fires occurring at the landscape level is that some are artificially ignited for agricultural purposes, such as the slash-and-burn technique, a permitted procedure in developing countries for efficiently removing post-harvest biomass. Prescribed fires are also used as preventive measures to avoid greater and more devastating fires. Some of these techniques, however, may result in fires that burn out of control due to special meteorological conditions or careless use and are impossible to suppress by local or current firefighting techniques, causing extensive damage (IBAMA 2013, CONAF 2013). Another source of uncontrollable fires is the illegal ignition with purposes of deforestation. According to CONAF (2013) the main causes of uncontrollable fires in Chile between the years 2003 to 2011 were: accidental (55%), intentional (28%), natural (0.4%) and unknown (16.6%). Yet, irrespective of ignition purpose, every fire has the potential to become uncontrolled and thus a real hazard in the short and long term for society (IBAMA 2013, Gill *et al.* 2013).

Several authors (see Malamud *et al.*, 2005) studying burned areas at a landscape level, irrespective of size or ignition source, have found a power-law (scale invariant) relationship between the number of burned areas in "unit" bins, expressed as an estimated density $\hat{f}(A_{BA})$, of the size of the burned areas A_{BA} of the form $\hat{f}(A_{BA}) \propto A_{BA}^{-D_f}$, where D_f is the fractal dimension estimated from the data (Caldarelli *et al.* 2001, Malamud *et al.*, 2005). Studies of the characteristic of burned areas in Australia, China, Italy and the U.S. have estimated fractal dimensions of the order $1.1 < D_f \leq 1.8$ (Malamud *et al.*, 2005).

For these purposes, in order to differentiate between controlled and uncontrolled fires, it was assumed that controlled fires at a landscape level generate

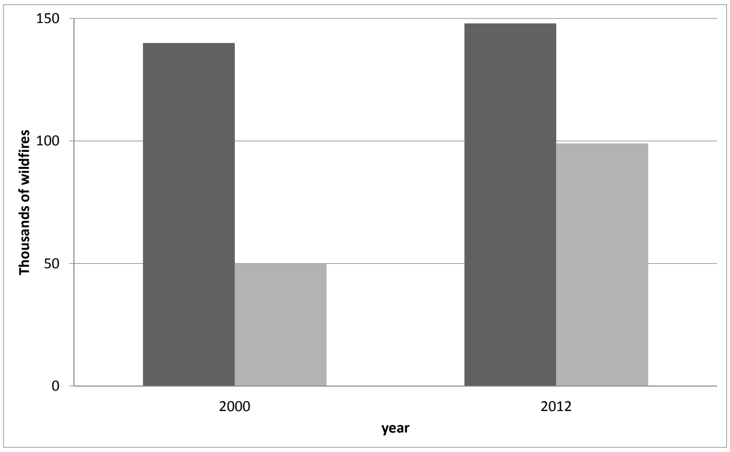

Figure 3.1: Increment in number of wildfires in the northern part of South America (dark gray) and Brazil (light gray). Computed using MODIS data, window 5

burned areas with relative simple geometrical shapes. Simple shapes have lower fractal dimension D_f when compared to more chaotic ones such as would be generated by uncontrolled fires. In this case, the fractal dimension of every single burned area spotted with MODIS was computed using the software Fragstats (McGarigal *et al.* 2012). Burned areas with $D_f \leq 1.1$ are classified as “due to controlled fire” and not considered in the analysis, while burned areas with $D_f > 1.1$ are classified as “uncontrolled” and included in the analysis.

3.3.2 Two-dimensional point process

The MODIS dataset provides information for burned areas on a grid with a resolution of 500×500m along with their date of occurrence. For these purposes the polygon and the centroid coordinates $u_i := (x_i, y_i)$ of every single burned area were computed, see Fig. 3.2 and 3.3 . Thus, every event recorded is uniquely determined by the triple (u_i, b_i, t_i), where $\{u_i \in A |\ i = 1, \ldots, n\}$ is the set of locations of burned areas which occurred in a region $A \subset \mathbb{R}^2$; $b_i \in \mathbb{R}$ corresponds to the burned area in km^2, and $t_i \in [2000, T]$ is the date at which MODIS first spotted the burned area. When the events u_i are graphically displayed over the region of study A, it is evident that they exhibit spatial variation, see for example Figure (3.4). This motivates the exploration of the characteristics of subregions where the spatial intensity, defined as the number of burned areas per km^2, appears to be higher, in order to find local patterns that might not be recognizable at larger scales. Below, a semi-parametric approach to identify patterns on desired subregions is presented. First, kernel smoothing to compute the spatial intensity is used. Second, the historical proportional damage occurred at chosen locations in order to generate maps of damage is determined. Third, a non-linear spatio-temporal relationship between the proportional damage and the average time between events at particular locations is explored.

The methodology avoids arbitrary classification of events, contrary to quadrat-counting techniques, and does not rely on the definition of clusters of events towards a parametric description of spatial intensity. Although the events are assumed to be realizations of a point process, no particular probability spatial-density function is assumed.

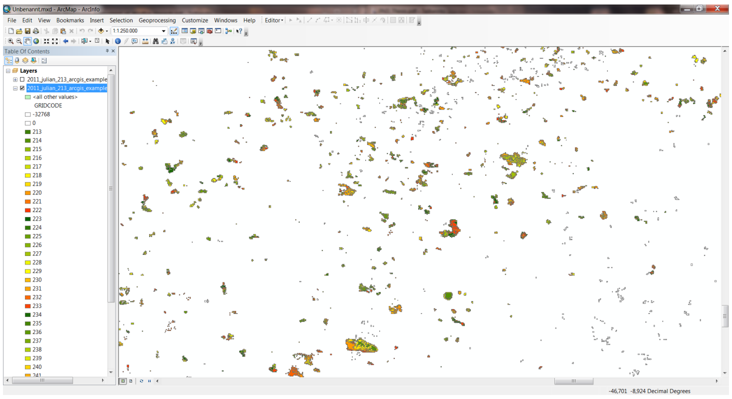

Figure 3.2: ArcGIS view of areas spotted by MODIS. Pixel with the same color were spotted the same day.

Following Rosenblatt (1956), let $u_1, ..., u_n$ be independent and identically distributed random variables with a continuous but unknown density function. Furthermore, let $u_1, ..., u_n$ be a partial realization of a point process, with spatial intensity function $\lambda(\varphi)$, $\varphi \in A$, representing the number of events per unit of area in the nearby locality of a location φ. In practice, as $\lambda(\cdot)$ is not known it must be replaced by a suitable estimate $\hat{\lambda}(\cdot)$, which should be a function taking on large values for high density regions and near zero values where data are sparse (Diggle and Marron, 1988). Building upon the work of Rosenblatt (1956) and Diggle (1985, 2003), Baddeley *et al.* (2000, 2008) propose a non-parametric estimator of $\lambda(\varphi)$, which takes the general

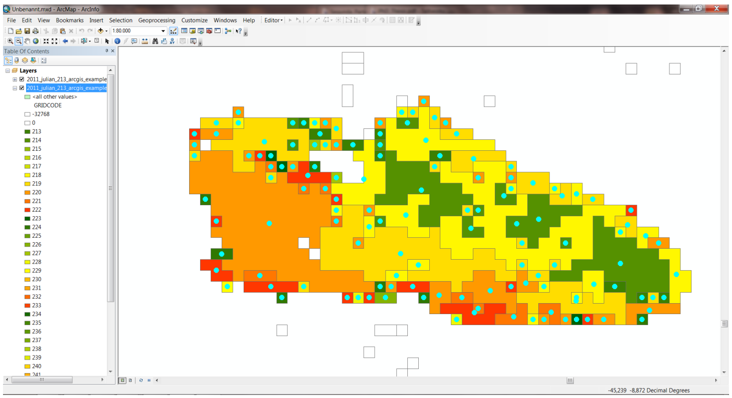

Figure 3.3: Zoom of Figure 3.2. Pixels with the same color and continuous area are consider as polygon and belonging to the same fire. Blue points represent the geometrical centroid of the polygons with coordinates $u_i := (x_i, y_i)$.

form

$$\hat{\lambda}_h(\varphi) = \frac{1}{h^2\ C_A(\varphi)} \sum_{i=1}^{n} k_h(u_i - \varphi), \qquad \forall\ \varphi, u_i \in A, \tag{3.1}$$

where $k_h(\varphi) = h^{-2}k(h^{-1}\varphi)$ is a smoothing kernel, the bandwidth $h > 0$ determines the amount of smoothing, and the kernel is defined as Gaussian $k(\varphi) = (2\pi)^{-1/2}exp(-\varphi^2/2)$. Theoretical properties of $k(\cdot)$ are explained by Scott (1992, chapter 6; and 2012). To avoid bias of $\hat{\lambda}_h(\cdot)$ at the boundaries of A, a kernel edge-correction term is used (Hazelton, 2008. Baddeley *et al.* 2008):

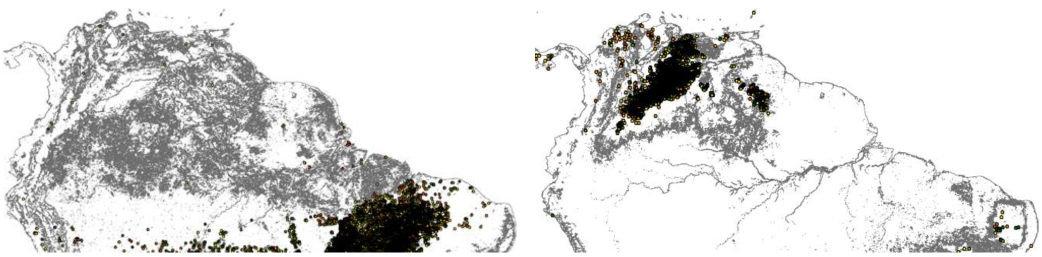

Figure 3.4: Spatial locations of burned areas. Each point represents the centroid of a burned area polygon spotted with MODIS between the years 2000 and 2012 in the northern part of South America. Seasonal aspects are observed, left figure from March to August, right figure from September to February. Gray pixels are not fire events

$$C_A(\varphi) = \int_A k_h(u-\varphi)d\varphi. \tag{3.2}$$

Following Scott (1992, p.133; 2012) and Sheather (2004), a bandwith h that is a function of the spatial dispersion and the number of events $u_i \in A$ is used. Specifically, the implemented version of equations (3.1) and (3.2) in the R package "spatstat" is used.

3.3.3 Subregions of spatial intensity

The estimated non-parametric spatial intensity $\hat{\lambda}_h(\cdot)$ in (3.1), having as units the number of burned-areas per km^2, allows to classify the region A, of every country studied, into subregions without making any assumptions on the probability distribution of the events. The goal is to compare summary statistics, like the percentage of damaged area and the average time between fires, of subregions with different spatial intensities. For every country, minimum $\min_{\varphi\in A} \hat{\lambda}_h(\varphi) := 0$, and maximum values $\omega := \max_{\varphi\in A} \hat{\lambda}_h(\varphi)$, are used as limits of an interval partitioned into three equal-length subintervals in order to generate three subsets $\hat{\Lambda}_{low}, \hat{\Lambda}_{med}$ and $\hat{\Lambda}_{high}$ of locations φ having low, medium and high number of events per km^2 respectively:

$$\begin{array}{rcl} \hat{\Lambda}_{low} & = & \{\varphi : \hat{\lambda}_h(\varphi) \in [0, \omega/3]\} \\ \hat{\Lambda}_{med} & = & \{\varphi : \hat{\lambda}_h(\varphi) \in (\omega/3, 2\omega/3]\} \\ \hat{\Lambda}_{high} & = & \{\varphi : \hat{\lambda}_h(\varphi) \in (2\omega/3, \omega]\}. \end{array} \tag{3.3}$$

Although the model does not require the interval to be partitioned, the procedure was performed in order to explore and compare burn-area activities at different sub-intervals of the spatial intensity. To make more readable forthcoming functions, which are conditioned to the subsets $\hat{\Lambda}_{low}, \hat{\Lambda}_{med}$ or $\hat{\Lambda}_{high}$, the $\hat{\Lambda}_{subreg}$ is defined as the general subset that represents any of the subsets in (3.3).

3.3.4 Random sample locations

For a spatial intensity subregion $\hat{\Lambda}_{subreg}$, estimated for every country, a random sample without replacement, of locations φ where a land use investment may take place, is used in order to study potential patterns common to a given $\hat{\Lambda}_{subreg}$. Patterns addressed in this study are: proportional damage of burned areas at particular locations, their recurrence time, and geographical assessment of locations up to a predefined threshold of damage.
For a random location $\varphi \in A$, the function $\hat{\lambda}_h(\varphi)$ (3.1) will return an estimate

of the number of burned areas per km^2 in the near vicinity of φ. This value is not expected to change drastically for events $\{u_i \in B |\ B \subset A\}$ near φ because $\hat{\lambda}_h(\cdot)$ is smoothed, see equation (3.1). Let $N_{BA} = |B| > 1$ be the number of burned area events $\{u_i\}$ to be found in the surroundings of φ, and $Area_\varphi$ be the area containing them and that can be estimated with $N_{BA}/\hat{\lambda}_h(\varphi)$. Thus, low spatial intensity levels will produce larger areas $Area_\varphi$ than high spatial intensity levels when N_{BA} is kept constant, and events further away diminish as a hazard for the random location φ as the area-size increases. Therefore, let $D_\varphi = \{u_i \in B |\ B \subset A,\ 0 < d(\varphi, u_i) < d_{\varphi u}\}$ be the set of events in B having an euclidean distance to φ less than a constant $d_{\varphi u}$, that because of their proximity to location φ may potentially affect its land's productivity.

3.3.5 Proportional burned-area damage

In order to assess the potential damage per hectare at a particular location φ, the *farm's proportional damage* $f_{t_{inv}} \in \mathbb{R}^+$ is defined as a threshold value of the proportion of land that a farm may lose due to damage caused by fire during the period of investment $(0, t_{inv}]$. This variable will help identify geographical coordinates of locations φ where damage has not yet surpassed the predetermined threshold. In order to compare potential damage between different spatial intensities, a threshold of $f_{t_{inv}} = 5\%$ is used. Setting arbitrarily a low threshold value will help identify locations with a record of low fire activity where land use investment can still be contemplated[1].
For a particular location φ, the *proportional damage* ρ_t, restricted to the set $\hat{\Lambda}_{subreg}$, up until time t, is computed as:

$$\rho_t(\varphi |\, \hat{\Lambda}_{subreg}) = Area_\varphi^{-1} \sum_{b_i:\ t_i \leq t,\ u_i \in D\varphi \cap \hat{\Lambda}_{subreg}} b_i, \tag{3.4}$$

where (u_i, b_i, t_i) is as defined in section (3.3.2).

3.3.6 Maps of locations with damage on productivity

For locations in $\hat{\Lambda}_{subreg}$, a spatial random sample with size $n_{\varphi, \hat{\Lambda}_{subreg}}$ of locations φ is generated and each $\rho_t(\varphi | \hat{\Lambda}_{subreg})$ is evaluated. This allow to build a hazard map with locations having either $0 < \rho_t(\varphi | \hat{\Lambda}_{subreg}) \leq f_{t_{inv}}$

[1]As mentioned in section 2.1, the popular Verified Carbon Standard considers PES and REDD projects with a historical low 5% damage as projects free of environmental risks (VCS, 2008, 2012).

or $\rho_t(\varphi|\hat{\Lambda}_{subreg}) > f_{t_{inv}}$. This "filter" helps to build hazard maps based on binomial proportions and confidence intervals that estimate the likelihood of finding damaged areas at given levels of spatial intensity.

Probability of occurrence with binomial proportions and confidence intervals

Let n be the size of a statistical sample of random locations φ. Out of them, let $n_{\varphi,\hat{\Lambda}_{subreg}}$ be the number of locations at a given subregion $\hat{\Lambda}_{subreg}$ where $|D_\varphi| > 0$. Thus, $\hat{q} = n_{\varphi,\hat{\Lambda}_{subreg}}/n$ is the estimated proportion of successes in a Bernoulli process out of n trials. Let also $n_{0<\rho\leq f_{t_{inv}}}$ be the number of locations where the damage has not yet exceeded the threshold $f_{t_{inv}}$. Thus, $\hat{q}_{f_{t_{inv}}} = n_{0<\rho\leq f_{t_{inv}}}/n_{\varphi,\hat{\Lambda}_{subreg}}$, is the estimated proportion of successes of locations where the historical damage (since the beginning of MODIS monitoring) has not yet surpassed the predefined $f_{t_{inv}} = 5\%$. Confidence intervals for the estimated likelihoods of finding locations φ with damage $\rho_t(\varphi|\hat{\Lambda}_{subreg}) > 0$, and of finding locations with damage up to a certain threshold $0 < \rho_t(\varphi|\hat{\Lambda}_{subreg}) \leq f_{t_{inv}}$, are obtained using Agresti score confidence intervals, Agresti and Coull 1998. This procedure is used to construct estimated maps from historical satellite information, of locations where the damage due to burning has not been surpassed during the investing time t_{inv}.

3.3.7 Average time between events

Let $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$ be the average time between events $\{u_k\}$, restricted to $\hat{\Lambda}_{subreg}$, up to time t and at location φ, defined as

$$\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg}) = \frac{1}{N_{BA}-1} \sum_{k=1,t_k:u_k\in D_\varphi\cap\hat{\Lambda}_{subreg}}^{N_{BA}-1} |t_{k+1}-t_k| \;\Leftrightarrow\; N_{BA} > 1, \quad (3.5)$$

having as units the interval-length in years between consecutive events. A nonlinear function to model the relationship between the average time between events $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$ and their proportional damage $\rho_t(\varphi|\hat{\Lambda}_{subreg})$ is used of the form:

$$ln\big[\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})\big] = \alpha + \beta \cdot ln\big[\rho_t(\varphi|\hat{\Lambda}_{subreg})\big] + \epsilon, \quad (3.6)$$

where α and β are regression parameters to be estimated and ϵ is the error term.

Equation (3.6) can be expressed as:

$$\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg}) = e^{\alpha} \cdot \big[\rho_t(\varphi|\hat{\Lambda}_{subreg})\big]^{\beta}. \quad (3.7)$$

Here, a sample average of events $\hat{N}_{BA}$ is used as an estimate of N_{BA} for locations having the same proportional damage $\rho_t(\varphi|\hat{\Lambda}_{subreg})$. $\hat{N}_{BA}$ is used to compute the proportional damage per event, up to time t:

$$\xi_t(\varphi|\hat{\Lambda}_{subreg}) := \rho_t(\varphi|\hat{\Lambda}_{subreg})/\hat{N}_{BA}, \tag{3.8}$$

and the total damage (%) per year:

$$\hat{\psi}_t(\varphi|\hat{\Lambda}_{subreg}) := \frac{\rho_t(\varphi|\hat{\Lambda}_{subreg})}{\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg}) \cdot \hat{N}_{BA}}. \tag{3.9}$$

On setting $\rho_t(\varphi|\hat{\Lambda}_{subreg}) = f_{t_{inv}}$ in Equation (3.7), the average time between events $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$ is estimated for a given *farm's proportional damage.*

3.4 Land-use portfolio under market risk

3.4.1 Multivariate portfolios incorporating higher-moments (HM)

In order to cope with the shortcomings of MV and VaR, while at the same time maintaining their intuitive optimization framework (2.7), significant efforts have been made to build model extensions that use alternative risk measures that relax the normality assumption. Jurczenko and Maillet (2006) propose that if $U(\cdot)$ is arbitrarily continuously differentiable, then it can be expressed as a Taylor series expansion of order K evaluated around the expected wealth:

$$U(W_{t+1}) = \sum_{j=0}^{K} \frac{U^{(j)}\big[E[U(W_{t+1})]\big]\big[W_{t+1} - E[U(W_{t+1})]\big]^j}{j!} + \xi_{j+1}, \tag{3.10}$$

where $U^{(j)}$ is the jth derivative for $j = 0, ..., K$ and ξ_{j+1} is the Taylor series remainder. Following Jondeau *et al.* (2007), by assuming that $\lim_{K\to\infty} \xi_{k+1} = 0$ and truncating the Taylor series expansion at the 4th order, the expected utility is approximated by

$$\begin{aligned} E\big[U(W_{t+1})\big] \;\approx\;& U\big[E[U(W_{t+1})]\big] + \frac{U^{(2)}\big[E[U(W_{t+1})]\big]cov_p}{2} \\ &+\frac{U^{(3)}\big[E[U(W_{t+1})]\big]skw_p}{3!} + \frac{U^{(4)}\big[E[U(W_{t+1})]\big]kur_p}{4!}, \end{aligned} \tag{3.11}$$

where $\mu_p = E[U(W_{t+1})]$, $cov_p = E\big[W_{t+1} - E[U(W_{t+1})]\big]^2$, $skw_p = E\big[W_{t+1} - E[U(W_{t+1})]\big]^3$ and $kur_p = E\big[W_{t+1} - E[U(W_{t+1})]\big]^4$ are respectively the mean, covariance, skewness and kurtosis of the family-farmers's portfolio return distribution. Without loss of generality, a utility function such as CARA (2.5) is substituted into (3.11) obtaining:

$$E\big[U(W_{t+1})\big] \approx -e^{-\lambda\mu_p}\left[1 + \frac{\lambda^2 cov_p}{2} - \frac{\lambda^3 skw_p}{6} + \frac{\lambda^4 kur_p}{24}\right]. \tag{3.12}$$

Equation (3.12) requires the computation of a portfolio's first four moments out of a sample of commodities' returns. Defining moments as functions of tensor products (Athayde and Florês, 2004; Jondeau and Rockinger, 2006), has the advantage that no particular distribution function must be considered. For n risky commodities and $\boldsymbol{\alpha}$ weight vector, the *q-th* central portfolio moment is $m_q = E[(r_p - \boldsymbol{\alpha'} \boldsymbol{\cdot} \boldsymbol{\mu})^q]$. Thus, the first four moments are calculated as:

$$\begin{aligned}
\mu_p &= E[r_p] = \boldsymbol{\alpha'} \boldsymbol{\cdot} \boldsymbol{\mu} \\
cov_p &= m_2 = \boldsymbol{\alpha'} \cdot \mathbf{M_2} \cdot \boldsymbol{\alpha} \\
skw_p &= m_3 = \boldsymbol{\alpha'} \cdot \mathbf{M_3} \cdot (\boldsymbol{\alpha} \otimes \boldsymbol{\alpha}) \\
kur_p &= m_4 = \boldsymbol{\alpha'} \cdot \mathbf{M_4} \cdot (\boldsymbol{\alpha} \otimes \boldsymbol{\alpha} \otimes \boldsymbol{\alpha})
\end{aligned}$$

where $\otimes$ is the tensor product of two vector spaces. The above definitions of skewness and kurtosis as central higher moments depart slightly from the traditional statistical definition of standardized central higher moments (Jondeau and Rockinger, 2006). As an example, for a multivariate portfolio with $n = 3$ risky commodities, $\mathbf{M_3}$ becomes a 3×9 matrix,

$$\mathbf{M_3} = \left[\begin{array}{ccc|ccc|ccc}
s_{111} & s_{112} & s_{113} & s_{211} & s_{212} & s_{213} & s_{311} & s_{312} & s_{313} \\
s_{121} & s_{122} & s_{123} & s_{221} & s_{222} & s_{223} & s_{321} & s_{322} & s_{323} \\
s_{131} & s_{132} & s_{133} & s_{231} & s_{232} & s_{233} & s_{331} & s_{332} & s_{333}
\end{array}\right], \tag{3.13}$$

with $s_{ijk} = E\left[(r_i - \mu_i)(r_j - \mu_j)(r_k - \mu_k)\right]$, calculated as

$$s_{ijk} = \frac{T}{(T-1)(T-2)} \sum_{t=1}^{T} (r_i - \mu_i)(r_j - \mu_j)(r_k - \mu_k) \tag{3.14}$$

where $\frac{T}{(T-1)(T-2)}$ is a factor that produces an unbiased estimator of coskewness (Heusser, 2009) and time $t = 1, ..., T$, for this particular case, years. The matrix $\mathbf{M_4}$ is 3×27 with

$$\mathbf{M_4} = \left[\begin{array}{ccc|ccc|cc}
k_{1111} & k_{1121} & k_{1131} & k_{1112} & k_{1122} & k_{1132} & & k_{3133} \\
k_{1211} & k_{1221} & k_{1231} & k_{1212} & k_{1222} & k_{1232} & \cdots & k_{3233} \\
k_{1311} & k_{1321} & k_{1331} & k_{1312} & k_{1322} & k_{1332} & & k_{3333}
\end{array}\right], \tag{3.15}$$

and $k_{ijkl} = E\left[(r_i - \mu_i)(r_j - \mu_j)(r_k - \mu_k)(r_l - \mu_l)\right]$, calculated as

$$k_{ijkl} = \frac{T(T+1)}{(T-1)(T-2)(T-3)} \sum_{t=1}^{T} (r_i - \mu_i)(r_j - \mu_j)(r_k - \mu_k)(r_l - \mu_l). \quad (3.16)$$

In order to find the weights $\boldsymbol{\alpha_t} = (\alpha_{1,t}, ..., \alpha_{n,t})'$ that maximize the next-period family-farmer's wealth W_{t+1}, allocated to the considered commodities, the approximation (3.12) is maximized:

$$\begin{aligned} \max_{\boldsymbol{\alpha}} \quad & -e^{-\lambda \boldsymbol{\alpha'} \cdot \boldsymbol{\mu}} \left[1 + \frac{\lambda^2 \boldsymbol{\alpha'} \cdot \mathbf{M_2} \cdot \boldsymbol{\alpha}}{2} - \frac{\lambda^3 \boldsymbol{\alpha'} \cdot \mathbf{M_3} \cdot (\boldsymbol{\alpha} \otimes \boldsymbol{\alpha})}{6} \right. \quad (3.17) \\ & \left. + \frac{\lambda^4 \boldsymbol{\alpha'} \cdot \mathbf{M_4} \cdot (\boldsymbol{\alpha} \otimes \boldsymbol{\alpha} \otimes \boldsymbol{\alpha})}{24} \right] \\ s.t. \quad & \boldsymbol{\alpha' e} = 1, \end{aligned}$$

where e is a $(n, 1)$ vector of ones. Note that λ can only be approximate to zero $\lambda \approx 0$ because when $\lambda = 0$ the maximization function 3.17 becomes constant (equal to 1).

3.4.2 Optimization with the Differential Evolution algorithm

The objective functions (2.7) and (3.17) were maximized using the statistical software R (R Core Team, 2008) and the optimization package "DEoptim" (Ardia *et al.,* 2012), based in the Differential Evolution (DE) search algorithm, which is similar to classic genetic algorithms (Price *et al.,* 2006). DE has the advantage of finding global optimal portfolios which are subject to non-linear constraints, and where the objective function is a non-linear proxy of risk and return (Ardia *et al.,* 2011). The PortfolioAnalytics framework allows any arbitrary R function to be part of the objective set, and allows the user to set the relative weighting that they want on any specific objective, and use the appropriately tuned optimization solver algorithm to locate portfolios that most closely match those objectives (Ardia *et al.,* 2011).

Introduced by Storn and Price (1997), DE is a search algorithm for global optimization over continuous spaces, which simple use and remarkable performance on continuous numerical minimization/maximization problems has been widely studied (Price *et al.,* 2006). Ardia *et al.,* (2011) describe DE in the following way:
"Let NP denote the number of parameter vectors (members) $x \in R^d$ in the

population. In order to create the initial generation, NP guesses for the optimal value of the parameter vector are made, either using random values between lower and upper bounds (defined by the user) or using values given by the user. Each generation involves creation of a new population from the current population members $\{x_i|i = 1, ..., NP\}$, where i indexes the vectors that make up the population. This is accomplished using *differential mutation* of the population members. An initial mutant parameter vector v_i is created by choosing three members of the population, x_{i_1}, x_{i_2} and x_{i_3}, at random. Then v_i is generated as $v_i := x_{i_1} + F \cdot (x_{i_2} - x_{i_3})$ where F is the differential weighting factor, effective values for which are typically between 0 and 1. After the first mutation operation, mutation is continued until d mutations have been made, with a crossover probability $CR \in [0, 1]$. The crossover probability CR controls the fraction of the parameter values that are copied from the mutant. If an element of the trial parameter vector is found to violate the bounds after mutation and crossover, it is reset in such a way that the bounds are respected (with the specific protocol depending on the implementation). Then, the objective function values associated with the children are determined. If a trial vector has equal or lower objective function value than the previous vector it replaces the previous vector in the population; otherwise the previous vector remains".

3.4.3 Type of compensation for avoidance of deforestation

Gray *et al.* (2004) analyzed how regular payments, such as the Agricultural Market Transition Act, shift the distribution of returns without changing the variability, while irregular payments (for example the Marketing Loan Program and the Subsidized Crop Revenue Coverage Insurance) increase the mean, reduce variability and change skewness, because only certain market conditions or crop failures trigger payments. For this study, a yearly and constant financial compensation paid to farmers is analyzed, so the expected returns increased without changing vulnerability to market risk, and therefore compared the models under regular conditions for family-farmers in developing economies.

3.4.4 Market risk-aversion scenarios and optimization routines

As discussed previously, encouraging forest protection at the family-farmer level may avoid further shrinkage of natural forest shares. One possibility is to pay financial compensations to farmers with the condition that no forest shall be converted to other land-use. In order to determine fair values, payments in US$ per hectare of forest per year (without including transaction costs) were increased stepwise and the portfolio was optimized with the Mean Variance approach (2.7) and the higher-order moments approach (3.17). Both models were used in each of the three countries considered (Brazil, Colombia and Ecuador), with and without financial compensation, and under both risk-aversion and risk-neutrality, for a total of eight scenarios per land.

As mentioned in section 2.2.1, the model that computes the optimal portfolios allows to set constraints (C_{LU}) to the proportion of the farm available for a certain commodity. This is useful for the case of crops that, for example, due to a deficit in soil nutrients or water regimes or due to high input costs are restricted to a small proportion of the total farm land. This is evidenced by Table 3.2 where crops, in spite of having the highest returns per hectare (see section 1.3), have only in average 6% of the total land use in South America. For purposes of comparison, two possibilities are considered here, one where the crop area may occupy the whole farm size (*i.e.* $0 \leq \alpha_{crop} \leq 100\%$), and a second possibility where crop is constrained to 6% (*i.e.* $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$).

When analyzing agricultural commodities, Holt and Laury (2002) and Benítez *et al.* (2006) proposed a coefficient of relative risk aversion $\gamma = 1.2$ that represents a risk-averse land-use investor. This corresponds to an absolute risk aversion of $\lambda = 0.016$, given that $\lambda = \frac{\gamma}{x}$, and using $x = 75$ as the average net revenue for all land uses, while for a risk-neutral investor $\lambda = 0$ is assigned. These values were used here in order to generate both risk-neutral and risk-averse scenarios.

All generated scenarios were obtained by using the utility function, with either the method of Mean Variance, see equation (2.6) or with the method of Higher-Order Moments, Eq.(3.12), for the maximization problems (2.7) and (3.17) respectively, in order to obtain optimal land-use portfolio weights that maximize the family-farmer returns within the given market-price risk. Land-use portfolio optimization was performed with the package "Deoptim()" (Ardia *et al.* 2011 and 2012) of the statistical computing program R (R Core Team, 2008), which computes global optimal portfolios weights $(\alpha_{1,t}, ..., \alpha_{n,t})$ for the above mentioned maximization problems. All portfolios were initiated without given a predefined value for the portfolios weights, see section 3.4.2. A total of 10.500 iterations were used for each computed portfolio.

Four scenarios for each constrained (*i.e.* $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$) and unconstrained crop (*i.e.* $0 \leq \alpha_{crop} \leq 100\%$) were generated in order to compare both models under different circumstances of risk-aversion and compensation:

- Scenario I: Risk-neutral farmer ($\lambda = 0$) without compensation for avoided deforestation

- Scenario II: Risk-neutral farmer with compensation for avoided deforestation.

- Scenario III: Risk-averse farmer ($\lambda > 0$) without compensation for avoided deforestation. Mean-Variance approach, and Higher Moments approach

- Scenario IV: Risk-averse farmer with compensation for avoided deforestation. Mean-Variance approach, and Higher Moments approach

- **Method** (**Mean Variance** or **Higher Moments**) stands for portfolio optimization with the Mean Variance approach, see eq.(2.7) or the Higher-Order Moments approach, see eq.(3.17)

- $\boldsymbol{\lambda}$ refers to the Coefficient of Absolute Risk Aversion (CARA), two scenarios are presented: $\lambda = 0$ (risk-indifferent) and $\lambda = 0.016$ (risk-averse) investor, see section 3.4.4 for details

- **FC** is the necessary financial compensation given to a family-farmer in $US\$$ per hectare per year

- α_{crop}, $\alpha_{pasture}$ and α_{forest} stand for weight of portfolio land-use of Crop, Pasture and Forest respectively, and sum, in every case, to 100%

- $\boldsymbol{\mu_p, cov_p, skw_p, kur_p}$ are the portfolio higher moments for the assigned portfolio weights α_{crop}, $\alpha_{pasture}$ and α_{forest}.

3.5 Integration of market and environmental risk for land use portfolio analysis

As considered in previous sections, $\mathbf{W_t}$ is the initial wealth of a family-farmer willing to allocate his land-use portfolio in n risky commodities. In previous sections it was discussed that land-use investments are not only vulnerable to market risks but to environmental risks like fires, floods, wind throws, droughts, etc. Thus, a thorough understanding of total risk is of vital importance for the sustainability of such investments. In this section, an approach to integrate market and environmental risk within a portfolio optimization framework is presented.

Returns $\mathbf{r_t} = (r_{1,t}, ..., r_{n,t})'$ of any land use investment are subject to market prices at which commodities can be sold, as well as subject to changes in productivity per hectare due to environmental hazards. The approaches used here to capture market risk information are the two methods explained before, *i.e.* the Mean Variance approach and the Higher-Order Moments approach presented in previews sections, which are models that represent the Gaussian and the non-Gaussian approach. To be consistent with the additional incorporation of environmental risk assessment, as introduced in Acevedo *et al.* 2014, changes in productivity are modeled with the approaches explained in previews chapters, where it was discussed how to compute the total damage $\hat{\psi}_t$ (%/year) at a chosen location and definition (3.9). Similarly to Eq. 2.2, but incorporating environmental risk assessment, returns are computed as:

$$r_{i,t} = \frac{price_{i,t}}{ton} \times prod_{i,t,\hat{\psi}_t} - \frac{cost_{i,t}}{hectare}, \tag{3.18}$$

where i represents a commodity to be included in the portfolio analysis, for this study case maize, cow milk and wood are considered as representative commodities of typical South American family-farming, see sections 3.1.1 to 3.1.3; $r_{i,t}$ is the return value in $US\$/ha$ of commodity i at time t. All return values at time t are included in the total return column vector $\mathbf{r_t} = (r_{1,t}, ..., r_{n,t})'$. Equation 3.18 differs from the original 2.2 in that productivity $prod_{i,t}$ in 2.2 does not include changes due to environmental risks. Thus, productivity[2]

[2]Following VCS standards, for destructive events, the carbon benefits generated by the destroyed part of the project are assumed to be completely lost. In this case, the number of years that loss continues equates to the remaining lifespan of the project, (VCS, 2008). For Maize it is assumed a complete productivity loss during the first year after fire and a reduction of productivity of 30% (with respect to a regular yearly production) for the second year (Guevara, 2005; Norgrove and Hauser, 2015). For pasture complete

of a commodity i at time $t \in (0, t_{inv}]$, section 3.3.5, is defined as

$$prod_{i,t,\hat{\psi}_t} = prod_{i,t} \times (1 - \hat{\psi}_t), \tag{3.19}$$

where $prod_{i,t}$ is computed out of national or regional productivity in $ton/hectare$ for agricultural commodities, and m^3/ha for forestry products. In locations with few or without previous record of environmental damage, for example locations in regions with low spatial intensity of events (see section 3.3.3, the total damage per year (see section 3.3.7) is defined as $\psi_t := 0$, while for regions where the land has been under hazard (*i.e.* with a historical record of burned areas), the productivity is affected by the damage per year $\hat{\psi}_t$ computed with equation (3.9). As explained in section 3.3.5, in order to assess the potential damage per hectare at a particular location φ, the *farm's proportional damage* $f_{t_{inv}}$ is used as a threshold value of the proportion of land that a farm may lose due to damage caused by fire during the period of investment $(0, t_{inv}]$. Thus, to compare potential damage between different spatial intensities (see section 3.3.3), a threshold of $f_{t_{inv}} = 5\%$ is used[3]. Setting arbitrarily a low threshold value will help identify locations with a record of low fire activity where land use investment can still be considered. After productivity values per hectare were computed, new portfolios were obtained by maximizing the utility function with both the method MV (2.6) and HM (2.7), which became the optimization problems (3.12) and (3.17) respectively.

In chapter 4 results of the above mentioned methodology are shown. For sake of simplicity, but without loss of generality, only portfolio results corresponding to risk-averse family-farmers having compensations are presented and further explored for the case of integration of environmental risks. Thus, optimal portfolios that maximize the farmer's return are computed for first: a scenario only under market risk with added compensation per hectare of forest, see section 4.4, and second: a scenario under both market and environmental risk, with added compensation per hectare of forest.

To integrate environmental risk to the portfolio optimization process, the vector of returns is modified by using equation (3.18). In order to compare the impact of fires on land-use portfolios at locations with different spatial-intensities, see section 3.3.3, a threshold of $f_{t_{inv}} = 5\%$ was used as the proportional burned-area damage ρ_t, section 3.3.5. Using the non-linear

productivity loss is assumed for the first year (DEPI, 1995 and 2009).

[3]As mentioned in section 2.1, the popular Verified Carbon Standard considers PES and REDD projects with a historical low 5% damage as projects free of environmental risks (VCS, 2008, 2012).

relationship obtained in Eq. (3.7), the recurrence of events at low spatial intensity was found. The same recurrence was used to determine the proportional burned-area damage, using again Eq. (3.7), at medium and high spatial intensity, see figure 4.7. Afterwards, φ values for higher intensities were found using (3.9). Thus, the returns were modified depending on the farm's geographical location and the historical record of damages at a particular location.

As in section 3.4.4, here too, four scenarios for each constrained (*i.e.* $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$) and unconstrained crop (*i.e.* $0 \leq \alpha_{crop} \leq 100\%$) were generated in order to compare both models under different circumstances of risk-aversion and compensation. Tables 4.12, 4.14 and 4.16 present the following information:

- **Scenario**
  Scenario IV represents land use portfolios under market risk, farmers with risk-aversion ($\lambda = 0.016$) and forest land use with yearly compensation.
  Scenario V represents land use portfolios under market plus environmental risk, farmers with risk-aversion ($\lambda = 0.016$) and forest land use with yearly compensation.

- **Method** (**Mean Variance** or **Higher Moments**) stands for portfolio optimization with the Mean Variance approach, see eq.(2.7) or the Higher-Order Moments approach, see eq.(3.17).

- **Compensation** is the necessary monetary value given to a family-farmer in $US\$$ per hectare per year, so that the farmer will not replace forest for other land uses.

- **Market risk**
  $\boldsymbol{\lambda}$ refers to the Coefficient of Absolute Risk Aversion (CARA). Here only the case of farmers with risk-aversion is presented $\lambda = 0.016$.

- **Environmental risk**
  - $\hat{\delta}_t$ is the average time between events, see section 3.3.7.
  - $\hat{\Lambda}_{subreg}$ represents the subregion of spatial intensity low ($\hat{\Lambda}_{low}$), medium ($\hat{\Lambda}_{med}$) and high ($\hat{\Lambda}_{high}$) computed using the record of burned areas, see section 3.3.3.
  - ρ_t is the *proportional damage*, see section 3.3.5.

- $\hat{N}_{BA}$ is the average number of burned area events found in the surroundings of φ, see section 3.3.4.
- ξ_t is the proportional damage per event, see section 3.8.

- α_{crop}, $\alpha_{pasture}$ and α_{forest} stand for weights of portfolio land-use of Crop, Pasture and Forest respectively, in every case $\alpha_{crop} + \alpha_{pasture} + \alpha_{forest}$ $= 100\%$

Chapter 4

Results

This chapter presents results for the modeling approach introduced in previous chapter.

4.1 Environmental risk assessment for land-use

Maps displaying the number of spotted burned-areas per km^2, *i.e.* the spatial intensity $\hat{\lambda}_h$ estimated with the kernel smoothed function (3.1), are presented in Fig. 4.1, for Ecuador, Colombia and Brazil respectively and a three dimensional plot of the kernel smoother function is shown for the case of Colombia in Fig. 4.2. As mentioned in section 3.3.3, the spatial intensity region was divided in three sub-regions representing low ($\hat{\Lambda}_{low}$), medium ($\hat{\Lambda}_{med}$) and high ($\hat{\Lambda}_{high}$) intensity regions in every country in order to compare summary statistics like the percentage of damaged area and the average time between fires. The sub-regions are depicted in Fig. 4.1 with blue, green and yellow respectively, and it is clearly seen that in all three countries the burned areas tend to concentrate at particular regions and that the spatial intensity varied significantly not only within regions but between countries as well. Brazil has the highest spatial intensity with 2.2 burned areas per square kilometer, more than one and a half times the highest spatial intensity of Colombia, which has 1.37 events/km^2 and more than seventy times the highest spatial intensity of Ecuador which has 0.03 events/km^2.

As mentioned in previous chapters, the conversion of forest land to agriculture has become the leading cause of the regional deforestation (FAO, 2011). Although there are several agents generating deforestation, see Table 2.2, in Latin America by far the most important agent of deforestation are

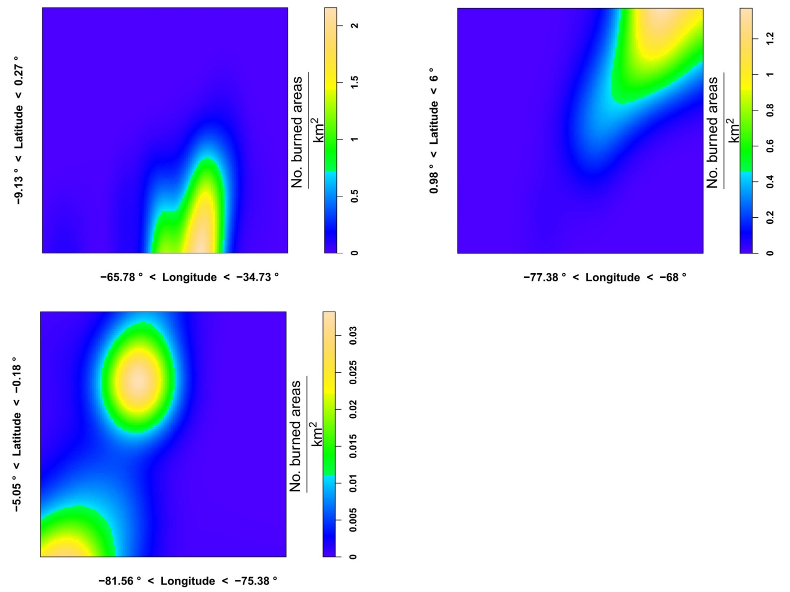

Figure 4.1: Kernel smoothed spatial intensity of fires in Brazil (top-left), Colombia (top-right) and Ecuador (bottom-left) from 2000 to 2012. $\hat{\Lambda}_{low}$ (blue pixels), $\hat{\Lambda}_{med}$ (green) and $\hat{\Lambda}_{high}$ (yellow)

slash-and-burn farmers (FAO Forestry Department, 2007) due to the fact that fires can easily get out of control and generate devastating and long lasting consequences mostly in forests. In section 1.3 an example was presented of how international publicity campaigns reporting about wrongdoing, of some multinational companies linked to the soybean supply, have helped reducing deforestation rates in the region nearby Santarém (State of Pará, Brazil). According to Kissinger *et al.* (2012) and Macedo *et al.* (2012), 2004 was a peak year of deforestation and since then the rate of forest clearing in Brazil has fallen by almost 75%. Although this might be true for some states it is unfortunately not true for the southern part of the states of Amazonas and Pará. Figure 4.1 shows that in Brazil the region covering -54° to -43° longitude and -4.4° to -9.1° latitude (*i.e* the southern part of States of Pará and Amazonas) has high activity of uncontrolled fires. Moreover, Fig. 4.4 shows that in years 2007, 2010 and 2012 the size of the total burned area per year of that Brazilian region was at least two times higher than the value of 2004, with a recorded peak of almost 70.000 km^2 in 2010. Colombia, on the contrary, has shown a small decrement on the total burned area per year since 2000. Ecuador remains with a relative low constant value. The information was computed out of the burned areas recognized with the sensor MODIS on board of the Terra satellite of NASA.

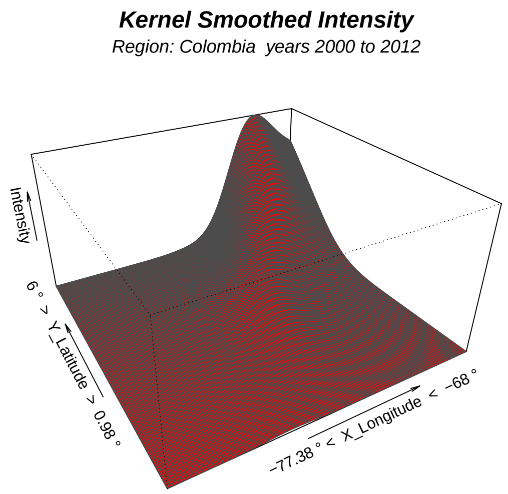

Figure 4.2: spatial intensity estimated with $\hat{\lambda}_h(u)$ in (3.1)

4.1.1 Hazard maps

As introduced in sections 3.3.4 and 3.3.5, for every subregion $\hat{\Lambda}_{subreg}$ a spatial random sample without replacement of locations φ is generated and the proportional damage $\rho_t(\varphi|\hat{\Lambda}_{subreg})$ is evaluated with function 3.4. This allows to build hazard maps with locations having either $0 < \rho_t(\varphi|\hat{\Lambda}_{subreg}) \leq f_{t_{inv}}$ or $\rho_t(\varphi|\hat{\Lambda}_{subreg}) > f_{t_{inv}}$. The threshold of $f_{t_{inv}}$ is arbitrarily set to 5%, because a low threshold value will help identify locations with a record of low fire activity where land use investment can still be contemplated [1]. This variable will also help identify geographical coordinates of locations φ where damage has not yet surpassed the predetermined threshold. Fig. 4.3 shows hazard maps for low, medium and high intensity regions of Brazil where it is shown that the higher the spatial intensity, the more events surpassed the 5% threshold damage per hectare, grey locations in the figure. Similar results were found for Colombia and Ecuador.

[1] A threshold value of 5% is also used by the Verified Carbon Standards to differentiate between project that need no further risk analysis (< 5% of project area damaged) and projects that need a deeper analysis and are required to present evidence of risk mitigation strategies (VCS, 2008, 2012)

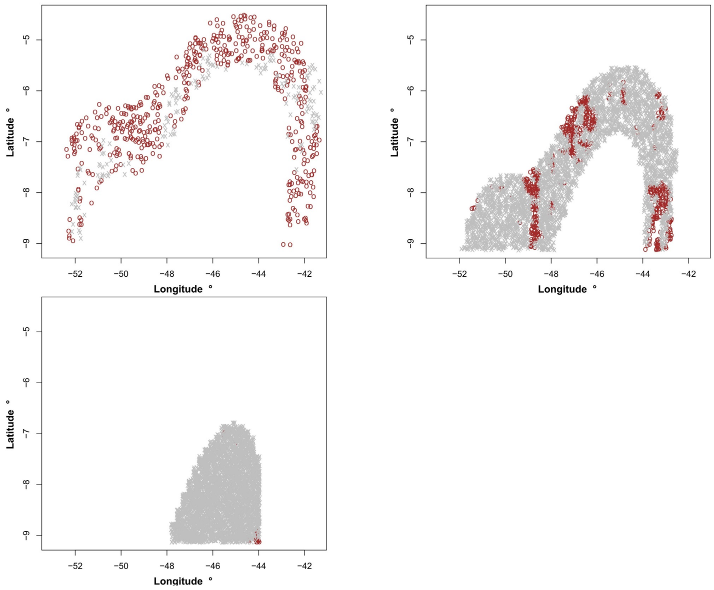

Figure 4.3: Hazard maps of Brazil for the spatial intensity regions: $\hat{\Lambda}_{low}$ (top-left), $\hat{\Lambda}_{med}$ (top-right) and $\hat{\Lambda}_{high}$ (bottom-left). Random sample of locations with total burned area damage of less than $f_{t_{inv}} = 5\%$ (brown circles) and more than 5% (grey crosses)

4.1.2 Probability of occurrence of a 5% damage per hectare: binomial proportions and confidence intervals

In order to estimate the probability of occurrence of finding the damage presented in the hazard-maps (Fig. 4.3), binomial proportions and their corresponding Agresti confidence intervals were built out of the successes of finding locations with certain damage levels. Results for locations having any damage $\hat{q} > 0$, and for locations with damage $0 < \hat{q}_{f_{t_{inv}}} < 5\%$, are presented in table 4.1, along with the confidence intervals. For example, for the high spatial intensity region (yellow pixels in figure 4.1) of Brazil: out of a random sample of $n = 20000$ locations, and for a $1-\alpha = 95\%$ confidence level, the estimated likelihood of finding locations u with any damage, $\rho_t(u|\hat{\Lambda}_{subreg}) > 0$, is $\hat{q} = 100\%$, out of them in only $\hat{q}_{f_{t_{inv}}} = 3\%$ of the cases the *farm's proportional damage* has not yet being surpassed *i.e.* $0 < \rho_t(u|\hat{\Lambda}_{subreg}) \leq f_{t_{inv}}$ see brown circles in figure[2] 4.3. Meanwhile, for the low spatial intensity region

[2]Due to storage size the actual figure shown was generated out of a 4 thousand sample size, but the results are similar. The estimated likelihood is computed out of a sample size of 20 thousand

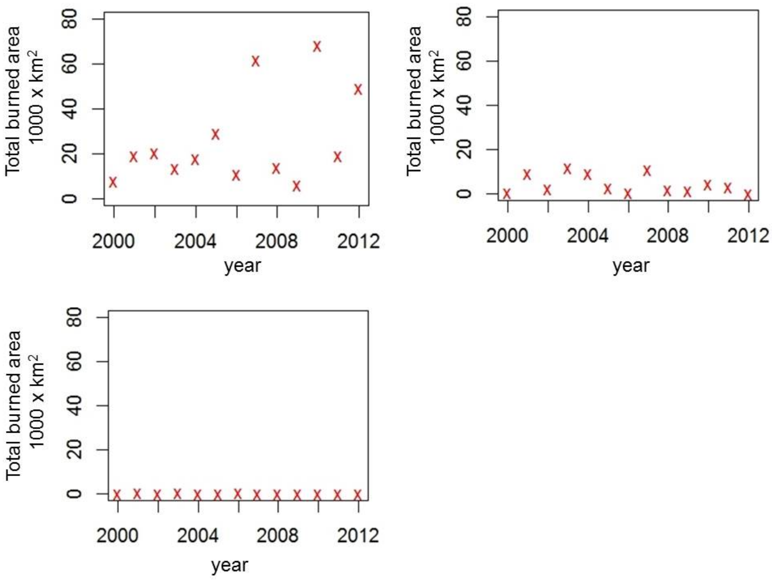

Figure 4.4: Record of burned areas in thousands of square kilometers per year, for Brazil (top-left), Colombia (top-right) and Ecuador (bottom-left)

(dark-blue pixels in figure 4.1) of Brazil: out of $n = 20000$ trials, the estimated likelihood of finding locations u with $\rho_t(u|\hat{\Lambda}_{subreg}) > 0$ is just $\hat{q} = 6\%$, but out of them in $\hat{q}_{f_{t_{inv}}} = 78\%$ of the cases the *farm's proportional damage* has not yet being surpassed (see brown circles in figure 4.3). This means that not only a farmer can expect more events (fires) per hectare in a high intensity region ($\hat{\Lambda}_{high}$) but also the proportional damage per hectare of every single fire is higher than at low spatial intensity regions $\hat{\Lambda}_{low}$, see Table 4.1. In Brazil and Colombia the number of burned areas, at medium and high spatial intensity, is such that almost every single random location has certain damage, *i.e.* the values greater than 98%.

It was also observed that for the spatial intensity levels studied (low, medium and high), the proportion of locations having damage less than the fixed threshold ($f_{t_{inv}} = 5\%$) decreased drastically as the spatial intensity increased. In Brazil (Table 4.1) the largest change occurred between the low and the high spatial intensities, with 60.2% of random locations in the low spatial intensity with "small" damage and only 0.8% of random locations in the high spatial intensity with "small" damage. This was followed by Colombia with 50.4% and 1.1% respectively. Meanwhile, Ecuador showed the smallest difference between proportions: 100% and 63%, respectively. This means that in Ecuador there is a predominance of events (at all spa-

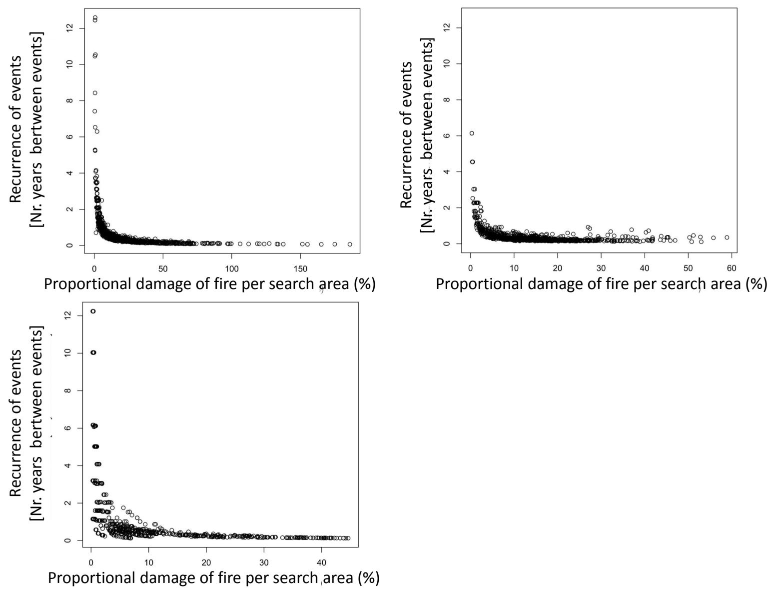

Figure 4.5: Nonlinear relationship between proportional damage of burned-areas and average time between events in Brazil (top-left), Colombia (top-right) and Ecuador (bottom-left) for the region with high spatial intensity $\hat{\Lambda}_{subreg} = \hat{\Lambda}_{high}$

tial intensities) with "small" damage ($0 < \hat{p}_{f_{t_{inv}}} < 5\%$), while in Brazil and Colombia this holds only at low spatial intensities (Table 4.1).

4.1.3 Average time between events and their relationship with damage

As introduced in section 3.3.7, a non-linear relationship between the average time between fire events and their damage per hectare was found, in all countries and at all spatial intensities, see Fig. (4.5). For the logarithmic transformation of the non-linear relationships, linear regressions for every spatial intensity were fitted, obtaining adjusted R^2 values ranging from 0.72 in Ecuador to 0.93 in Brazil, see Fig. 4.6 and Table 4.2.

Figures depicting the estimated exponential function 3.7, between the average time of events and the degree of damage per event, are presented in Fig. 4.7. Interestingly, in spite that the three countries present different values of spatial-intensities, when the damage is high enough, *e.g.* $\rho_t > 20\%$, a similar value of recurrence was observed in all cases $\hat{\delta}_t(u) < 0.5$ years. That

Table 4.1: Probability of occurrence of a given damage per hectare: binomial proportions and confidence intervals

Land	$\hat{\lambda}_h$	Locations with any damage			Locations with damages $\leq f_{t_{inv}} = 5\%$		
		$Low_{CI}\%$	$\hat{p}$ %	$Up_{CI}\%$	$Low_{CI}\%$	$\hat{p}_{f_{t_{inv}}}$ %	$Up_{CI}\%$
Brazil	Low	6.1	6.4	6.7	57.5	60.2	62.8
	Med	98.6	98.8	99.0	14.8	15.5	16.2
	High	99.9	100.0	100.0	0.6	0.8	0.9
Colombia	Low	6.4	6.8	7.1	47.8	50.4	53.1
	Med	99.95	99.98	100.0	15.1	15.6	16.1
	High	100.0	100.0	100.0	1.0	1.1	1.3
Ecuador	Low	0.3	0.4	0.5	89.6	100.0	100.0
	Med	2.4	2.7	3.0	98.0	100.0	100.0
	High	33.1	34.0	35.0	61.4	63.0	64.6

$Low_{CI}\%$ and $Up_{CI}\%$ correspond to Agresti's confidence intervals, lower and upper values respectively. See sections and 3.3.6 and 4.1.2

Table 4.2: Multiple R^2 for the linear regression between proportional damage of burned-areas and average time between events

Spatial intensity region	Brazil R^2	Colombia R^2	Ecuador R^2
$\hat{\Lambda}_{low}$	0.90	0.70	0.71
$\hat{\Lambda}_{med}$	0.92	0.70	0.71
$\hat{\Lambda}_{high}$	0.93	0.72	0.72

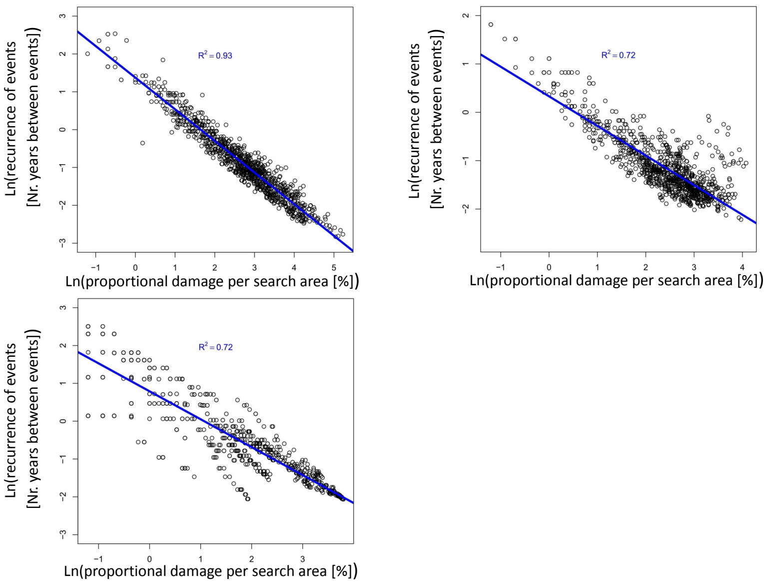

Figure 4.6: Regression between proportional burned-areas damaged and average time between events in Brazil (top-left), Colombia (top-right) and Ecuador (bottom-left) for the region with high spatial intensity $\hat{\Lambda}_{subreg} = \hat{\Lambda}_{high}$, ln denotes natural logarithm and R^2 the multiple R^2 from a linear regression

means that in all three countries, and all spatial intensities, when locations have more than two events per year in the nearby locality, one could expect damage at least as bad as 20% for the location.

As seen in Fig. (4.7) the same number of years between fire events $\hat{\delta}_t(\varphi|\hat{\Lambda}_{subreg})$ produces different damage ρ_t at different spatial intensity regions $\hat{\Lambda}_{low}$ (black dashed line), $\hat{\Lambda}_{med}$ (blue dashed line) and $\hat{\Lambda}_{high}$ (red dashed line). This is because a fixed average time between events, (table 4.3), at high spatial intensity $\hat{\lambda}_h$ has fewer events N_{BA} (table 4.3), but a greater damage per event ξ_t (table 4.3), than the same fixed average time between events at medium or lower spatial intensity $\hat{\lambda}_h$. This trend was found in all three countries studied.

4.2 Non-Gaussian distributed commodity prices

For the three commodities used as representative of the land uses: crop, pasture and forest, in the countries studied Brazil, Colombia and Ecuador,

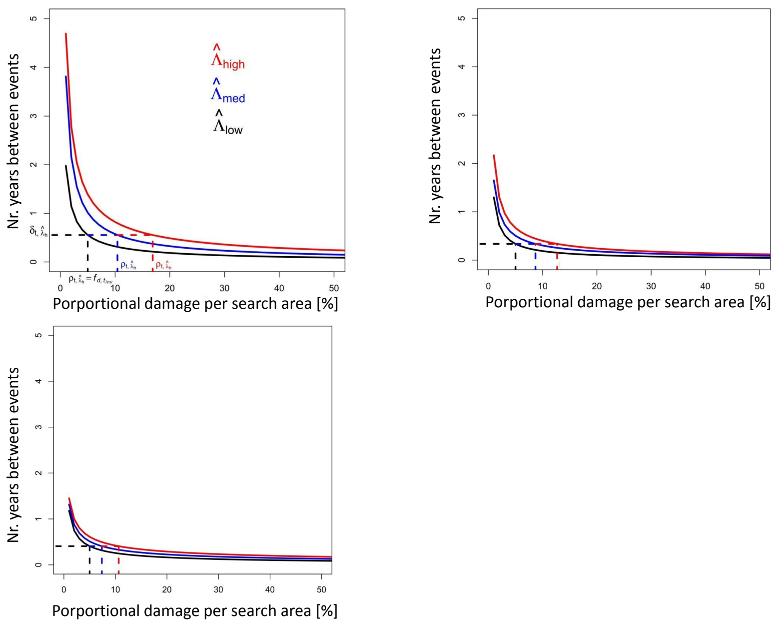

Figure 4.7: Nonlinear relationships estimated with equation (3.7) between proportional burned-areas and average time between events in Brazil (top-left), Ecuador (top-right) and Colombia (bottom-left) for different spatial-intensity regions: $\hat{\Lambda}_{low}$ (black solid line, adjusted $R^2 = 0.90$), $\hat{\Lambda}_{med}$ (blue solid line, adjusted $R^2 = 0.92$) and $\hat{\Lambda}_{high}$ (red solid line, adjusted $R^2 = 0.93$). Here the *farm's proportional damage* at low spatial-intensity was fixed to 5%, corresponding to 0.56 years between events (horizontal dashed lines).

it was found that none of the commodities followed a Gaussian distribution. Table (4.4) presents the return moments of the three land-uses studied - crop, pasture and forest - for each country, together with a Kolmogorov-Smirnov test of normality. It is evident, from the skewness (skw_p) and kurtosis (kur_p), that none of the returns from the individual land-uses are symmetrically distributed as their higher moments depart from zero. This is verified in all cases by the p-values of the normality test performed with a 5% significance, see column seven of Table (4.4). A visual inspection of the histograms of the crop studied for Brazil, Colombia and Ecuador, see figures (4.8), (4.9) and (4.10) respectively, shows as well that the commodities depart from normality as they do not show the typical bell-shape of Gaussian histograms.

Table 4.3: Comparison of constant average time between events $\hat{\delta}_t(u|\hat{\Lambda}_{subreg})$ at different spatial-intensities $\hat{\lambda}_h$.

Land	Environmental Risk*				
	$\hat{\delta}_t(u\|\hat{\Lambda}_{subreg})$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t
Brazil	0.56	Low	5.0	23	0.22
	0.56	Med	10.4	11	0.94
	0.56	High	16.4	7	2.34
Colombia	0.41	Low	5.0	24	0.21
	0.41	Med	7.4	19	0.39
	0.41	High	10.6	11	0.96
Ecuador	0.33	Low	5.0	22	0.23
	0.33	Med	8.7	18	0.50
	0.33	High	12.7	10	1.27

*The recurrence value $\hat{\delta}_t(u|\hat{\Lambda}_{subreg})$ used corresponds to a damage $f_{t_{inv}} = 5.0\%$ at low spatial-intensity level (column 4, first row), see section 3.3.7 and Figure 4.7. See sections 3.3.5 and 3.3.7 for explanations of how ρ_t, $\hat{N}_{BA}$ and ξ_t were computed.

Table 4.4: Moments of the return distribution and Kolmogorov-Smirnov Normality test. See also histograms 4.8 to 4.10

Land	Land-use	μ $\frac{US\$}{ha \cdot yr}$	var	skw	kur	Kolmogorov $p-value$
Brazil	Crop	114	10554,5	2,26	7,35	< 2.2e-16
Brazil	Pasture	74,2	1083,3	0,04	-0,27	< 2.2e-16
Brazil	Forest	8,2	71,6	-1,05	2,72	8.796e-10
Colombia	Crop	147,8	8684,3	1,16	2,00	2.22e-16
Colombia	Pasture	105,5	7448,4	2,09	6,96	2.22e-16
Colombia	Forest	55,9	494,5	-0,4	-0,72	3.442e-15
Ecuador	Crop	122,2	4924,6	0,3	1,7	<2.2e-16
Ecuador	Pasture	65,7	1352,8	-0,2	0,1	<2.2e-16
Ecuador	Forest	20,7	182,2	-0,9	0,6	0.001493

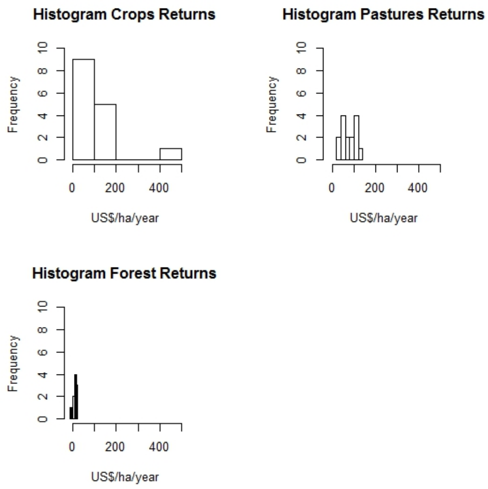

Figure 4.8: Histogram of Returns for Brazil

4.3 Returns of commodities and higher moments

Based on the time-series for commodity prices and productivity, crop produced the highest mean return per hectare of all land-uses studied for each of the three countries analyzed, with values ranging from 122 in Ecuador to 148 $\frac{US\$}{ha \cdot yr}$ in Colombia (Table 4.4). Pasture yielded in all three countries the second highest returns, ranging from 66 in Ecuador to 105 $\frac{US\$}{ha \cdot yr}$ in Colombia. Forestry showed the lowest results in all three countries, with values ranging from 8 in Brazil to 56 $\frac{US\$}{ha \cdot yr}$ in Colombia. In all cases it was found that any alternative (crop or pasture) has higher returns than forest. In Brazil, where the greatest differences were found, forest generated 14 times less returns per hectare than crop and 9 times less return per hectare than pasture. The smallest difference, with respect to an alternative commodity, was found in Colombia where pasture's return are just 1.8 times higher than forest's.

Crop and pasture present not only the highest and second highest mean returns, respectively, but the highest and second highest variance of the three commodities studied in all three countries. Natural forest presents the lowest variance in all countries. Unlike risk-neutral family-farmers, see section 2.2.2, risk-averse ones consider market price risk when deciding what portfolio suits them best. In the case of the Modern Portfolio Theory with the

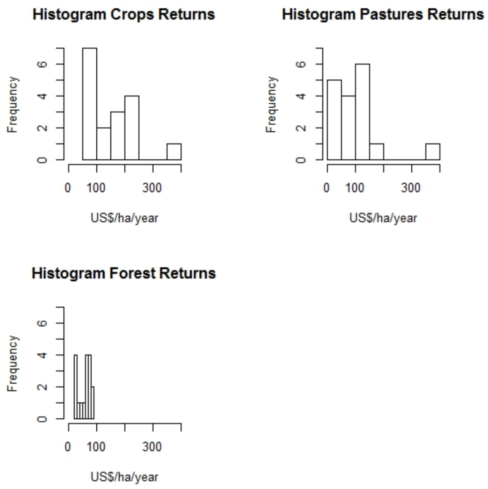

Figure 4.9: Histogram of Returns for Colombia

Mean-Variance approach, variance is used as proxy of risk, which is minimized for a given return value, thus a high variance is punished even if the variability is due to high positive returns. In the case of the Higher-Moment approach, a high variance is punished only if it has a negative skewness.

Skewness determines whether the distribution of returns is symmetrical, right tailed or left tailed. A skewness greater than zero reflects whether the variance is made up of positive increments in returns. Interestingly, Table 4.4, column five, shows that, (except pasture in Ecuador) crop and pasture present in all countries a positive skewness. Forest on the contrary is negative in all three countries, which evidences that the variance is made up mostly of drop in returns. Thus, family-farmers may expect sporadic decrements in returns when investments are made in this particular commodity. The higher the negative value from skewness is, and the larger the variance is, the greater the decrement in returns of the particular land use. This result is relevant because it may force a higher compensation in order to avoid conversion from forest to more profitable land uses, in this case crop or pasture.

Positive kurtosis is observed in Colombian crop and pasture, Brazilian crop and forest and in all land uses studied in Ecuador (Table 4.4). Positive kurtosis roughly means that the variance is more influenced by infrequent extreme deviations than when kurtosis is less than or equal to zero. This may be beneficial, as long as the skewness remains positive, as both aspects

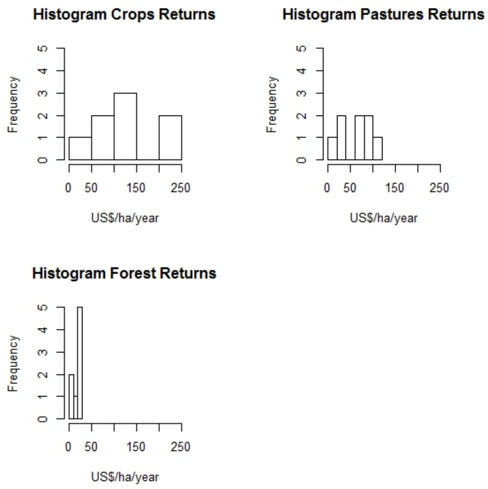

Figure 4.10: Histogram of Returns for Ecuador

are linked to positive returns.

4.4 Land-use portfolio scenarios

A total of 10.500 iterations were used for each computed portfolio, see Figures 4.11 to 4.13. For scenarios with financial compensation **FC**, scenarios II and IV, the amount compensated ($US\$$ per hectare per year) was increased from 0 up to an amount that would keep the proportion of forest, of family-farmer land-use portfolio, at least equal to the current forest country levels *i.e.* Brazil 62%, Colombia 55% and Ecuador 39%, see Table 3.2. Additional portfolios were computed for farms where crop can not have more than 6% of the total land use to simulate average conditions of South American farms, see sections 2.2.1 and 3.4.

4.4.1 Scenario I: Risk-neutrality ($\lambda \approx 0$) without compensation

When considering a risk-neutral[3] ($\lambda \approx 0$) attitude towards investments in the absence of compensation (scenario I), Mean Variance (Eq. 2.6) and Higher-

[3] λ can only be near zero ($\lambda \approx 0$) because when $\lambda = 0$ the maximization function 3.17 becomes constant (equal to 1)

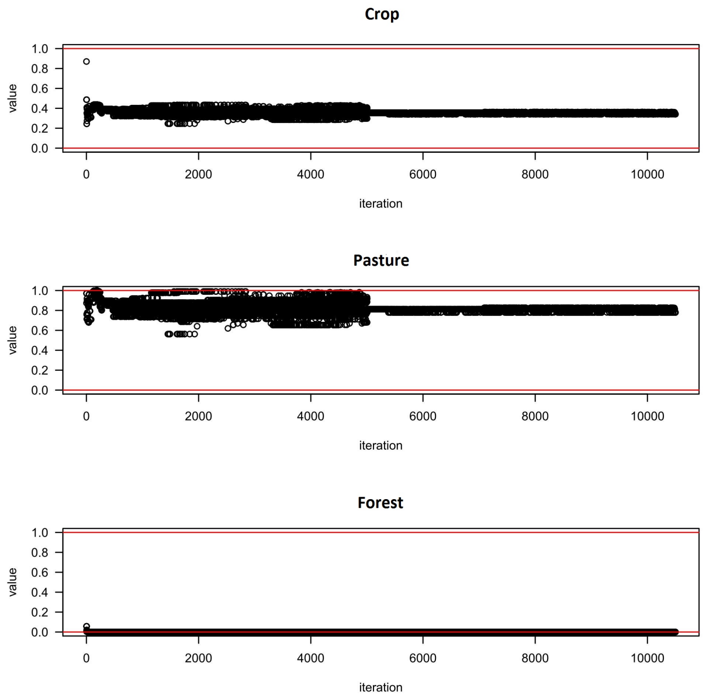

Figure 4.11: Optimal portfolio weights for Brazil, $\boldsymbol{\alpha_t} = (\alpha_{crop}, \alpha_{pasture}, \alpha_{forest})'$ obtained after 10500 iterations for final optimal portfolio weights of 30% Crop, 70% Pasture and 0% Forest, see Table 4.5, Scenario III with Higher-Order Moments with the optimization package "DEoptim" (Ardia, 2012) in the statistical software R (R Core Team, 2008).

Order Moments (Eq. 3.12) behaved similarly[4] in all of the countries studied (see the first row in tables 4.5, 4.7 and 4.9). Both models chose a 100% crop portfolio which represents the highest financial yield: 114, 148 and 122 $\frac{US\$}{ha \cdot yr}$ for Brazil, Colombia and Ecuador respectively. Higher-Order Moments behaves similar to Mean-Variance approach because, when $\lambda \approx 0$, the variance, skewness and kurtosis have almost no relevance and, in both methods, the only relevant variable to maximize is the mean return μ_p.

For the case of farms where crop is constrained to $\alpha_{crop} \leq 6\%$ of the total land use, see Tables 4.6, 4.8 and 4.10, both models behave the same, 94%

[4]Only when the distribution of returns has a perfect normal distribution (*i.e.* skewness and kurtosis are zero) then the Mean Variance and Higher-Order Moments approaches produce exactly the same results, in all other cases the larger the departure from normality the larger the difference in results

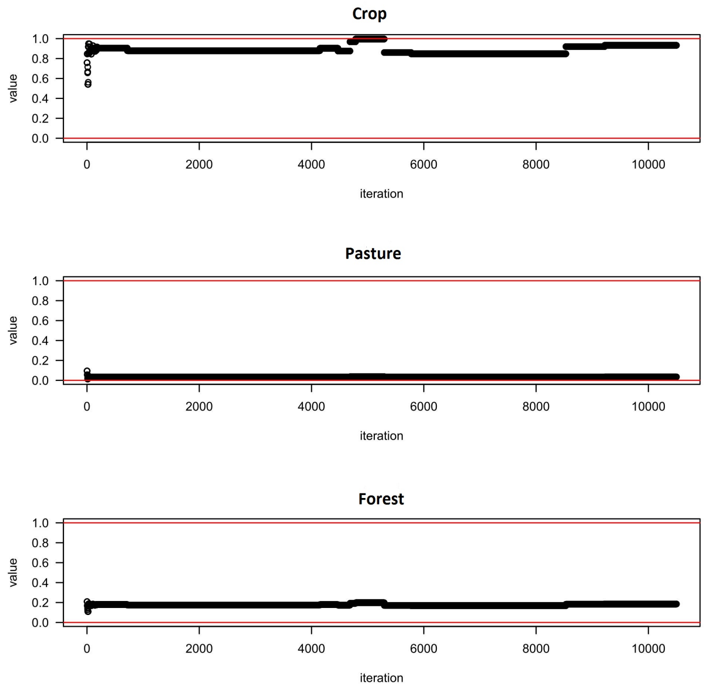

Figure 4.12: Optimal portfolio weights for Colombia, $\boldsymbol{\alpha_t} = (\alpha_{crop}, \alpha_{pasture}, \alpha_{forest})'$ obtained after 10500 iterations for final optimal portfolio weights of 81% Crop, 3% Pasture and 16% Forest, see Table 4.7, Scenario III with Higher-Order Moments with the optimization package "DEoptim" (Ardia, 2012) in the statistical software R (R Core Team, 2008).

of the land is assigned to pasture, the second most profitable land use, and only 6% for crop.

4.4.2 Scenario II: Risk-neutrality ($\lambda \approx 0$) with compensation

When compensations were added for the risk-neutrality case, the results obtained from both models changed dramatically in all three countries from a 100% crop portfolio to a 100% forest portfolio. This occurs when the mean of crop return μ_{crop} is surpassed by forest-returns plus the added compensation of 106, 91 and 102 $\frac{US\$}{ha \cdot yr}$ ($\mu_{forest} + \mathbf{FC}$) for Brazil, Colombia and Ecuador respectively (see the first row in tables 4.5, 4.7 and 4.9). Similarly to scenario I and because $\lambda \approx 0$, only the mean return is relevant for the maximization

Table 4.5: Brazil†. Representative of a large South American economy.

	Method	λ	FC $\frac{US\$}{ha \cdot yr}$	α_{crop} %	$\alpha_{pasture}$ %	α_{forest} %	μ_p	cov_p	skw_p	kur_p
Scenario I	Both	≈ 0	0	100	0	0	114	10554.5	2.3	7.3
Scenario II	Both	≈ 0	106	0	0	100	114.2	71.5	-1	2.7
Scenario III	Mean Variance	0,016	0	24	76	0	83.7	1769.1	0.8	2.5
Scenario III	Higher Moments	0,016	0	30	70	0	86.1	2097.2	1.1	3.5
Scenario IV	Mean Variance	0,016	59,2	25	13	62	79.9	901.9	1.7	5.7
Scenario IV	Higher Moments	0,016	59,5	33	5	62	83.2	1352.2	2	6.3

† All abbreviations used here are explained in section 3.4.4. The current distribution of returns of Brazil is shown in Fig. 4.8.

Table 4.6: Brazil†. With constrained crop $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$).

	Method	λ	FC $\frac{US\$}{ha \cdot yr}$	α_{crop} %	$\alpha_{pasture}$ %	α_{forest} %	μ_p	cov_p	skw_p	kur_p
Scenario I	Both	≈ 0	0	6	94	0	76.6	1160.8	0.1	0
Scenario II	Both	≈ 0	72.8	6	0	94	83	134.5	-0.2	2.3
Scenario III	Both	0.016	0	6	94	0	76.6	1160.8	0.1	0
Scenario IV	Mean Variance	0.016	59.8	6	32	62	74.3	357.8	0.5	2.6
Scenario IV	Higher Moments	0.016	60.1	6	32	62	74.4	357.9	0.5	2.6

† All abbreviations used here are explained in section 3.4.4. The current distribution of returns of Brazil is shown in Fig. 4.8. Results of this table were computed with a crop constrained of $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$) as explained in sections 2.2.1, 2.2.1 and 3.4.4

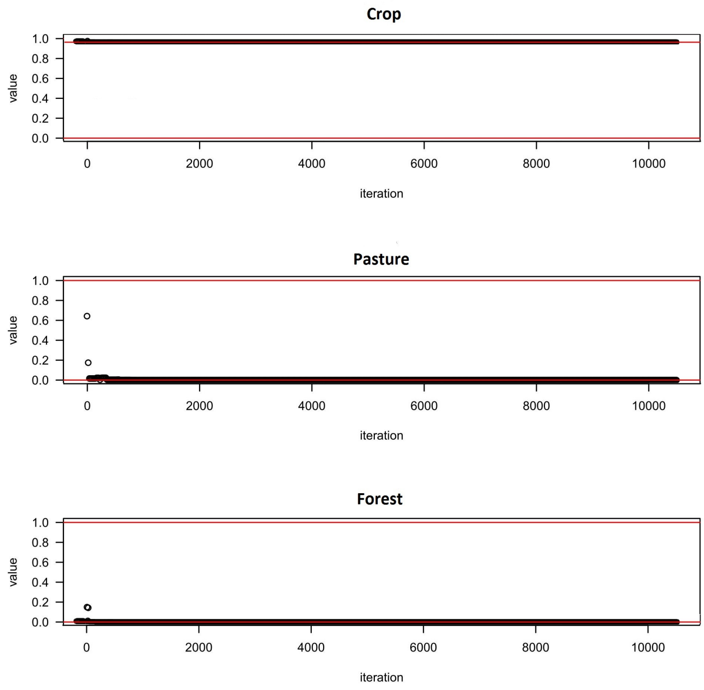

Figure 4.13: Optimal portfolio weights for Ecuador, $\boldsymbol{\alpha_t} = (\alpha_{crop}, \alpha_{pasture}, \alpha_{forest})'$ obtained after 10500 iterations for final optimal portfolio weights of 100% Crop, 0% Pasture and 0% Forest, see Table 4.9, Scenario I with Higher-Order Moments. With the optimization package "DEoptim" (Ardia, 2012) in the statistical software R (R Core Team, 2008).

process. For risk-neutral family-farmers, only mean returns are relevant when deciding what investments are more attractive. Therefore, the land-use with the highest possible return is preferred. For all other scenarios computed, the expected return and the risk play a role, as both models Mean Variance and Higher-Order Moments search for portfolios that maximize returns and minimize risk.

For the case of farms where crop is constrained to $\alpha_{crop} \leq 6\%$ of the total land use, see Tables 4.6, 4.8 and 4.10, both models behave the same, assigning 6% of the land to crop and when the compensation is added 94% of the land is assigned to forest instead. Compensations for this scenario go from 52 to 73 $\frac{US\$}{ha \cdot yr}$, which is in all cases a lower value than the corresponding non-constrained portfolio. This lower values are due to the lower returns of pasture when compared against crop, so smaller compensation is necessary to replace pasture by forest.

4.4.3 Scenario III: Risk-aversion ($\lambda = 0.016$) without compensation

Risk-averse farmers will consider not only the mean return of a commodity as a decisive factor, but a risk measure that will inform of commodities that offer greater but less stable return. In all countries, the method of higher-moments chose portfolio weights that produced a slightly higher return, see Tables 4.5 to 4.9. In the case of Brazil and Ecuador, both models chose similar portfolio weights with a zero proportion of forest, a situation that clearly foster transition from forest to more attractive land-uses. In Brazil and Ecuador forest has not only low returns (compared to crop or pasture) but it shows negative skewness and positive kurtosis, (see Table 4.4), that means that the variance is influenced by drop in forest returns (skewness < 0) and by frequent extreme deviations (kurtosis > 0), this situation is avoided by the Higher-Order Moment approach by generating a portfolio with a zero proportion of forest. In the case of Mean-variance, a zero forest portfolio is chosen due more to the low returns of forest compared to crop and pasture. Colombia not only showed the highest returns of forest 56 $\frac{US\$}{ha \cdot yr}$ (see Table 4.4, column three), but the highest forest skewness of all countries and a negative kurtosis, meaning that the variance is less influenced by infrequent negative extreme deviations in return. This combination allowed both models, Mean-Variance and Higher-Order moments, to chose a portfolio with a proportion of 23% and 16% respectively. Thus, a higher compensation is necessary in the latter case to stop deforestation and transition from forest to other land-use.

In the case of portfolios where risk is proxied by Mean Variance (eq. 2.7), variance becomes the only measure of risk which is included in the optimization. Thus, in the case of portfolios departing from a Gaussian distribution, high covariance will be avoided by the Mean Variance approach, even if these values are due to positive increments in returns (*i.e.* skewness > 0). As a result, not only the mean portfolio return μ_p (column 8), but also the variance of the Mean Variance portfolios are smaller than those obtained with Higher-Order Moments - see Brazil (Table 4.5, scenario III and IV), Colombia (Table 4.7, scenario I, III and IV) and Ecuador (Table 4.9, scenario III) *i.e.* scenarios where higher moments are included, in addition to the mean, to compute the portfolios.

Table 4.7: Colombia†. Representative of a medium-sized South American economy.

Scen.	Method	λ	FC $\frac{US\$}{ha \cdot yr}$	α_{crop} %	$\alpha_{pasture}$ %	α_{forest} %	μ_p	cov_p	skw_p	kur_p
Scenario I	Both	≈ 0	0	100	0	0	147.9	8689.6	1.2	2
Scenario II	Both	≈ 0	91,2	0	0	100	148.3	483.1	-0.6	-0.5
Scenario III	Mean Variance	0,016	0	63	14	23	121.0	4473.1	1.6	3.9
Scenario III	Higher Moments	0,016	0	81	3	16	132.1	6059.2	1.2	2.2
Scenario IV	Mean Variance	0,016	31.8	45	0	55	115.4	2190.7	0.9	0.9
Scenario IV	Higher Moments	0,016	44.5	45	0	55	122.4	2191.2	0.9	0.9

† All abbreviations used here are explained in section 3.4.4. The current distribution of returns of Colombia is shown in Fig. 4.9.

Table 4.8: Colombia†. With constrained crop $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$).

	Method	λ	FC $\frac{US\$}{ha \cdot yr}$	α_{crop} %	$\alpha_{pasture}$ %	α_{forest} %	μ_p	cov_p	skw_p	kur_p
Scenario I	Both	≈ 0	0	6	94	0	108	7054.9	2.3	7.7
Scenario II	Both	≈ 0	57.3	6	0	94	116.4	523.9	-0.6	-0.6
Scenario III	Mean Variance	0.016	0	6	43	51	83.3	1756.0	2.1	7.7
Scenario III	Higher Moments	0.016	0	6	48	46	80.9	1924.3	2.1	7.4
Scenario IV	Mean Variance	0.016	14.4	6	39	55	89.3	1516.5	2.0	7.3
Scenario IV	Higher Moments	0.016	16.0	6	39	55	90.2	1515.8	2.1	7.3

† All abbreviations used here are explained in section 3.4.4. The current distribution of returns of Colombia is shown in Fig. 4.9. Results of this table were computed with a crop constrained of $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$) as explained in sections 2.2.1, 3.4 and 3.4.4

Under risk-aversion without compensation (scenario III), both Mean Variance and Higher-Order Moments produced diversified portfolios in Brazil and Colombia, but chose an almost 100% crop portfolio in Ecuador. This might be due to the fact that crop in Ecuador not only offer the highest value in mean returns when compared to other land-uses, but also hold positive skewness, which means that the returns are expected to be positive. In Brazil, both models produced α_{crop} and $\alpha_{pasture}$ portfolios but with different weights. Colombia is the only country where, under scenario III, both models chose a diversified portfolio which included forest without the need to compensate. Interestingly too, in all countries the weight of Crop portfolios was higher with the Higher-Order Moments than with the Mean Variance case. The opposite is true for Forest and Pasture too.

For the case of farms where crop is constrained to $\alpha_{crop} \leq 6\%$ of the total land use, see Tables 4.6, 4.8 and 4.10, both models assign in all cases 6% of the land to crop. Because skewness and kurtosis are very near zero for Brazil and Ecuador, both models behave exactly the same as expected. The mos interesting case is Colombia that due to highest returns per hectare of forest of the three countries studied, see Table 4.4, and positive skewness and curtosis shows a high percentage of forest included in the portfolio (51% for the Mean-variance model and 46% for the Higher-Order moments) even without any compensation added. Colombia also present the highest average return of portfolios (83 $\frac{US\$}{ha \cdot yr}$ for Mean-variance model and 81 $\frac{US\$}{ha \cdot yr}$ for the Higher-Order moments) followed by Brazil (76 $\frac{US\$}{ha \cdot yr}$) and Ecuador (69 $\frac{US\$}{ha \cdot yr}$)

Table 4.9: Ecuador†. Representative of a small South American economy.

	Method	λ	FC $\frac{US\$}{ha \cdot yr}$	α_{crop} %	$\alpha_{pasture}$ %	α_{forest} %	μ_p	cov_p	skw_p	kur_p
Scenario I	Both	≈ 0	0	100	0	0	122,2	4924,6	0,3	1,7
Scenario II	Both	≈ 0	102	0	0	100	122,6	182,8	-0,9	0,6
Scenario III	Mean Variance	0,016	0	97	3	0	120,5	4709,8	0,3	1,8
Scenario III	Higher Moments	0,016	0	100	0	0	122,2	4924,6	0,3	1,7
Scenario IV	Mean Variance	0,016	54	61	0	39	103,6	1755,9	0,5	1,9
Scenario IV	Higher Moments	0,016	56.7	61	0	39	103,6	1755,9	0,5	1,9

† All abbreviations used here are explained in section 3.4.4. The current distribution of returns of Ecuador is shown in Fig. 4.10.

4.4.4 Scenario IV: Risk-aversion ($\lambda = 0.016$) with compensation

When compensation was added, both models produced diversified portfolios where the required forest proportion was reached: Brazil 62%, Colombia 55% and Ecuador 39%, see Table 3.2. In all countries, higher compensation was needed when the portfolio optimization included skewness and kurtosis to measure risk, *i.e.* using Higher-Order Moments. In Ecuador, the Higher-Order Moments required a compensation of $57\frac{US\$}{ha \cdot yr}$ while Mean Variance needed $54\frac{US\$}{ha \cdot yr}$; in Brazil, $59{,}5\frac{US\$}{ha \cdot yr}$ and $59{,}2\frac{US\$}{ha \cdot yr}$ respectively; and in Colombia, $44\frac{US\$}{ha \cdot yr}$ and $32\frac{US\$}{ha \cdot yr}$ were needed. Of all the scenarios studied, scenario IV presents the highest compensations (with both models) overall. This means this scenario represents the highest land-use opportunity cost for forest, a value that must be compensated if forest is to be retained.

For the case of farms where crop is constrained to $\alpha_{crop} \leq 6\%$ of the total land use, see Tables 4.6, 4.8 and 4.10, both models produced diversified portfolios. Due to the lower returns of pasture when compared with crop and because of the 6% crop constrain, the average returns of all portfolios are lower than the returns produced by portfolios without any constraint. This also influence the necessary compensation which in all cases is lower than the needed compensation for portfolios without any constraint. Compensations go from from 14 $\frac{US\$}{ha \cdot yr}$ (Colombia) to 60 $\frac{US\$}{ha \cdot yr}$ (Brazil).

4.5 Considering fire risks in land-use portfolio modeling

Financial compensations in $\frac{US\$}{ha \cdot yr}$ within a market risk framework were presented in sections 3.4 and 4.4 to determine the necessary monetary value to be pay to family-farmers in order to keep the proportion of forest at farm level equal to the current national levels of 62% in Brazil, 55% in Colombia and 39% in Ecuador, see Table 3.2. The goal in this section is to use the same compensation values but apply them to regions with different environmental risk of fire, *i.e.* $\hat{\Lambda}_{low}, \hat{\Lambda}_{med}$ and $\hat{\Lambda}_{high}$ for all three countries studied, in order to determine changes in the proportion of forest in the new computed optimal portfolios.

The values for scenario IV in tables 4.12, 4.14 and 4.16, where already presented in Tables 4.5 to 4.9 and discussed in section 4.4. Here, the same values for scenario IV are shown again for purposes of comparison when environmental risk is included in the portfolio, scenario V.

When environmental risk is included, and all other factors kept constant (scenario V), both models Mean Variance and Higher-Order Moments produced portfolios with less amount of forest share than portfolios optimized only for market risk conditions (scenario IV), see tables 4.12, 4.14 and 4.16 for Brazil, Colombia and Ecuador respectively. Brazil presents the highest values of decrement 27% of forest share: From 62% (scenario IV) to 35% (scenario V with Mean Variance method), followed by Colombia and Ecuador with a maximum decrement of 4%. Both models did not show a significant difference, showing a maximum difference of 3% in Brazil, 2% in Colombia and 0% in Ecuador.

In oder to compare the impact of compensations in land-use investments located in low, medium and high risk regions, a constant compensation was used and the change of forest proportion[5] per hectare was observed, see tables 4.12 to 4.16. Brazil showed the greatest decrement of forest share in the optimal portfolios, at all spatial intensities. The less decrement in Brazil was shown in regions of low spatial intensities, with decrements of 6% (Mean-Variance approach) and 7% (Higher-Order Moments), followed by medium spatial intensity, with decrements of 13% and 12% respectively. Colombia and Ecuador showed a relatively small decrement in forest share of 1% and 2% respectively, in the low spatial intensity and a maximum decrement of 4% for the high spatial intensity. For the case of farms where crop is constrained to $\alpha_{crop} \leq 6\%$ of the total land use a similar decrement of forest proportion, with respect to the case without constraint of crop area, for the three countries studied was observed. The main difference is that for the constrained case is that pasture increase the proportion of land used instead of crop.

[5]Following VCS standards, for destructive events, the carbon benefits generated by the destroyed part of the project are assumed to be completely lost. In this case, the number of years that loss continues equates to the remaining lifespan of the project, (VCS, 2008)

Table 4.10: Ecuador†. With constrained crop $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$).

	Method	λ	FC $\frac{US\$}{ha \cdot yr}$	α_{crop} %	$\alpha_{pasture}$ %	α_{forest} %	μ_p	cov_p	skw_p	kur_p
Scenario I	Both	≈ 0	0	6	94	0	69.1	1358.3	-0.2	0.4
Scenario II	Both	≈ 0	52.3	6	0	94	76.0	153.9	-0.8	1.3
Scenario III	Both	0,016	0	6	94	0	69.1	1358.3	-0.2	0.4
Scenario IV	Mean Variance	0,016	33.9	6	55	39	64.8	653.7	-0.1	0.1
Scenario IV	Higher Moments	0,016	33.9	6	55	39	64.8	653.7	-0.1	0.1

† All abbreviations used here are explained in section 3.4.4. The current distribution of returns of Ecuador is shown in Fig. 4.10. Results of this table were computed with a crop constrained of $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$) as explained in sections 3.4 and 3.4.4

Table 4.11: Brazil†. Optimal land-use portfolio weights under market risk with and without integration of environmental risk.

Scenario	Portfolio	Compensation $\frac{US\$}{ha \cdot yr}$	Market Risk λ	Environmental Risk* $\hat{\delta}_t$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t	Portfolio % α_{crop}	$\alpha_{pasture}$	α_{forest}
IV	Mean Variance	59.2	0.016	-	-	-	-	-	25	13	62
V	Mean Variance	59.2	0.016	0.56	Low	5	23	0.22	25	18	56
				0.56	Med	10.4	11	0.94	26	25	49
				0.56	High	16.4	7	2.34	25	40	35
IV	Higher Moments	59.5	0.016	-	-	-	-	-	33	5	62
V	Higher Moments	59.5	0.016	0.56	Low	5	23	0.22	33	10	57
				0.56	Med	10.4	11	0.94	33	17	50
				0.56	High	16.4	7	2.34	33	29	38

† All abbreviations used here are explained in section 3.5. *The recurrence value $\hat{\delta}_t$ used corresponds to a damage $f_{t_{inv}} = 5\%$ at low spatial-intensity level, see section 3.3.7 and figure 4.7

Table 4.12: Brazil†. Optimal land-use portfolio weights under market risk with and without integration of environmental risk. With constrained crop $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$).

Scenario	Portfolio	Compensation $\frac{US\$}{ha \cdot yr}$	Market Risk λ	Environmental Risk* $\hat{\delta}_t$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t	Portfolio % α_{crop}	$\alpha_{pasture}$	α_{forest}
IV	Mean Variance	59.8	0.016	-	-	-	-	-	6	32	62
V	Mean Variance	59.8	0.016	0.56	Low	5	23	0.22	6	37	57
				0.56	Med	10.4	11	0.94	6	42	52
				0.56	High	16.4	7	2.34	6	46	48
IV	Higher Moments	60.1	0.016	-	-	-	-	-	6	32	62
V	Higher Moments	60.1	0.016	0.56	Low	5	23	0.22	6	40	54
				0.56	Med	10.4	11	0.94	6	48	46
				0.56	High	16.4	7	2.34	6	63	31

† All abbreviations used here are explained in section 3.5. *The recurrence value $\hat{\delta}_t$ used corresponds to a damage $f_{t_{inv}} = 5\%$ at low spatial-intensity level, see section 3.3.7 and figure 4.7. Results of this table were computed with a crop constrained of $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$) as explained in sections 2.2.1, 3.4 and 3.5

Table 4.13: Colombia†. Optimal land-use portfolio weights under market risk with and without integration of environmental risk.

Scenario	Portfolio	Compensation	Market Risk	Environmental Risk*					Portfolio %		
		$\frac{US\$}{ha \cdot yr}$	λ	$\hat{\delta}_t$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t	α_{crop}	$\alpha_{pasture}$	α_{forest}
IV	Mean Variance	31.8	0.016	-	-	-	-	-	45	0	55
				0.41	Low	5	24	0.21	46	0	54
V	Mean Variance	31.8	0.016	0.41	Med	7.4	19	0.39	46	0	54
				0.41	High	10.6	11	0.96	47	0	53
IV	Higher Moments	44.5	0.016	-	-	-	-	-	45	0	55
				0.41	Low	5	24	0.21	47	0	53
V	Higher Moments	44.5	0.016	0.41	Med	7.4	19	0.39	48	0	52
				0.41	High	10.6	11	0.96	49	0	51

† All abbreviations used here are explained in section 3.5. *The recurrence value $\hat{\delta}_t$ used corresponds to a damage $f_{t_{inv}} = 5\%$ at low spatial-intensity level, see section 3.3.7 and figure 4.7

Table 4.14: Colombia†. Optimal land-use portfolio weights under market risk with and without integration of environmental risk. With constrained crop $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$).

Scenario	Portfolio	Compensation	Market Risk	Environmental Risk*					Portfolio %		
		$\frac{US\$}{ha \cdot yr}$	λ	$\hat{\delta}_t$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t	α_{crop}	$\alpha_{pasture}$	α_{forest}
IV	Mean Variance	14.4	0.016	-	-	-	-	-	6	39	55
				0.41	Low	5	24	0.21	6	40	54
V	Mean Variance	14.4	0.016	0.41	Med	7.4	19	0.39	6	40	54
				0.41	High	10.6	11	0.96	6	41	53
IV	Higher Moments	16.0	0.016	-	-	-	-	-	6	39	55
				0.41	Low	5	24	0.21	6	51	53
V	Higher Moments	16.0	0.016	0.41	Med	7.4	19	0.39	6	42	52
				0.41	High	10.6	11	0.96	6	43	51

† All abbreviations used here are explained in section 3.5.*The recurrence value $\hat{\delta}_t$ used corresponds to a damage $f_{t_{inv}} = 5\%$ at low spatial-intensity level, see section 3.3.7 and figure 4.7. Results of this table were computed with a crop constrained of $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$) as explained in sections 2.2.1, 3.4 and 3.5

Table 4.15: Ecuador†. Optimal land-use portfolio weights under market risk with and without integration of environmental risk.

Scenario	Portfolio	Compensation	Market Risk	Environmental Risk*					Portfolio %		
		$\frac{US\$}{ha \cdot yr}$	λ	$\hat{\delta}_t$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t	α_{crop}	$\alpha_{pasture}$	α_{forest}
IV	Mean variance	54.5	0.016	-	-	-	-	-	61	0	39
				0.33	Low	5	22	0.23	62	0	38
V	Mean variance	54.5	0.016	0.33	Med	8.7	18	0.50	63	0	37
				0.33	High	12.7	10	1.27	65	0	35
IV	Higher Moments	56.7	0.016	-	-	-	-	-	61	0	39
			0.016	0.33	Low	5	22	0.23	62	0	38
V	Higher Moments	56.7	0.016	0.33	Med	8.7	18	0.50	63	0	37
			0.016	0.33	High	12.7	10	1.27	65	0	35

† All abbreviations used here are explained in section 3.5. *The recurrence value $\hat{\delta}_t$ used corresponds to a damage $f_{t_{inv}} = 5\%$ at low spatial-intensity level, see section 3.3.7 and figure 4.7

Table 4.16: Ecuador†. Optimal land-use portfolio weights under market risk with and without integration of environmental risk. With constrained crop $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$).

Scenario	Portfolio	Compensation	Market Risk	Environmental Risk*					Portfolio %		
		$\frac{US\$}{ha \cdot yr}$	λ	$\hat{\delta}_t$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t	α_{crop}	$\alpha_{pasture}$	α_{forest}
IV	Mean variance	33.9	0.016	-	-	-	-	-	6	55	39
V	Mean variance	33.9	0.016	0.33	Low	5	22	0.23	6	58	36
				0.33	Med	8.7	18	0.50	6	63	31
				0.33	High	12.7	10	1.27	6	64	30
IV	Higher Moments	33.9	0.016	-	-	-	-	-	6	55	39
V	Higher Moments	33.9	0.016	0.33	Low	5	22	0.23	6	59	35
			0.016	0.33	Med	8.7	18	0.50	6	63	31
			0.016	0.33	High	12.7	10	1.27	6	67	27

† All abbreviations used here are explained in section 3.5. *The recurrence value $\hat{\delta}_t$ used corresponds to a damage $f_{t_{inv}} = 5\%$ at low spatial-intensity level, see section 3.3.7 and figure 4.7. Results of this table were computed with a crop constrained of $0 \leq \alpha_{crop} \leq C_{LU_{crop}} = 6\%$) as explained in sections 2.2.1, 3.4 and 3.5,

Chapter 5

Discussion

5.1 Environmental risk assessment for land-use portfolios

Section 3.3 presents an original modeling approach designed to assess environmental risk and to facilitate the integration of such assessment into the land-use portfolio optimization, like the one presented in sections 3.4 and 3.5. The goal of the modeling approach is to classify farms geographically by the impact that fire hazard might have in agricultural and forestry investments of family-farmers. Thus, zoning regions by risk helps to determine the potential financial impact that environmental hazards may have in particular regions in order to avoid losses from actors involved in agriculture: subsistence and commercial farmers, governments, insurance and financial providers, and also initiatives like PES or REDD+. Zoning also facilitates the avoidance of PES or REDD+ projects in regions not suitable for forestry or agriculture due to higher environmental risks, and thus actively helps as a risk mitigation strategy, see chapter 1.

The geographical location of fires, the recurrence of fire events per year and their damage per hectare are the main variables studied in the modeling approach, presented in section 3.3, because they can easily be included in the historical productivity analysis. A kernel-smoothed function (3.1) was used to estimate the spatial intensity function, *i.e.* number of burned areas per hectare. The semi-parametric approach has the advantage of not having to assume any particular probability distribution function for the point process analyzed: That proved to be relevant because within every country the intensity and spatial location showed variations in a way that will make the assumption of a particular distribution untenable. The results were used to classify every country into sub-regions of low, medium and high spatial intensity; although this subdivision is not necessary, it was done in order to compare similar fire regimes (frequency of ignition) and the size of damaged areas in different country zones. In order to quantify the recurrence of fire events per year at different spatial intensity regions, a sample of random locations was generated and the historical record of every location was analyzed in terms of time-frequency and damage generated (total historical burned area).

Relatively high correlations, around $R^2 = 0.92$ in Brazil, and $R^2 = 0.71$ in Colombia and Ecuador were found when a log-linear function between the recurrence of events per year and the proportional damage was fitted, see sections 3.3.5, 3.3.7 and 4.1.3. Contrary to what was expected, *i.e.* that small burn-areas were more frequent than bigger ones, it was found that greater damage has higher frequency of recurrence. That pattern was seen in all three countries and all spatial intensities. When spatial intensities are compared, keeping the recurrence per year constant, high intensities show higher damage. This was observed in all countries and with relatively high correlation values, see figure 4.6 and table 4.2. This means that farms located in high risk regions will not only have higher probability of having fire in their nearby locality, but every fire is more likely to generate a greater damage than at lower spatial intensities. This could also mean that high spatial intensity regions have indeed more fires ignited for deforestation purposes, due to the frequency and extended size of the damages. This is particularly relevant in Brazil where the data showed single fires burning up to one thousand square kilometers in a couple of days.

The Voluntary Carbon Standard uses a historical environmental damage value of 5% to distinguish REDD+ projects without significant environmental damage ($< 5\%$) from projects where further risk analysis is required ($\geq 5\%$). For this study, a threshold damage value of 5% was arbitrarily defined without loss of generality, as it can easily be increased/decreased without changing the scope of the approach. The 5% value was defined as a maximum damage per hectare tolerated by a farmer willing to invest in forest and other land-use activities. Maps with random locations surpassing and non-surpassing the 5% threshold were found for all countries and in all spatial intensities, see figure 4.3 and section 4.1.2. The value of damage at random locations was computed out of historical records of burned areas obtained from satellite images (Terra satellite, MODIS sensor) and assessed with the functions presented in section 3.3. The methodology is useful to generate zones where farming can be considered. In all countries, low spatial intensity regions showed that most random locations did not surpass the 5%

threshold, making them ideal candidates for projects willing to include forest as a land-use portfolio asset. In a similar way, high spatial intensity regions showed that most random locations did surpass the mentioned threshold, making them not ideal for forest investments due to the long recovery process that a forest has after fire.

MODIS cannot observe the earth's surface when cloud cover is present (NASA, 2012), so partial or total cloud cover may induce a bias in the interpretation of signals of the Spectroradiometer (MODIS) on board the Terra satellite, that affects the real size and location of burned areas. Orographic effects can also play a role as they can influence the type and size of clouds that form in different altitudes (Tan, 2012). The presence of clouds in the Andes mountains of Colombia and Ecuador is most likely the main reason for the relatively lower correlation values $R^2 = 0.72$, between the log-transformed average time of events $\hat{\delta}_t(u|\hat{\Lambda}_{subreg})$ and the proportion of damage $\rho_t(u|\hat{\Lambda}_{subreg})$ (eq.3.6), when compared against Brazil, $R^2 = 0.93$, see figure 4.6 and table 4.2. This could also be the reason for the low spatial intensity values of Ecuador, which present fires almost exclusively in its high mountain range, with a maximum of 0.03 events/km^2 (figures 3.4 and 4.1).
In MODIS, every pixel identified as a burned area is classified with a number from 1 to 4, representing most to least confidence respectively (Boschetti *et al.* 2009). For the present study, all pixels classified as burned area were used. A potential improvement, though this might also yield a more conservative risk model, could be obtained by using only pixels classified with the highest degree of confidence. In spite of the relatively lower correlation values in Ecuador and Colombia between the average time of events and the proportion of damage, the relationship is still statistically significant in all countries and at every spatial intensity. Future research of such a relationship could yield a better assessment of hazard and risk at the landscape level.

According to Roy *et al.* (2005), satellite remote sensing provides the only means of monitoring vegetation burning from a regional to global scale due to the huge areas that must be covered in a single day. Providers of remote sensing information can be classified by different factors like the type of sensors on board of the vehicle, the time-lapse with which they cover the earth, the image resolution, price of acquisition, etc. The two most relevant variables are arguably the latter ones. Some providers, like NASA, offer historical information for free but at a lower resolution level (500m x 500 m) see Table 3.4, while RapidEye sells high resolution information (couple of cm per pixel) for 0.95 €/km^2 RapidEye (2014). When vast extensions must be covered several times per year, the higher prices may become a constraint. Thus a compromise between resolution and price must be found depending on the goal of the project. For smaller regions, new technology is facilitating the use of Unmanned Aerial Vehicles (UAV) or Remote Piloted Vehicles (RPV) due to development not only of light drones but also of visual, multi- and hyper-spectral cameras which are very light and offer high resolution images (MIT, 2014), such commercial drones can fly at altitudes of up to 4000 m and cover thousands of hectares in a single day (Bormatec, 2014). Although the technology is still in its infancy (Herbold, 2013), the much lower prices of data acquisition facilitates the development of models and assessment tailored for every region. Although hardly a competitor, drones may be used in the near future to complement information acquired via satellite remote sensing, and thus provide highly accurate but less expensive information at global and regional scales.

In the present study, there was in average a greater burned area per event in regions with higher spatial density than in lower ones for all three countries studied. This observation may be taken into account when designing ex-ante risk management strategies. Policies encouraging the use of adequate agricultural techniques and promoting forest protection may strongly reduce the risk of wildfires. Slash-and-burn is a common agricultural technique widely used in South America to clear the land after harvests. Other use of fire involves deforestation in order to convert original forest lands to land uses and get higher returns. The high spatial intensity values found in this study, of up to 1.4 and 2.2 burned areas per km^2 in Colombia and Brazil respectively, reflect not only the extended use of such techniques, but that many of the fires become uncontrolled, even in humid tropical regions where fires were largely absent since the last glacial maximum (Pausas and Keeley, 2009). According to Aragão and Shimabukuro (2010) fire-free land-management can substantially reduce fire incidence by as much as 69%. This could greatly increase the number of regions that could use forest as a relevant asset alternative within the PES and REDD+ initiatives and could facilitate the control of intentional fires in the region.

Policy makers could also consider relocating rural households operating in high-risk regions as a governmental ex-ante management strategy that could be less expensive than, as usual, coping with the damage in the aftermath, an approach that has proven vastly ineffective (Barnett *et al.*, 2008). Former UN Secretary General Kofi Annan reported in October 2005 that flash appeals had generated on average only 16% of the requested funds (Barnett *et al.*, 2008).In fact, rural smallholders currently use migration as one of the informal means of self-insurance. However, the implied risk premium for self-insurance strategies is usually paid by the farmers with few or no governmental support in developing countries (Barnett *et al.*, 2008). Governments in such economies have started to show support and be active in the promotion of market-based risk management (*e.g.* insurance), as this approach can reduce the needs and scope for government interventions and thereby decrease the costs incurred by governments in ex-post coping activities (World Bank, 2011). However, traditional insurance is out of reach for most rural households, and the relatively new microinsurance is still under development and has been focused more on drought and floods. Hopefully this risk assessment approach can contribute to better insight into the understanding of environmental risks and their potential impacts at farm level.

Proposed changes of the Voluntary Carbon Standards risk rating system

As mentioned in section 2.1, more than a third of the voluntary market in 2009 were credits traded using the Voluntary Carbon Standard (VCS) (Hamilton et al. 2010, Jagger *et al.* 2010). VCS also follows the validation and verification of projects according to Kyoto CDM Standards (VCS, 2010). This is unfortunately not the case of many national PES and conservation incentive programs, where such validation and verification are almost totally absent (FONAFIFO *et al.* p.36, 2012). Although the VCS' risk rating system (Fig 2.1) offers a structured classification of natural risks, it misses valuable information like the probability of occurrence. It is clearly not the same to have 80% farm damage due to fire within the next 25 years with a probability of occurrence of 1%, and to have the same damage and return period with 95% occurrence probability. Although different distributions like binomial, Poisson, Pareto and Gumbel can be used to compute the probability of occurrence of certain events, the choice of a probability distribution is mainly determined by whether the conclusions want to be drawn from the center of the distribution or from the extremes. For extreme values, also known as fat-tails, the relatively easy-to-use Peaks Over Threshold can be used (Klüppelberg and Stelzer, 2014). Such procedure could be useful to determine the return period of extreme fires in a region. For the particular case of this study, however, it is more relevant to find locations for projects where the natural risk (due to fire) goes from non-significant ($< 5\%$ historical carbon loss) to highly significant or (Fail) Fig 2.1.

Based on binomial proportions, the Agresti intervals present the probability of occurrence of locations where the damage has surpassed the 5% threshold of damage, see table 4.1. Independent of the approach to compute the probability of occurrence, its value can be added to the VCS risk rating table in order to improve the overall accuracy of the system so that project-related actors can take more adequate decisions. Table 5.1 presents an improved version of the VCS risk rating system. The main changes are the introduction of the probability of occurrence for different return periods and a revaluation of when project proposals should fail or not.

Table 5.1: Proposed improvement for the Non-Permanence Risk Rating Table presented in VCS (2012, p.14), see Table 2.1

Score for natural risks (LS)												
	$< 10yr$			$10yr \leq TI < 25yr$			$25yr \leq TI < 50yr$			$50yr \leq TI < 100yr$		
	$P_c \leq 10$	$10 < P_c \leq 50$	$50 \leq P_c$	$P_c \leq 10$	$10 < P_c \leq 50$	$50 \leq P_c$	$P_c \leq 10$	$10 < P_c \leq 50$	$50 \leq P_c$	$P_c \leq 10$	$10 < P_c \leq 50$	$50 \leq P_c$
Catastrophic $70\% \leq$ loss of carbon stocks	F	F	F	F	F	F	F	F	F	F	F	F
Devastating $50\% \leq$ loss of carbon stocks $< 70\%$	F	F	F	F	F	F	F	F	F	F	F	F
Major $25\% \leq$ loss of carbon stocks $< 50\%$	30	F	F	20	30	F	10	20	30	5	10	20
Minor $5\% \leq$ loss of carbon stocks $< 25\%$	20	30	F	10	20	30	5	10	20	0	5	10
Insignificant loss of carbon stocks $< 5\%$	1	2	5	0	1	2	0	0	1	0	0	0
No loss loss of carbon stocks $= 0\%$	0	0	0	0	0	0	0	0	0	0	0	0

Mitigation (M)	
Prevention measures applicable to the risk factor are implemented	0.75
Project proponent has proven history of effectively containing natural risk	0.50
Both of the above = 0.75 x 0.50	0.38
None of the above	1

Score for each natural risk applicable to the project = LS x M	
Fire (F)	
Pest and disease outbreaks (PD)	
Extreme weather (W)	
Geological risk (G)	
Other natural risks (ON)	
Total Natural Risk = F + PD + W + G + ON	

Where yr means year, TI is the time interval between damaging events, P_c is the probability of occurrence in % and F means that the project has unacceptable high risk and therefore fails, see section 2.1.

The sample of random location points used to generate the binomial proportions can also be used to generate maps of risk for a specific threshold of damage, see for example the case of Brazil (Fig. 4.3) where every location has either a cumulative damage of $\leq 5\%$ (depicted with brown circle) or $> 5\%$ (grey cross). Of course the value of the threshold can be changed to estimate any damage and its probability of occurrence for a location of interest. Independently of the approach to compute the estimated damage and its probability of occurrence, their value should be added to the VCS Non-Permanence Risk Analysis (Table 2.1) in order to improve the overall accuracy of the system so that project related actors can take more adequate decisions.
Table 5.1 present an improved version of the VCS risk rating system, the main changes are the introduction of the probability of occurrence for different time intervals between events and a revaluation of when project proposal should fail or not. Thus for example, events damaging more than 50% of the project area shall fail in all cases, whereas an event damaging between 25 to 50% of the project area within the next 10 years shall only be considered if its probability of occurrence is less than 10%. Although the score values of Table 5.1 are only suggested values that may be adjusted to national or international requirements, the methodology proposed here integrates valuable information provided by the probability of occurrence that may be computed using the methodology presented by Acevedo-Cabra *et al.* (2014).

5.2 Land-use portfolios under market risk

Previous chapters presented current methodologies used to compute optimal portfolios when historical changes in commodity prices are taken into account, *i.e.* market-risk. The main difference between several existing approaches is whether the approach assumes the commodity prices to be Gaussian or non-Gaussian distributed. Assuming Gaussian distributed prices makes the computation of portfolios easier and facilitates the logical understanding of the approach. Several attempts have been made, see section 2.2.3, to generate an approach able to capture risk in multivariate portfolios under non-Gaussian markets, an issue that is still under research (Klüppelberg and Brodin 2008). From the approaches mentioned in section 2.2 and 3.4, the Higher-Order moment model offers both a relatively easy understanding of the approach and the relaxation of the Gaussian assumption. In addition to these advantages, the Higher-Order moments method is consistent with the Arrow-Pratt measure of absolute risk aversion and is a parametric approach that works even in markets with relatively little historical information, *e.g.*

the market of agricultural and forest commodities in developing countries. This is not the case for some of the most sophisticated methods mentioned in section 2.2.3. Another drawback from such approaches is that they either get extremely complicated or do not work in multivariate portfolios.

In section 4.4, results for a comparison between the Higher-Order moments approach and the Mean-Variance method were presented. Both methods used national information from Brazil, Colombia and Ecuador, and three different land-uses (Crop, Pasture and Forest) in order to compute an optimal portfolio informing which land-use proportions to have in order to maximize the returns of typical family-farmers in the three countries. For all three countries studied, the required compensation payments obtained with the Higher-Order moments were slightly higher than those presented by recent studies in the same region *e.g.* (Knoke *et al.* 2011). However, the main finding is that both models do not depart significantly from each other, when compared in terms of financial compensation. Colombia showed the greatest difference in compensation with a value of 12.7 $\frac{US\$}{ha \cdot yr}$ higher with the Higher-Order moments than with the Mean-Variance. In Brazil and Ecuador the maximum difference was just 1.7 $\frac{US\$}{ha \cdot yr}$ higher compensation with the Higher-Order moments. Both models also showed similarities in the weights of the optimal portfolios founded.

An explanation for the similarity of results in both models is the frequency of input data, because the values from FAO data are averaged yearly. Thus, intra-month peaks that could have provided valuable information for the Higher-Order moments are reduced to a mere yearly average. Another problem is the use of national data. Here again for FAO purposes, regional data are averaged to a national value repeating the reduction to average above mentioned. When mean values are used, both models should behave very similarly, because when data tends to be Gaussian, the Higher-Order moments converge to the Mean-Variance approach. For this research it was not possible to get historical records of daily or monthly official prices for the commodities and countries studied. FAO data used in all cases is a national estimate of historical records.

An interesting fact of all optimal portfolios obtained is that they have a high proportion of crops within the portfolio. However, not all pasture land is apt to be converted to crops which means that even higher compensations should be paid to maintain forest at its current levels. Therefore the compensations presented here, although plausible in some regions, do not necessarily reflect the reality of every farm (as here an average farm was used). Thus, higher compensations can be expected in farms or regions where not all pastures can be converted to crops.

Another scenario where cropland has a limited available area of the farm, due to for example deficit of nutrients or water supply in some areas of the farm, showed that when an area constraint of 6% was set to cropland the remaining space was mainly filled by pastures for the scenarios without compensation. This was the case of Colombia and Ecuador due to the lower returns per hectare-year of pastures, with respect to crop. Thus, the necessary compensation to increase the share of forest was lower compared to the scenario where no constraint was set to cropland. The difference in compensation between constrained and unconstrained scenarios is of 18 $\frac{US\$}{ha \cdot yr}$ (Mean-Variance) and 28 $\frac{US\$}{ha \cdot yr}$ (Higher-Order moments) in Colombia and 20 $\frac{US\$}{ha \cdot yr}$ (Mean-Variance) and 23 $\frac{US\$}{ha \cdot yr}$ (Higher-Order moments) in Ecuador. For the case of Brazil, both scenarios of constrained and unconstrained cropland area produce portfolios with a high proportion of pasture and therefore setting a cropland as constrained did not significantly change the portfolio weights or the compensation.

5.3 Integration of Market and Environmental Risk

Section 3.5 explains an approach to include the assessment of environmental risks, section 3.3, in the land-use portfolio optimization approach, section 3.4.1. The goal of such approach is to determine, based on historical records, the potential impact of environmental hazards in the portfolio returns at a particular geographical location.

As it was expected, the inclusion of the environmental risk assessment (here in the form of fire) in the portfolio produced a decrement in the share of forest in all countries in a similar proportion in both the crop constrained and the unconstrained scenarios. Thus, in Brazil a 5% damage at low spatial intensity corresponds to 16.4% at high spatial intensity; Ecuador and Colombia follow with 12.7% and 10.6% respectively. Therefore, the same investment of land-use per hectare has a much higher potential damage at higher spatial intensity regions. These values were used to compute the decrement of forest share in the optimal land-use portfolios.
Brazil presents the highest decrement of forest when environmental risk is

integrated into the portfolios. For the low spatial intensity with 5% area damaged, the optimal portfolio reduces its forest share 5% (from scenario without including environmental risk), and 12% and 24% at medium and high spatial intensities respectively, which corresponds to the surroundings areas of Amazon's rain forest. Colombia and Ecuador present in the worst case (high spatial intensity) a reduction of at most 4% in the share of forest for the optimal portfolios. However, by increasing the fixed threshold of 5%, much higher values of damage at all intensities and all countries can be obtained. Thus it is clear that the fixed threshold was not used to determine the worst possible damage ad different intensities, but to determine regions where land-use investments including forest could be considered.

At the same time that forest share decreases at higher intensities, pasture or crop increases by a similar proportion. This actually reflects the existing situation in South America where forests are replaced by other land-uses with higher returns to investment. Forests thus, not only become less interesting because a farmer receives less per hectare, but forests have a much longer recovery period (decades) in the aftermath of uncontrolled fire events compared to other land-uses.

Contrary to what some authors like Kissinger *et al.* (2012) argue, the size of burned areas has unfortunately increased in Brazil in the last years, see Fig. 4.4. This again highlights the relevance of environmental risk assessments within the problematic deforestation that seems not to have decreased, at least in Brazil.

5.4 REDD+ and land-use portfolios

Within the forest and global warming perspective, REDD+ has evolved as one of the most promising Payments for Ecosystem Services (PES) at a global level. REDD+ monetarily compensates family-farmers for every hectare of forest that they avoid to replace with other land-uses like crop or pasture. In addition to its primary goal, although not originally thought as such, REDD+ may also become an instrument to partially alleviate poverty of family-farmers in developing regions by generating an alternative income out of forestry, an activity that otherwise has been seen as of secondary importance in a region where many governments still foment the expansionism of agriculture. In the particular case of South America, 53% of rural households live below the poverty line (ECLAC, 2010), thus REDD+ could find several family-farmers who are willing to cooperate with this new alternative. One important step towards sustainable PES is to find fair and competitive prices where actors who are involved benefit. Several authors have studied the topic of fair financial prices to be paid to family-farmers due to PES with values of financial compensation ranging from US$ 40 to US$ 170 per hectare per year for different countries in South America, confirming thus that the results presented here within a purely market-risk perspective are plausible. However, not only fair prices within a purely market-risk perspective should be contemplated, but assessments of other risks such as environmental ones should also be included for a more realistic overview of the situation and to determine how sustainable a project can be in a particular region. In the case of regions with a record of environmental risk, either much higher compensation payments should be paid, a rather unrealistic assumption, or all parts involved in such projects should be aware that the sustainability of such projects could be seriously compromised.

For the particular case of forest as land-use activity, fire is one of the most devastating environmental risks that affects stands as it may pass decades before a forest stand recovers to its original conditions. In the case of South American countries, this becomes even more important when it is known that, either through intentional or unintentional fires, the region has the highest global rates of deforestation through fires and illegal logging, see section 1.1. Thus, environmental risk assessment of hazards such as fire becomes particularly relevant for the sustainability of initiatives such as REDD+ in the region. Another relevant factor to take into account is that family-farmers are usually ill prepared to face risks. As it was mentioned in previous chapters, family-farmers are constrained to low effective risk-mitigation strategies which costs are usually entirely paid for themselves, with little or no governmental or private sector support. Thus, any attempt to establish sustainable approaches to halt deforestation should take into account not only the market but also the environmental risk that family-farmers and other actors might face if they decide to cooperate with such initiatives. Fully understanding the risks to which family-farmers may be subject to, will allow a better planning and sustainability of initiatives like REDD+ to halt deforestation.

Chapter 6

Conclusions

This chapter is organized as follows: sections 6.1 to 6.3 conclude on the particular topics addressed for this research, that is: environmental risk, market risk, integration of market risk, and finalizes with a short discussion of the benefits that improved modeling may provide for the sustainability of PES and REDD+ projects.

6.1 Environmental risks

MODIS cannot observe the earth's surface when cloud cover is present (NASA, 2012), so partial or total cloud cover may induce a bias in Terra's interpretation of signals that affects the real size and location of burned areas. Orographic effects can also play a role as they can influence the type and size of clouds that form in different altitudes (Tan, 2012). However, the results obtained with the modeling approach are statistically significant. An alternative to satellite imagery is the use of Unmanned Aerial Vehicles (UAVs) or Remote Piloted Vehicles (RPVs) which can be equipped with sensors similar to the ones used by satellites. Due to the fact that UAVs and RPVs fly at lower height, compared to satellites, they could fly below cloud level as well and thus spot environmental damage. A drawback, however, is that they can cover less area per image than satellite imagery.

In order to model the spatial intensity, it was assumed that fire events were independent. According to Peng *et al.* (Peng, 2005), and for the case of California wildfires, if a particular location burns one year, then it is perhaps less likely to burn the next year, thus the processes are not independent. However, Nichols (Nichols, 2011) studying the same region, found that year to year dependence was rather a weak factor. In the particular case of wildfire activities in tropical forests, once an area is deforested there is a high likelihood that highly frequent management fires, which may become uncontrolled, will follow particularly in pastures (Balch, 2011). Thus, there is a high likelihood that repeated fires, including slash-and-burn fires, take place over a multi-year period after forest felling (Balch, 2011).

In the present study, there was on average a greater burned area per event in regions with higher spatial density than in lower ones for all three countries studied. This observation may be taken into account when designing ex-ante risk management strategies. Policies encouraging the use of adequate agricultural techniques and promoting forest protection may strongly reduce the risk due to wildfires. Slash-and-burn is a common agricultural technique widely used in South America to clear the land after harvests. Other use of fire involves the conversion of original forestlands to other land uses. The high spatial intensity values, found in this study, of up to 1.4 and 2.2 burned areas per km^2 in Colombia and Brazil respectively, reflect not only the extended use of such techniques but that many of the fires become uncontrolled, even in humid tropical regions where fires were largely absent since the last glacial maximum (Pausas and Keeley, 2009). According to (Aragao and Shimabukuro, 2010) fire-free land-management can substantially reduce fire incidence by as much as 69%.

Policy makers could also consider relocating rural households operating in high risk regions as a governmental ex-ante management strategy that could be less expensive than, as usual, coping with the damage in the aftermath, an approach that has proven vastly ineffective (Barnett, 2008). Former UN Secretary General Kofi Annan reported in October 2005 that flash appeals had generated on average only 16% of the requested funds (Barnett, 2008). In fact, rural smallholders currently use rural migration as one of the informal means of self-insurance. However, the implied risk premium for self-insurance strategies is usually paid by the farmers with little or no governmental support in developing countries (Barnett, 2008). So far, governments in such economies have shown support and are active in the promotion of market-based risk management (*e.g.* insurance), as this approach can reduce the needs and scope for government interventions and thereby decrease the costs incurred by governments in ex-post coping activities (World Bank, 2011). However, traditional insurance is out of reach for most rural households, and the relatively new microinsurance is still under development and has been focused more on drought and floods. It is thought that this risk assessment approach can contribute to better insight into the understanding of environmental risks and their potential impacts at farm level.

The methodology for the assessment of environmental fire damage developed in the present study can be easily adapted to other kinds of environmental risk. In the case of floods, the spectral reflection of water can be captured using multi-spectral cameras on board of satellites or aircrafts. Although more difficult to detect, droughts can be recognized using proxy values like the Normalized Difference Vegetation Index (NDVI), that can be computed from multi-spectral cameras and can be compared to existing spectral libraries in order to know whether the plants are under water stress. Thermo cameras can be used to spot some types of water or soil pollution. As long as a particular environmental damage is recognized, the presented methodology in this study can be used to assess its spatio-temporal impact.

6.2 Land-use portfolios under market risk

When considering land-use portfolios exclusively under market risk it was found that the necessary financial compensations obtained with the Higher-Order moments model do not depart significantly from the Mean-Variance model. Both models showed also similarities in the weights of the optimal portfolios founded and therefore in the land-use diversification. An explanation for these similarities is the frequency of input data used, because the values from FAO data are averaged yearly. Thus, intra-month peaks that could have provided valuable information for Higher-Order moments are reduced to a merely yearly average. Another problem is the use of national data. Here again for FAO purposes, regional data are averaged to a national value repeating the reduction to average above mentioned. In theory when mean values are used, both models should behave very similarly, because when data tends to be Gaussian distributed, Higher-Order moments converge to Mean-Variance as the skewness and kurtosis approaches zero and the effect of higher moments disappear. For this research it was not possible to get historical records of daily or monthly official prices for the commodities and countries studied. FAO data used in all cases are yearly national estimates of historical records.

Since 2014 some regions of Colombia have been starting to collect data of prices and productivity on a monthly and even weekly basis (DANE 2011). This information together with the use of models like Higher-Order moments could improve the results obtained with the portfolio analysis presented here. In any case, when considering the potential land-use investments of family-farmers in developing markets, close attention should be paid to the "non-normal" behavior of the price distribution of commodities. Many financial or statistical approaches used as decision support tools assume a Gaussian distribution in direct or indirect form. More often than not, however, the statistical evidence shows that prices of commodities in such markets tend to have skewed and heavy-tailed distributions; these translate to an underestimation of market risk and therefore underestimation of expected returns. In regions with a significant proportion of farmers living under the poverty line, and with a strong tendency for such rural households to abandon agriculture in favor of rural-urban migration, an overestimation of returns by policy makers, financial analysts, or any other players involved in the process might only worsen the situation. In the case of South America, the incorporation of compensation payments in exchange for keeping forested land has, at least, two potential positive effects - mitigation of global climate change (Stern, 2006) and a positive shift in the annual income of family-farmers.

6.3 Integration of Market and Environmental Risk

As was expected, the inclusion of the environmental risk assessment (here in the form of fire) in the portfolio produced a decrement in the share of forest in all countries. This was obtained by dividing every country into spatial regions of high, medium and low activity (number of burned areas per hectare). For all regions the recurrence of events (number of years between fires) was computed. The recurrence of events, of an arbitrarily low threshold[1] of damage of 5% per hectare at low activity region, was computed in order to compare damage between regions. The same recurrence of events was used to find the spatial characteristics of events at higher spatial intensities. Thus, the recurrence of events in Brazil that generate a 5% damage per hectare at low spatial intensity corresponds to a 10.4% and 16.4% at medium and high spatial intensities; see Table 4.12.

Keeping constant the financial compensation found for portfolios exclusively with market-risk, it was observed how much the forest share in the portfolios decreased at low, medium and high spatial intensities. The same effect was mentioned by Knoke *et al.* (2014) when studying the increment of

[1]A threshold value of 5% is also used by the Verified Carbon Standards to differentiate between projects that need no further risk analysis (< 5% of project area damaged) and projects that need a deeper analysis and are required to present evidence of risk mitigation strategies (VCS, 2008, 2012)

food prices in Ecuador. For this study it was also observed that the higher the spatial intensity of environmental risk, the less is the share of forest in the portfolio in all countries. This highlights the importance of finding regions with a historical low record of fires in order to establish sustainable REDD+ projects.

Brazil presents the highest decrement of forest when environmental risk is integrated into the portfolios. For this particular case, the arbitrarily fixed 5% threshold used was not meant to determine the worst possible damage at different intensities, but rather to determine regions where land-use investments including forest could be considered, gray crosses in Figure 4.3. The methodology thus reports not only about optimal returns of a diversified investment, but the sustainability of such at different locations. This allowed to observe that, while forest share of a portfolio decreases at higher intensities, pasture and crop increase at similar proportions. This reflects the actual situation in South America where forests are replaced by other land-uses with higher returns on investment. Forested land thus not only becomes less interesting because a farmer receives less per hectare, but it has a much longer recovery period (decades) in the aftermath of uncontrolled fire events compared to other land-uses.

6.3.1 REDD+ and land-use portfolios

Within the forest and global warming perspective, REDD+ has evolved as one of the most promising PES at the global level. REDD+ monetarily compensates family-farmers for every hectare of forest that they avoid to replace with other land-uses such as crop or pasture. In addition to its primary goal, although not originally thought as such, REDD+ may also become an instrument to partially alleviate poverty of family-farmers in developing regions by generating an alternative income out of forestry, an activity that otherwise has been seen as of secondary importance in a region where many governments still foment the expansionism of agriculture. In the particular case of South America, 53% of rural households live below the poverty line (ECLAC, 2010). Thus REDD+ could find several family-farmers willing to cooperate with this new alternative. One important step towards reaching sustainable PES (particularly REDD+) is to find fair and competitive prices where actors who are involved benefit.

Several authors have studied the topic of fair financial prices to be paid to family-farmers due to PES, either by comparing two mutually exclusive land uses (Grieg-Gran, 2005; Knoke *et al.* 2008; Butler *et al.* 2009) or including more than two land uses (Benitez *et al.* 2009; Castro *et al.* 2013; Hildebrandt and Knoke 2011; and Knoke *et al.* 2011) with values of financial compensation ranging from US$ 40 to US$ 170 per hectare per year for different countries in South America. This thus confirms that the results within a purely market-risk perspective are plausible. However, none of the authors mentioned included potential changes in compensations due to environmental risks. Inclusion of such risks should be contemplated to get a more realistic overview of the situation and to determine the sustainability of projects in particular regions. This study reveals how relevant the inclusion of such assessment is, even in areas of low risk. In the case of regions with a record of environmental risk, either much higher compensation payments should be paid, a rather unrealistic assumption, or all parts involved in such projects should be aware that the sustainability of such projects could be seriously compromised.

For the special case of forest as a land-use activity, fire is one of the most devastating environmental hazards affecting stands as decades may pass before a forest stand recovers to its original conditions. In the case of South American countries, this becomes even more important since, either through intentional or unintentional fires, the region has the highest global rates of deforestation through fires and illegal logging. Thus, environmental risk assessment of hazards such as fire becomes particularly relevant for the sustainability of initiatives such as REDD+ in the region. Another relevant factor to take into account is the fact that family-farmers are usually ill-prepared to face risks. Family-farmers are constrained to low effective risk-mitigation strategies, which costs are usually entirely paid for themselves with little or non governmental or private sector support. Thus, any attempt to establish sustainable approaches to halt deforestation should take into account not only the market, but also the environmental risk that family-farmers and other actors might face if they decide to cooperate with such initiatives. Full understanding of the risks to which family-farmers may be subject to will allow for better planning and sustainability of initiatives like REDD+ to halt deforestation.

6.3.2 Sustainability of PES and REDD+ projects

Since the early days of the Kyoto Protocol there has been a debate about the permanence of forest carbon related emission reductions and GHG removals (Trines 2008, Murray *et al.*, 2007). Forest carbon is considered particularly vulnerable because emission reductions and removals could be reversed, either by natural events (fires, droughts, floods) or due to failure of a project or policy to control the drivers, underlying causes, and agents of deforestation (Seifert-Granzin, 2011). The discussion has led to a situation in which GHG removals due to AR activities under the CDM can only generate temporary credits or are excluded from compliance markets altogether (as in the case of the European Union Emissions Trading System). However, voluntary carbon markets accept REDD+ and AR credits generated within a comprehensive risk accounting and monitoring framework (Seifert-Granzin, 2011). In Cancun in 2010, the United Nations Framework Convention on Climate Change (UNFCCC) decided that developing countries should develop and provide "robust and transparent national forest monitoring systems for the monitoring and reporting of" REDD+ activities (FONAFIFO *et al.*, 2012; UNFCCC, 2011). Unfortunately, as mentioned in previous chapters, the implementation of risk monitoring systems has been the exception and not the rule. From the few standards that offer a coherent risk assessment, the Voluntary Carbon Standard has become a very popular method to validate projects[2]. However, as it was shown in the previous chapter, the VCS risk assessment lacks very relevant information (probability of occurrence) that may help to classify projects as sustainable or not sustainable. This difference in turn may help all actors involved in PES or REDD+ projects to avoid incurring unnecessary costs. Based on the environmental risk analysis derived from satellite imagery and presented in the previous chapter, a more complete risk assessment table was presented in Table 5.1. The table is a complement of the VCS table of risk analysis currently in use.

[2]Recent market surveys clearly point to a preference among buyers and investors for projects validated under the VCS, as it offers the most comprehensive standard, covering all relevant AFOLU activities, and is based on IPCC guidelines (Seifert-Granzin, 2011; Merger *et al.* 2011)

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Appendix A

Publications

Assessment of Wildfire Hazards with a Semiparametric Spatial Approach

Ricardo Acevedo-Cabra, Yolanda Wiersma, Donna Ankerst & Thomas Knoke

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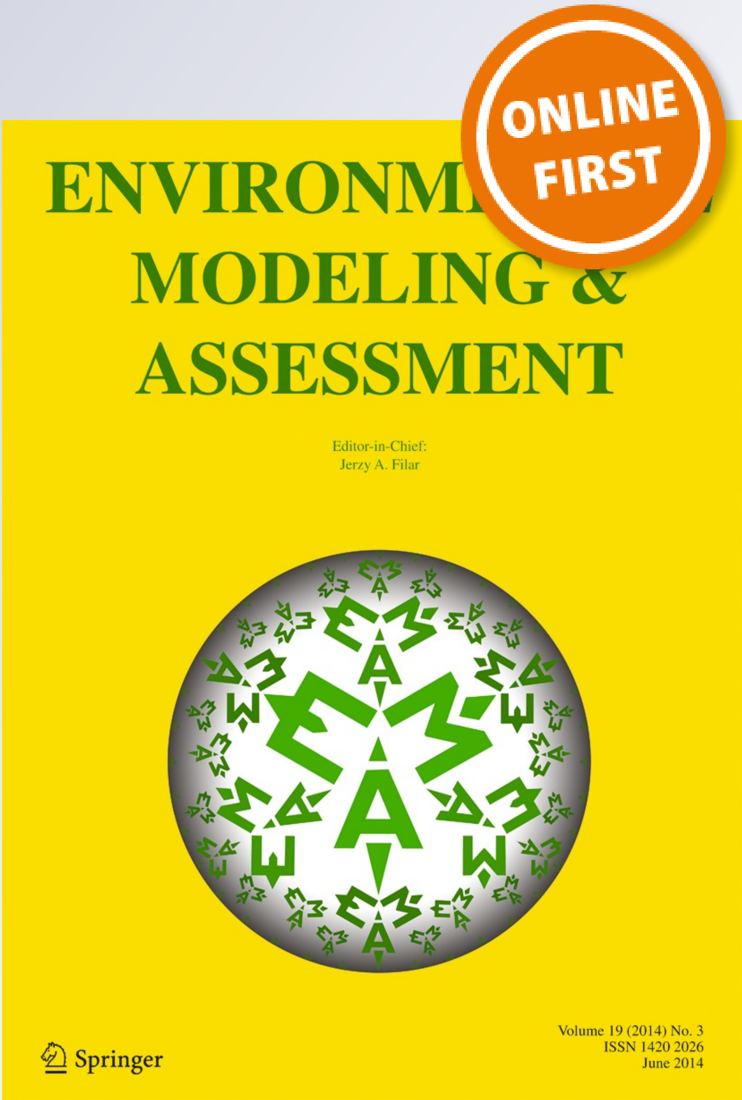

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Assessment of Wildfire Hazards with a Semiparametric Spatial Approach

A Case Study of Wildfires in South America

Ricardo Acevedo-Cabra · Yolanda Wiersma · Donna Ankerst · Thomas Knoke

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Abstract Rural households in agricultural economies are vulnerable to several environmental risks such as fires, floods, and droughts that may affect their productivity in whole or in part. These hazards are especially relevant in developing countries where farmers have few or no access to traditional risk-transfer techniques, such as insurance and finance, and where low governmental investments in rural infrastructure, risk assessment techniques, or early warning systems makes the aftermath of such hazards more expensive and results in slower recovery for those who are affected. In this paper, we use historical satellite data (Terra) of burned areas in South America to fit a semiparametric spatial model, based on kernel smoothing and on a nonlinear relationship between average time between events and damage, to assess the environmental hazard affecting the land's productivity. The results were twofold: first, we were able to develop a spatial assessment of fire hazard, and second, we were able to evaluate how much a farmer may lose in terms of productivity per hectare due to the environmental hazard. The methodology may be easily adapted to other world regions; to different environmental hazards such as floods, windbreak, windthrow, or related land-use changes; or to integrate various environmental hazards simultaneously, as long as they can be monitored via remote sensing (e.g., satellite imagery, aerial photographs, etc).

Keywords Environmental risk assessment · Kernel smoothing · Semiparametric · Average time between events · Fire risk · Satellite imagery

1 Introduction

Recent decades have been marked by rapid changes in fire regimes as a result of significant shifts in human population [38]. The most common socioeconomic factors contributing to fire regime changes are activities related to agriculture and fire suppression [38]. The latter factor is particularly relevant in the western US due to a combination of fire-suppression policies, ideal weather conditions, and low ecosystem resilience [34]. The former factor is currently more relevant in tropical areas due to policies that promote the conversion of original forest cover to other land uses [2]. In order to counteract such policies, two types of regimes have emerged, a policy and a voluntary driven one. The first one is currently being established under the United Nations Framework Convention on Climate Change (UNFCC). The second regime is an effort to create a financial value for the carbon stored in forests, offering incentives for developing countries to reduce emissions from forested lands, and invest in low-carbon paths to sustainable development [54]. The incentives are supported by the United Nations under the name REDD+ (Reducing Emissions from Deforestation and Forest Degradation). Thus, the REDD+ mechanism

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rewards developing countries for the mitigation of greenhouse gas emissions [53], which has now been extended to include conservation, management, and enhancement of forest carbon stocks [30]. Although land use investments (pasture, forest, crops, etc.) are subject to several hazards like commodity price vulnerability, environmental risks, change in agricultural or forestry policies, and so on, most authors have focused mostly in market risk, i.e., the economic vulnerabilities and risk concerning cost-effective compensations under the REDD+ program [11, 23, 29]. However, fires can have enormous economic consequences, as demonstrated in an analysis of social capital and fire contagion by [50]. Therefore, a thorough understanding not only of market risk but of environmental risks affecting land use investments, specially of fire in forest investments, is of particular importance for the sustainability of mechanisms such as REDD+ [42] or for any investment involving forest due to the long-time impact of fires in the forest. The goal of this research was to obtain summary statistics like average return periods and percentage of land damaged due to fires in particular regions in South America where the investment may take place. To that end, our objectives were:

1. To explore spatial intensity of fires using a methodology that does not assume any particular probability distribution of events.
2. To generate maps of percentage of damage and summary statistics of locations at particular spatial intensities.
3. To obtain the average return periods of damage at any chosen location.

In order to address these objectives, we use spatiotemporal information from the Moderate Resolution Imaging Spectroradiometer (MODIS NASA, from year 2000 onwards) in three forest-relevant countries of South America: Brazil, Colombia, and Ecuador. The statistics obtained will be used in future research to integrate environmental risk with the above traditional analysis of market risk of land use investments. The paper is organized as follows: Section 2 outlines the relevance of the wildfires issue in South America and the difference between controlled and uncontrolled fires; Section 3 introduces the semiparametric approach; and Section 4 presents results for small, medium, and large South American economies. The paper ends with a discussion and conclusion section.

2 Wildfires in South America

According to the State of the World's Forests [19], South America has an estimated 864 million hectares covered by forest, which represents almost half of its total land cover. These abundant forest resources account for 21 % of the world's forest areas and 57 % of its primary forests. Yet, between 1990 and 2010, South America lost more than 82 million hectares of forest (corresponding to almost 10 % of its total forest area by 2010), a value three times higher than the average global forest loss during the same period [19]. Due to higher returns on investments for some agricultural commodities, the conversion of forests to agriculture has become the leading cause of the regional deforestation [19]. This occurs mainly through illegal logging and intentionally ignited fires. According to [55], this effect is magnified in regions with drought severity, proximity to roads and rivers, and extended use of pastures and agricultural crops.

Some of the most heavily forested countries in South America are Brazil (520 million hectares), Colombia (60 million hectares), and Ecuador (10 million hectares), which combined represent 70 % of the total South American forest [18]. In terms of GDP (nominal), the three countries rank in a similar fashion, where Brazil is the largest South American economy, Colombia the third biggest, and Ecuador one of the smallest economies. Thus, South America's abundant forest resources and its above-average deforestation rates make the region a natural target for any international policy intended to halt deforestation. In [55], it is argued that policies to promote low-fire land use systems and access to education, as well as the improvement of early warning systems and other mechanisms, could help towards reducing fire in the region.

2.1 Historical and Ecological Role of Wildfires

Most of the area of Brazil, Colombia, and Ecuador is labeled by Pivello [40] as "fire-sensitive". The Cerrado area of Brazil is notable in that it is considered to be "fire-dependent and/or fire-influenced" [40]. This region has been prone to natural fires caused by lightning strikes. The combination of a marked dry season and highly flammable vegetation biomass has contributed to the system's coevolution with fire [33, 49]. The presence of fire in the three countries is closely tied to anthropogenic activity [38]. Paleontological evidence shows that indigenous people used fire throughout this region as a regular part of their agricultural practice [10]. The Amazonian rain forest, in contrast, does not generally burn naturally owing to the moist climate. However, in a broad literature review, [40] showed that wildfires can occur in the Amazon, mostly due to a mix of drought conditions and human activities. Dry conditions are often correlated with El Niño events, and humans have burned the Amazon as part of slash-and-burn agriculture practices for millennia [20]. Ecologically, natural wildfires in the Cerrado serve to maintain the savannah system and have influenced the species composition to favor those that regrow quickly following fires or have a high proportion of belowground biomass [40]. In the Amazonian forests, traditional slash-and-burn practices by indigenous groups resulted in soils with a high charcoal content. The newly-opened plots were cultivated for a number of years and then left to regrow [40]. Although modern slash-and-burn practices have been shown to result in net deforestation, traditional burning activities were highly controlled and planned carefully to ensure the continued regeneration of forest resources [40]. In the present day, low-intensity fires in El Niño years have been shown to contribute up to 5 % of annual anthropogenic carbon emissions [36], although this may be higher when delayed tree mortality up to 3 years post-fire is taken into account [7]. Recently, fire frequency and intensity in South America have increased Fig. 1. The chief culprit is suspected to be climate change. As dry seasons get longer and drier, low humidity generates ideal conditions for natural fire ignitions or intentional fires. The later being an agricultural management practice with undesired and often uncontrollable effects due to non normal weather conditions [36].

2.2 Consequences of Uncontrolled Fire

The effects of fires depend very much on their intensity and the interval between subsequent fires [5, 24]. Experimental work, based on inventory measurements of 50-ha treatment plots that manipulated fire frequency and intensity along the forest-savanna boundary in the southeastern Amazon, showed that cumulative tree and liana mortality rates increased with consecutive annual fires, and that three annual 50-ha burns resulted in moderate increases in mortality compared with once-burned plots [5, 6]. Repeated fires can reduce soil nutrients and affect tree growth [6], which is important for land owners whose livelihoods depend on soil fertility, either for crops or plantations. Fires can have enormous economic consequences, as demonstrated in an analysis of social capital and fire contagion by Simmons [50]. In tropical forests, once an area is deforested there is a high likelihood that highly frequent management fires will follow, particularly in pastures [6]. Thus, repeated fires, including slash-and-burn fires, take place over a several-year period after forest felling [6]. Although fires ignited for management techniques are not intended to be spread further than the area under management, some may become uncontrolled and spread over thousands of hectares due to special meteorological conditions (extended dry seasons, strong winds, and low pressure) and lack of proper mechanisms to suppress them.

3 Materials and Methods

A thorough classification of existing spatial simulation models of fire and vegetation dynamics was presented in [27]. Using the 44 best known models, the classification was based on what was modeled: vegetation succession, fire ignition, fire spread, and fire effects. However, none of the models presented carried the spatial detail required to accurately model the potential effects of fire to highly valued resources [13]. Moreover, the outputs of these models were difficult to downscale to address forest- and project-scale issues [13]. Other authors have focused on the development of summaries of wildfire activity rather than the simulation of the events [28, 31, 34]. Unfortunately, temporal summaries that involve the description and/or modeling of each spatial subregion separately often depend critically on the rather arbitrarily chosen boundaries of the spatial regions, and parametric summaries suffer the further disadvantage of reliance on model assumptions [37], like the assumption that the data follow a particular probability distribution. In order to assess the US Burning Index (BI), an index used by fire departments in 90 % of all US counties, Peng et al. [39] used a space-time conditional-intensity point process

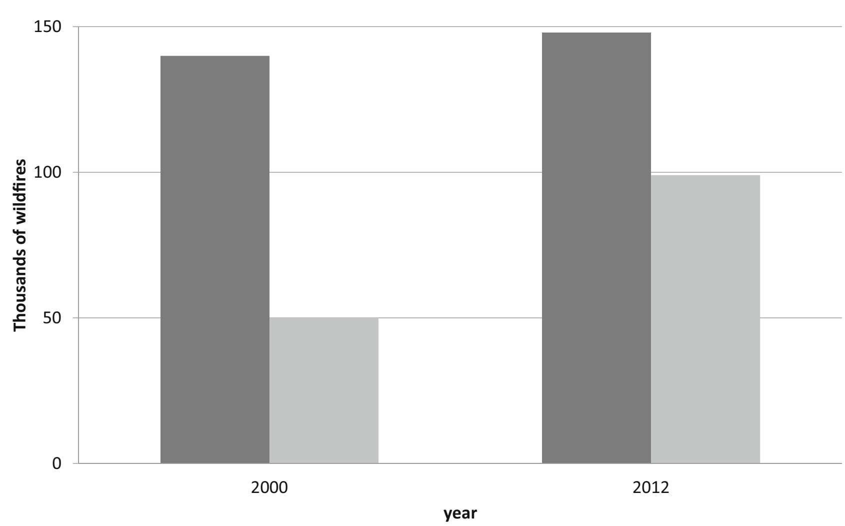

Fig. 1 Increment in number of wildfires in the northern part of South America (*dark gray*) and Brazil (*light gray*). Computed using MODIS data, window 5

based on kernel smoothers and found that BI does not perform substantially better than the space-time process for the case of Los Angeles county wildfires. Using prototype point processes, Nichols et al. [37] presented an approach that summarized and described wildfires using prototype point processes, which provided useful and easily interpretable summaries of central tendency. Particular advantages of prototypes are that they are entirely non-parametric and do not require that the underlying process be stationary or isotropic [37]. The selection of the prototype, however, is to some extent dependent upon the rather arbitrary choice of penalties in a multi-dimensional spike time distance function [47]. Another disadvantage is that prototyping in multiple dimensions is computationally expensive, especially if there are several thousand data points to consider [37]. In order to assess fire risk, we propose a semiparametric model that uses kernel smoothing to assess the spatial intensity, that is, the number of events per kilometer squared. Kernel smoothing shares most of the advantages of prototype point processes, such as the ability to work with highly non-stationary events, both in space and time, and does not require that the underlying process be isotropic [3]. This is a major convenience in the case of wildfires in tropical regions, where certain locations and months are more prone to be ignited than others, and fires are strongly non-isotropic, since wildfires are more likely to spread in certain directions, for example, in the direction of prevailing winds [41]. Our semiparametric approach further explores a spatiotemporal dependence found in all three tropical countries studied: Brazil, Colombia, and Ecuador, in order to analyze the average time between events and their relationship to damage. Finally, a geographical representation of the damage per hectare at particular locations, obtained using binomial proportions of the historical data, is presented. Our statistical model uses historical remote sensing information, which shows burned areas detected by the NASA Terra satellite from year 2000 onwards, to determine the potential damage at chosen locations where land-use investment may take place and to determine the land-use productivity change per year until 2012. The methodology can be used as a decision support system to determine local and regional changes in productivity per hectare that could be expected due to the environmental hazard of fire. It could be easily adapted to other world regions; to different environmental hazards like floods, windbreak, windthrow, or related land-use changes; or to integrate various environmental hazards simultaneously, as long as they can be monitored via remote sensing (e.g., satellite imagery, aerial photographs, etc).

3.1 MODIS Data and ArcGIS Classification

Satellite remote sensing provides the only practical means of monitoring biomass burning over large areas [26]. Yet, the timing and spatial extent of actual fires cannot be estimated reliably as the satellite may not pass over when burning occurs and because clouds may preclude active fire detection. Burned area mapping algorithms that examine spectral changes on the landscape, rather than relying on hotspot detection, are generally insensitive to these effects as spectral changes induced by burning persist through time [26]. The Moderate Resolution Imaging Spectroradiometer (MODIS), onboard the Terra satellite from NASA, provides valuable information on long-term observations of the Earth's land, oceans, and atmosphere. In order to detect burned areas the *MODIS Burned Area product* (hereafter just: MODIS) uses the generic change algorithm [44], the output is free to download as geotiff. The data comprise of a daily 500 × 500 m grids, from the year 2000 onwards, containing per-pixel information on approximate burn date and confidence of detection. For our purposes, we used data from MODIS window 5, corresponding to the northern part of South America, which includes Colombia, Ecuador, and the northern part of Brazil. We converted the data using ArcGIS from raster to polygons, and computed polygon areas, coordinates of centroids and dates of occurrence for every burned area recognized from 2000 to 2012.

3.2 Burned Areas from Controlled and Uncontrolled Fires

One important distinction for fires occurring at the landscape level is that some are artificially ignited for agricultural purposes, such as the slash-and-burn technique, a permitted procedure in developing countries for efficiently removing post-harvest biomass. Prescribed fires are also used as preventive measures to avoid greater and more devastating fires. Some of these techniques, however, may result in fires that burn out of control due to special meteorological conditions or careless use and are impossible to suppress by local or current firefighting techniques, causing extensive damage [14, 25]. Another source of uncontrollable fires is the illegal ignition with purposes of deforestation. According to CONAF [14], the main causes of uncontrollable fires in Chile between the years 2003 and 2011 were accidental (55 %), intentional (28 %), natural (0.4 %), and unknown (16.6 %). Yet, irrespective of ignition purpose, every fire has the potential to become uncontrolled and thus a real hazard in the short- and long-term for society [21, 25]. Several authors studying burned areas at a landscape level [31], irrespective of size or ignition source, have found a power-law, scale invariant, relationship between the number of burned areas in "unit" bins, expressed as an estimated density $\hat{f}(A_{BA})$ of the size of the burned areas A_{BA} of the form $\hat{f}(A_{BA}) \propto A_{BA}^{-D_f}$, where D_f is the fractal dimension estimated from the data [12, 31]. Studies of the characteristic of burned areas in Australia, China, Italy, and the USA have estimated fractal dimensions of the order $1.1 < D_f \leq 1.8$ for uncontrolled fires [31]. For our purposes, in order to differentiate between controlled and uncontrolled fires, we assume that controlled fires at a landscape level generate burned areas with relative simple geometrical shapes. Simple shapes have lower fractal dimension D_f when compared to more chaotic ones such as would be generated by uncontrolled fires. In our case, the fractal dimension of every single burned area spotted with MODIS was computed using the software Fragstats [32]. Burned areas with $D_f \leq 1.1$ are classified as "due to controlled fire" and not considered in the analysis, while burned areas with $D_f > 1.1$ are classified as "uncontrolled" and included in the analysis.

3.3 Two-dimensional Point Process

The MODIS dataset provides information for burned areas on a grid with a resolution of 500×500 m along with their date of occurrence. For our purposes, we computed the polygon and the centroid coordinates $u_i := (x_i, y_i)$ of every single burned area. For our purposes, every event recorded is uniquely determined by the triple (u_i, b_i, t_i), where $\{u_i \in A| \ i = 1, \dots, n\}$ is the set of locations of burned areas which occurred in a region $A \subset \mathbb{R}^2$; $b_i \in \mathbb{R}$ corresponds to the burned area in kilometer squared, and $t_i \in [2000, T]$ is the date at which MODIS first spotted the burned area. When the events u_i are graphically displayed over the region of study A, it is evident that they exhibit spatial variation, see for example Fig. 2. This motivates us to explore the characteristics of subregions where the spatial intensity, defined as the number of burned areas per kilometer squared, appears to be higher, in order to find local patterns that might not be recognizable at larger scales. Below, we present a semiparametric approach to identify patterns on desired subregions. First, we use kernel smoothing to compute the spatial intensity. Second, we determine the historical proportional damage occurred at random locations in order to generate maps of damage. Third, we explore a nonlinear spatiotemporal relationship between the proportional damage and the average time between events at particular locations. The methodology avoids arbitrary classification of events, contrary to quadrat-counting techniques, and does not rely on the definition of clusters of events towards a parametric description of spatial intensity. Although the events are assumed to be realizations of a point process, no particular probability density function is assumed.

Following Rosenblatt [43], let $u_1, \dots, u_n$ be independent and identically distributed random variables with a continuous but unknown density function. Furthermore, let $u_1, \dots, u_n$ be a partial realization of a point process, with spatial intensity function $\lambda(\varphi)$, $\varphi \in A$,representing the number of events per unit of area in the nearby locality of a location φ. In practice, as $\lambda(\cdot)$ is not known it must be replaced by a suitable estimate $\hat{\lambda}(\cdot)$, which should be a function taking on large values for high density regions and near zero values where data are sparse [17]. Building upon the work of Rosenblatt [43] and Diggle [15, 16], Baddeley et al. [3, 4] propose a nonparametric estimator of $\lambda(\varphi)$, which takes the general form:

$$\hat{\lambda}_h(\varphi) = \frac{1}{h^2 \, C_A(\varphi)} \sum_{i=1}^{n} k_h(u_i - \varphi), \qquad \forall \, \varphi, u_i \in A, \quad (1)$$

where $k_h(\varphi) = h^{-2}k(h^{-1}\varphi)$ is a smoothing kernel, the bandwidth $h > 0$ determines the amount of smoothing, and the kernel is defined as Gaussian $k(\varphi) = (2\pi)^{-1/2}exp(-\varphi^2/2)$. Theoretical properties of $k(\cdot)$ are explained by Scott [45, 46]. To avoid bias of $\hat{\lambda}_h(\cdot)$ at the boundaries of A, a kernel edge-correction term is used [3, 22]:

$$C_A(\varphi) = \int_A k_h(u - \varphi) d\varphi. \quad (2)$$

Following Scott [45, 46] and Sheather [48], we use a bandwith h that is a function of the spatial dispersion and the number of events $u_i \in A$. We use the implemented version of Eqs. 1 and 2 in the R package "spatstat".

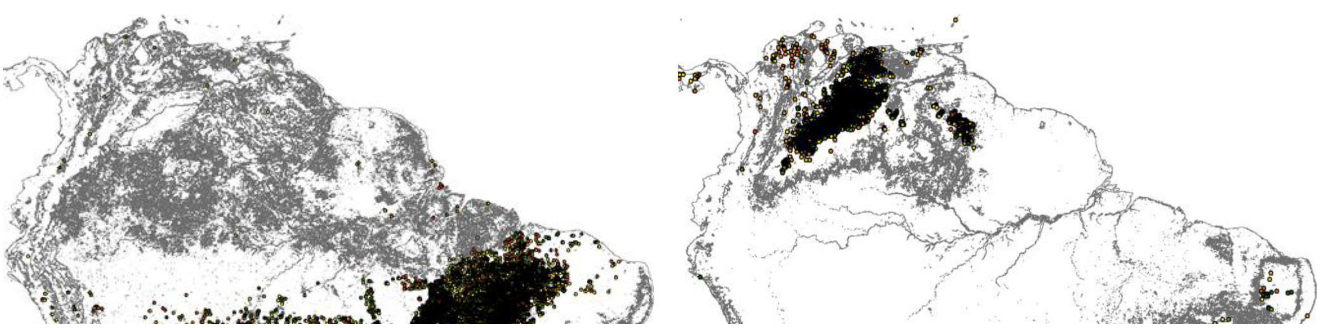

Fig. 2 Spatial locations of burned areas. Each point represents the centroid of a burned area polygon spotted with MODIS between the years 2000 and 2012 in the northern part of South America. Seasonal aspects are observed, (*left figure*) from March to August and (*right figure*) from September to February. *Gray pixels* are not fire events

3.4 Subregions of Spatial Intensity

The estimated nonparametric spatial intensity $\hat{\lambda}_h(\cdot)$ in Eq. 1, having as units the number of burned areas per kilometer squared, allows to classify the region A, of every country studied, into subregions without making any assumptions on the probability distribution of the events. The goal is to compare summary statistics, like the percentage of damaged area and the average time between fires, of subregions with different spatial intensities. For every country, minimum $\min_{\varphi \in A} \hat{\lambda}_h(\varphi) := 0$ and maximum values $\omega := \max_{\varphi \in A} \hat{\lambda}_h(\varphi)$ are used as limits of an interval partitioned into three equal-length subintervals in order to generate three subsets $\hat{\Lambda}_{low}$, $\hat{\Lambda}_{med}$, and $\hat{\Lambda}_{high}$ of locations φ having low, medium, and high number of events per kilometer squared, respectively:

$$\begin{aligned} \hat{\Lambda}_{low} &= \{\varphi : \hat{\lambda}_h(\varphi) \in [0, \omega/3]\} \\ \hat{\Lambda}_{med} &= \{\varphi : \hat{\lambda}_h(\varphi) \in (\omega/3, 2\omega/3]\} \\ \hat{\Lambda}_{high} &= \{\varphi : \hat{\lambda}_h(\varphi) \in (2\omega/3, \omega]\}. \end{aligned} \tag{3}$$

Although the model does not require the interval to be partitioned, the procedure was performed in order to explore and compare burn area activities at different subintervals of the spatial intensity. To make more readable forthcoming functions, which are conditioned to the subsets $\hat{\Lambda}_{low}$, $\hat{\Lambda}_{med}$ or $\hat{\Lambda}_{high}$, we define $\hat{\Lambda}_{subreg}$ as the general subset that represents any of the subsets in Eq. 3.

3.5 Random Sample Locations

For a spatial intensity subregion $\hat{\Lambda}_{subreg}$, estimated for every country, a random sample without replacement, of locations φ where a land use investment may take place, is used in order to study potential patterns common to a given $\hat{\Lambda}_{subreg}$. Patterns addressed in this study are proportional damage of burned areas at particular locations, their recurrence time, and geographical assessment of locations up to a predefined threshold of damage. For a random location $\varphi \in A$, the function $\hat{\lambda}_h(\varphi)$ (Eq. 1) will return an estimate of the number of burned areas per kilometer squared in the near vicinity of φ. This value is not expected to change drastically for events $\{u_i \in B | \; B \subset A\}$ near φ because $\hat{\lambda}_h(\cdot)$ is smoothed, see Eq. 1. Let $N_{BA} = |B| > 1$ be the number of burned area events $\{u_i\}$ to be found in the surroundings of φ, and $Area_\varphi$ be the area containing them and that can be estimated with $N_{BA}/\hat{\lambda}_h(\varphi)$. Thus, low spatial intensity levels will produce larger areas $Area_\varphi$ than high spatial intensity levels when N_{BA} is kept constant, and events further away diminish as a hazard for the random location φ as the area-size increases. Therefore, let $D_\varphi = \{u_i \in B | \; B \subset A, \; 0 < d(\varphi, u_i) < d_{\varphi u}\}$ be the set of events in B having an euclidean distance to φ less than a constant $d_{\varphi u}$, that because of their proximity to location φ may potentially affect its land's productivity.

3.6 Proportional Burned Area Damage

In order to assess the potential damage per hectare at a particular location φ, we define the *farm's proportional damage* $f_{t_{inv}} \in \mathbb{R}^+$ as a threshold value of the proportion of land that a farm may lose due to damage caused by fire during the period of investment $(0, t_{inv}]$. This variable will help to identify the geographical coordinates of locations φ where damage has not yet surpassed the predetermined threshold. In order to compare potential damage between different spatial intensities, we will use a threshold of $f_{t_{inv}} = 5\ \%$. Setting arbitrarily a low threshold value will help to identify the locations with a record of low fire activity where land use investment can still be contemplated. For a particular location φ , we compute the *proportional damage* ρ_t, restricted to the set $\hat{\Lambda}_{subreg}$, up until time t as:

$$\rho_t(\varphi | \; \hat{\Lambda}_{subreg}) = Area_\varphi^{-1} \sum_{b_i :\; t_i \le t, \; u_i \in D\varphi \cap \hat{\Lambda}_{subreg}} b_i, \tag{4}$$

where (u_i, b_i, t_i) is as defined in Section 3.3.

3.7 Maps of Locations with Damage on Productivity

For locations in $\hat{\Lambda}_{subreg}$, we generate a spatial random sample with size $n_{\varphi, \hat{\Lambda}_{subreg}}$ of locations φ and evaluate each $\rho_t(\varphi | \hat{\Lambda}_{subreg})$. This allow us to build a hazard map with locations having either $0 < \rho_t(\varphi | \hat{\Lambda}_{subreg}) \le f_{t_{inv}}$ or $\rho_t(\varphi | \hat{\Lambda}_{subreg}) > f_{t_{inv}}$. This "filter" helps to build hazard maps based on binomial proportions and confidence intervals that estimate the likelihood of finding damaged areas at given levels of spatial intensity.

3.7.1 Binomial Proportions and Confidence Intervals

Let n be the size of a statistical sample of random locations φ. Out of them, let $n_{\varphi, \hat{\Lambda}_{subreg}}$ be the number of locations at a given subregion $\hat{\Lambda}_{subreg}$ where $|D_\varphi| > 0$. Thus, $\hat{q} = n_{\varphi, \hat{\Lambda}_{subreg}}/n$ is the estimated proportion of successes in a Bernoulli process out of n trials. Let also $n_{0<\rho\le f_{t_{inv}}}$ be the number of locations where the damage has not yet exceeded the threshold $f_{t_{inv}}$. Thus, $\hat{q}_{f_{t_{inv}}} = n_{0<\rho\le f_{t_{inv}}}/n_{\varphi, \hat{\Lambda}_{subreg}}$, is the estimated proportion of successes of locations where the historical damage (since the beginning of MODIS monitoring) has not yet surpassed the predefined $f_{t_{inv}} = 5\ \%$. Confidence intervals for the estimated likelihoods of finding locations φ with damage $\rho_t(\varphi | \hat{\Lambda}_{subreg}) > 0$, and of finding locations with damage up to a certain threshold $0 < \rho_t(\varphi | \hat{\Lambda}_{subreg}) \le f_{t_{inv}}$, are obtained using Agresti score confidence intervals [1]. This procedure is used to construct estimated maps from historical satellite information, of locations where the damage due to burning has not been surpassed during the investing time t_{inv}.

3.8 Average Time Between Events

Let $\hat{\delta}_{t\varphi}(u|\,\hat{\Lambda}_{subreg})$ be the average time between events $\{u_k\}$, restricted to $\hat{\Lambda}_{subreg}$, up to time t and at location φ, defined as:

$$\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg}) = \frac{1}{N_{BA}-1} \sum_{k=1,t_k:u_k \in D_\varphi \cap \hat{\Lambda}_{subreg}}^{N_{BA}-1} |t_{k+1} - t_k| \;\Leftrightarrow\; N_{BA} > 1, \tag{5}$$

having as units the interval-length in years between consecutive events. We used a nonlinear function to model the relationship between the average time between events $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$ and their proportional damage $\rho_t(\varphi|\hat{\Lambda}_{subreg})$, see for example Fig. 5, of the form:

$$ln\left[\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})\right] = \alpha + \beta \cdot ln\left[\rho_t(\varphi|\hat{\Lambda}_{subreg})\right] + \epsilon, \tag{6}$$

where α and β are regression parameters to be estimated and ϵ is the error term. Equation (6) can be expressed as:

$$\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg}) = e^{\alpha} \cdot \left[\rho_t(\varphi|\hat{\Lambda}_{subreg})\right]^{\beta}. \tag{7}$$

We used the sample average of events $\hat{N}_{BA}$ as an estimate of N_{BA} for locations having the same proportional damage $\rho_t(\varphi|\hat{\Lambda}_{subreg})$. $\hat{N}_{BA}$ is used to compute the proportional damage per event, up to time t:

$$\xi_t(\varphi|\hat{\Lambda}_{subreg}) := \rho_t(\varphi|\hat{\Lambda}_{subreg})/\hat{N}_{BA}, \tag{8}$$

and the total damage (%) per year:

$$\hat{\psi}_t(\varphi|\hat{\Lambda}_{subreg}) := \frac{\rho_t(\varphi|\hat{\Lambda}_{subreg})}{\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg}) \cdot \hat{N}_{BA}}. \tag{9}$$

On setting $\rho_t(\varphi|\hat{\Lambda}_{subreg}) = f_{t_{inv}}$ in (7), we estimate the average time between events $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$ for a given *farm's proportional damage*.

4 Results

4.1 Spatial Intensities of MODIS' Spotted Burned Areas

Maps displaying spatial intensities $\hat{\lambda}_h$, the number of spotted burned areas per kilometer squared are presented in Fig. 3, for Brazil, Colombia, and Ecuador, respectively. In the three countries, the burned areas tended to concentrate at particular regions, and the spatial intensity varied significantly between countries. Brazil has the highest spatial intensity with 2.2 burned areas per square kilometer, more than one and a half times the highest spatial intensity of Colombia, which has 1.37 events/km^2 and more than 70 times the highest spatial intensity of Ecuador which has 0.03 events/km^2.

4.2 Damage Per Hectare: Binomial Proportions and Confidence Intervals

In order to estimate the likelihood of finding the damage presented in the hazard-maps (Fig. 4), we built binomial proportions and their corresponding Agresti confidence intervals out of the successes of finding locations with certain damage levels. Results for locations having any damage $\hat{q} > 0$, and for locations with damage $0 < \hat{q}_{f_{t_{inv}}} < 5$ %, are presented in Table 1, along with the confidence intervals. For example, for the high spatial intensity region (yellow pixels in Fig. 3) of Brazil: out of a random sample of $n = 20{,}000$ locations, and for a $1 - \alpha = 95$ % confidence level, the estimated likelihood of finding locations φ with $\rho_t(\varphi|\hat{\Lambda}_{subreg}) > 0$ is $\hat{q} = 100$ %, out of them in only $\hat{q}_{f_{t_{inv}}} = 1$ % of the cases the *farm's proportional damage* has not yet being surpassed, i.e., $0 < \rho_t(\varphi|\hat{\Lambda}_{subreg}) \leq f_{t_{inv}}$ (see brown circles in Fig. 4) [comment: due to storage size the actual figure shown was generated out of a 4,000 sample size, but the results are similar. The estimated likelihood is computed out of a sample size of 20,000]. Meanwhile, for the low spatial intensity region (dark-blue pixels in Fig. 3) of Brazil: out of $n = 20,000$ trials, the estimated likelihood of finding locations φ with $\rho_t(\varphi|\hat{\Lambda}_{subreg}) > 0$ is just $\hat{q} = 6$ %, but out of them in $\hat{q}_{f_{t_{inv}}} = 60$ % of the cases the *farm's proportional damage* has not yet being surpassed (see brown circles in Fig. 4).

As expected, the proportion of damage increases as the spatial intensity increases from low to high in all three countries, see Table 1. In Brazil and Colombia, the number of burned areas, at medium and high spatial intensity, is such that almost every single random location has certain damage, i.e., the values greater than 98 %.

It was also observed that for the spatial intensity levels studied (low, medium, and high), the proportion of locations having damage less than the fixed threshold ($f_{t_{inv}} = 5$ %) decreased drastically as the spatial intensity increased. In Brazil (Table 1), the largest change occurred between the low and the high spatial intensities, with 60.2 % of random locations in the low spatial intensity with "small" damage and only 0.8 % of random locations in the high spatial intensity with "small" damage. This was followed by Colombia with 50.4 and 1.1 %, respectively. Meanwhile, Ecuador showed the smallest difference between proportions: 100 and 63 %, respectively. This means that in Ecuador there is a predominance of events (at all spatial intensities) with

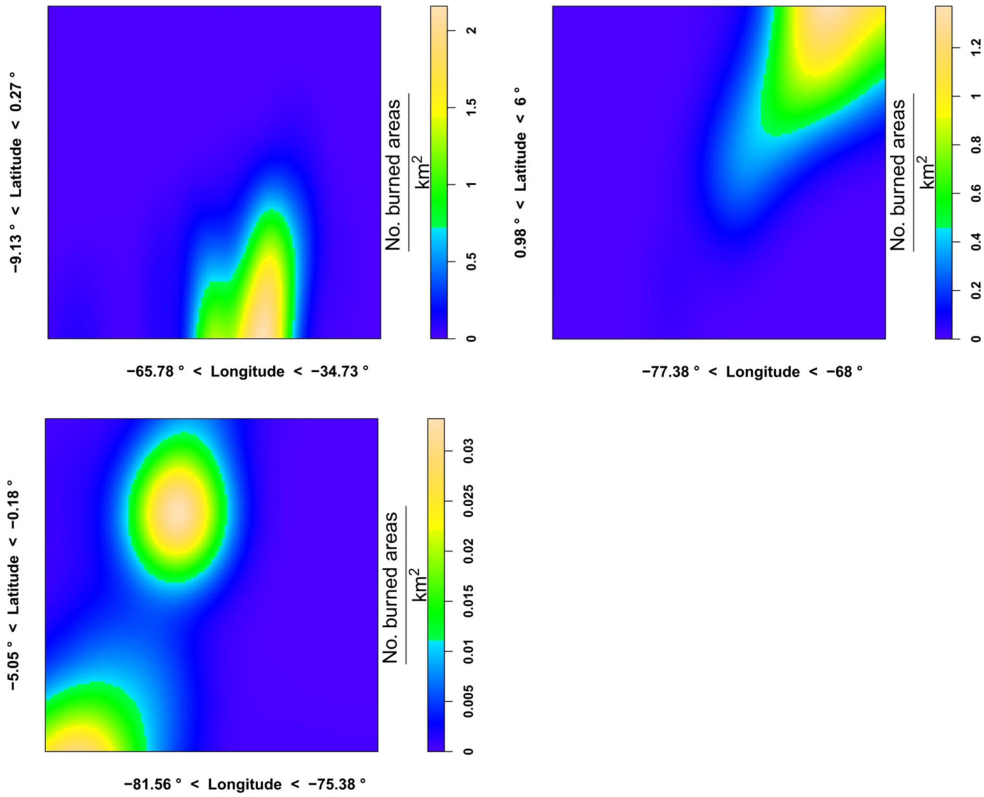

Fig. 3 Kernel smoothed spatial intensity of fires in Brazil (*top-left*), Colombia (*top-right*), and Ecuador (*bottom-left*) from 2000 to 2012. $\hat{\Lambda}_{low}$ (*blue pixels*), $\hat{\Lambda}_{med}$ (*green*), and $\hat{\Lambda}_{high}$ (*yellow*)

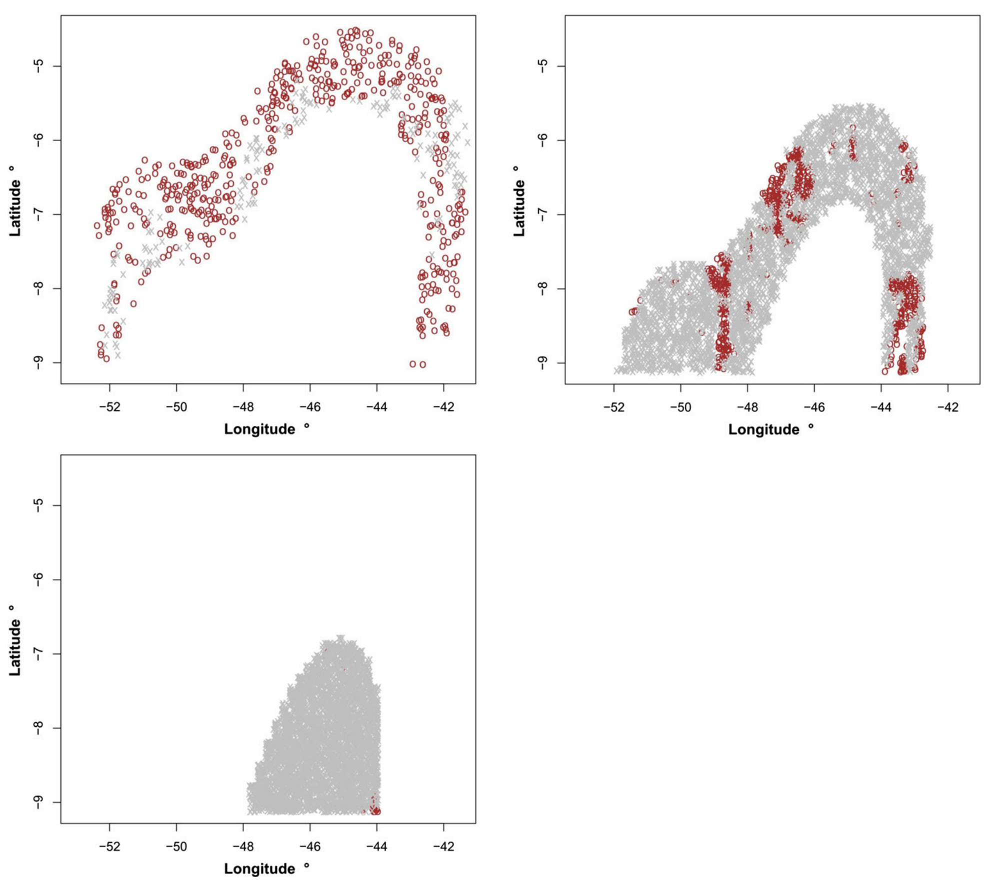

Fig. 4 Hazard maps of Brazil for the spatial intensity regions: $\hat{\Lambda}_{low}$ (*top-left*), $\hat{\Lambda}_{med}$ (*top-right*), and $\hat{\Lambda}_{high}$ (*bottom-left*). Random sample of locations with total burned area damage of less than $f_{t_{inv}} = 5$ % (*brown circles*) and more than 5 % (*grey crosses*)

Table 1 Damage per hectare: binomial proportions and confidence intervals

Land	Spatial intensity	Locations with any damage Low_{CI} (%)	$\hat{q}$ (%)	Up_{CI} (%)	Locations with damages ≤ 5 % Low_{CI} (%)	$\hat{q}_{5\%}$ (%)	Up_{CI} (%)
	Low	6.1	6.4	6.7	57.5	60.2	62.8
Brazil	Med	98.6	98.8	99.0	14.8	15.5	16.2
	High	99.9	100.0	100.0	0.6	0.8	0.9
	Low	6.4	6.8	7.1	47.8	50.4	53.1
Colombia	Med	99.95	99.98	100.0	15.1	15.6	16.1
	High	100.0	100.0	100.0	1.0	1.1	1.3
	Low	0.3	0.4	0.5	89.6	100.0	100.0
Ecuador	Med	2.4	2.7	3.0	98.0	100.0	100.0
	High	33.1	34.0	35.0	61.4	63.0	64.6

Low_{CI}%, Up_{CI}% correspond to lower and upper values of the confidence intervals for $\hat{q}$

"small" damage ($0 < \hat{p}_{f_{t_{inv}}} < 5$ %), while in Brazil and Colombia this holds only at low spatial intensities (Table 1).

When damage at different intensity levels was compared, by keeping constant the event regime $\hat{\delta_{t\varphi}}$ (Fig. 7), higher damage at higher spatial intensity levels was observed (Table 3). This is because, for the same event regime $\hat{\delta_{t\varphi}}$, a single event at higher spatial intensities damaged more (ξ_t) than a single event at lower spatial intensities (Table 3). This trend was found in all three countries studied.

4.3 Average Time Between Events and Their Relationship with Damage

As presented in Section 3.8, we found nonlinear relationships between the average time between events and the damage Fig. 5, in all three countries and at all spatial intensities (Fig. 6). For the logarithmic transformation of the nonlinear relationships, we fitted linear regressions for every spatial intensity, obtaining adjusted R^2 values ranging from 0.72 in Ecuador (low spatial

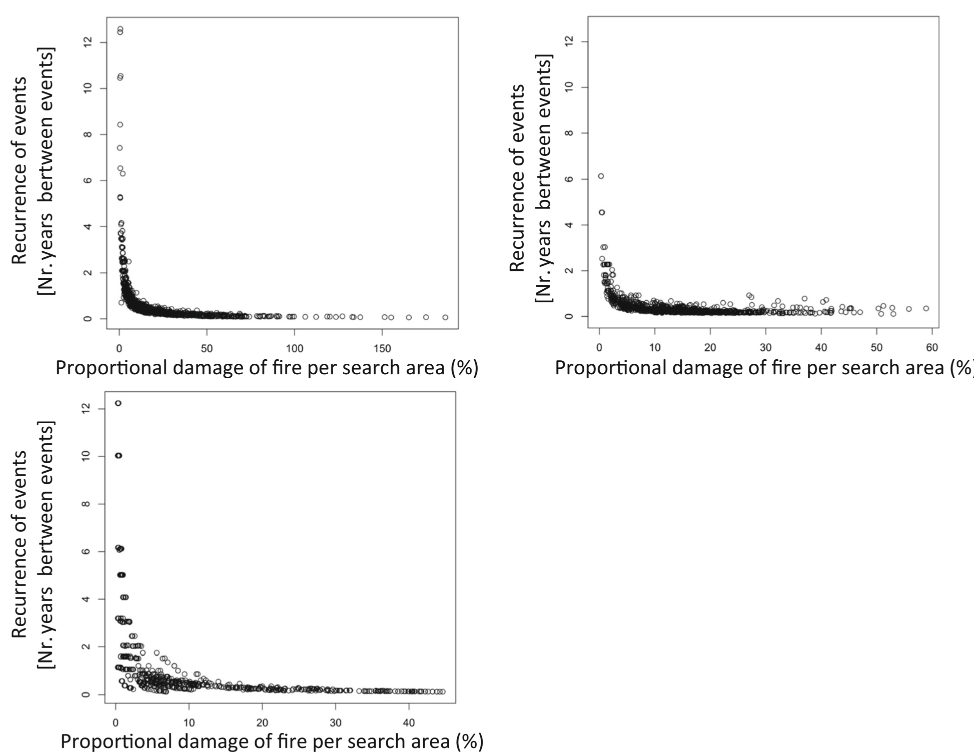

Fig. 5 Nonlinear relationship between proportional damage of burned areas and average time between events in Brazil (*top-left*), Colombia (*top-right*), and Ecuador (*bottom-left*) for the region with high spatial intensity $\hat{\Lambda}_{subreg} = \hat{\Lambda}_{high}$

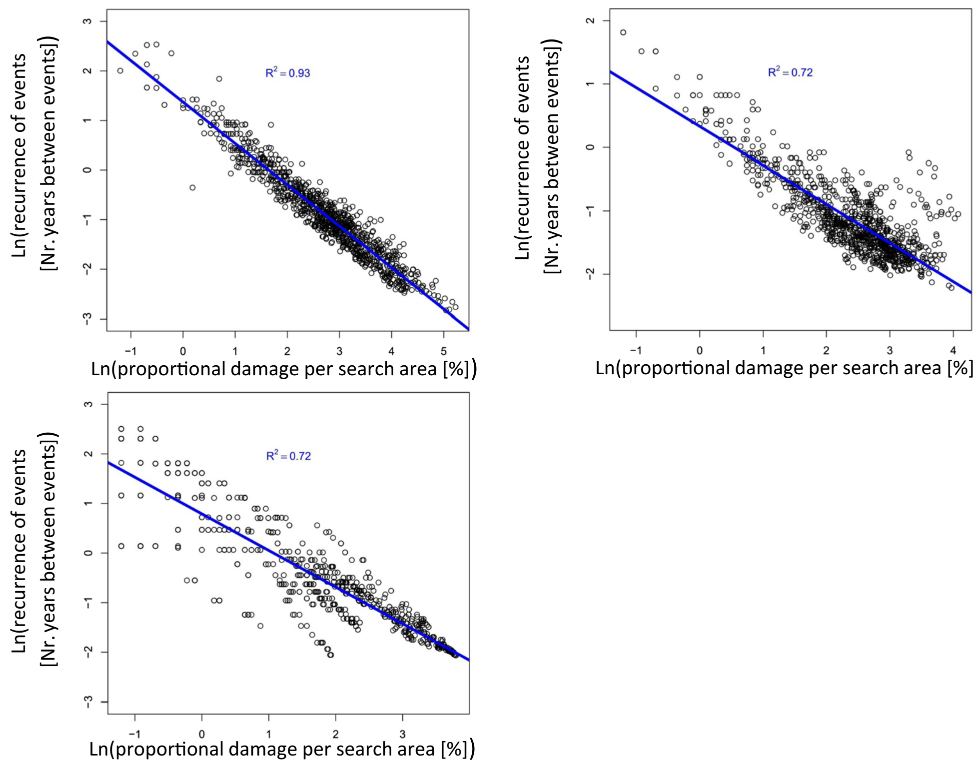

Fig. 6 Regression between proportional burned-areas damaged and average time between events in Brazil (*top-left*), Colombia (*top-right*), and Ecuador (*bottom-left*) for the region with high spatial intensity $\hat{\Lambda}_{subreg} = \hat{\Lambda}_{high}$, *Ln* denotes natural logarithm and R^2 the multiple R^2 from a linear regression

intensity) to 0.93 in Brazil (high spatial intensity), see Table 2.

The average time between events with respect to the degree of damage per event is presented in Fig. 7. Interestingly, in spite of the three countries presenting different values of spatial-intensities, when the damage is high enough, e.g., $\rho_t > 20$ %, a similar value of recurrence was observed in all cases $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg}) < 0.5$ years. That means that in all three countries, and all spatial intensities, when locations have more than two events per year in the nearby locality, one could expect damage at least as bad as 20 % for the location. It was observed that when comparing damage under the same regimes (same average time between events $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$) but under different spatial intensities, the total damage ρ_t was higher for higher spatial intensities (Table 3). This is due to the fact that at higher spatial intensities there is greater damage per event than at lower spatial intensities, this trend was observed in all three countries.

Table 2 Multiple R^2 for the linear regression between proportional damage of burned areas and average time between events

Spatial intensity region	Brazil R^2	Colombia R^2	Ecuador R^2
$\hat{\Lambda}_{low}$	0.90	0.70	0.71
$\hat{\Lambda}_{med}$	0.92	0.70	0.71
$\hat{\Lambda}_{high}$	0.93	0.72	0.72

4.4 Summary of Damages Per Region

As seen in Fig. 7, the same average time between events (fire regimes) $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$ produces different damage ρ_t at different spatial intensity levels $\hat{\Lambda}_{low}$ (black solid line), $\hat{\Lambda}_{med}$ (blue solid line), and $\hat{\Lambda}_{high}$ (red solid line). This is because a fixed average time between events, (Table 3, column 4), at the high spatial intensity region $\hat{\Lambda}_{high}$ has fewer events N_{BA} (Table 3, column 7), but a greater damage per event ξ_t (Table 3, column 8), than the same fixed average time between events at medium or lower spatial intensity region $\hat{\Lambda}_{low}$.

5 Discussion and Conclusions

MODIS cannot observe the earth's surface when cloud cover is present [35], so partial or total cloud cover may induce a bias in Terra's interpretation of signals that affects the real size and location of burned areas. Orographic effects can also play a role as they can influence the type and size of clouds that form in different altitudes [51]. We think that the presence of clouds in the Andes mountains of Colombia and Ecuador is the main reason for the relative lower correlation values $R^2 = 0.72$, between the log-transformed

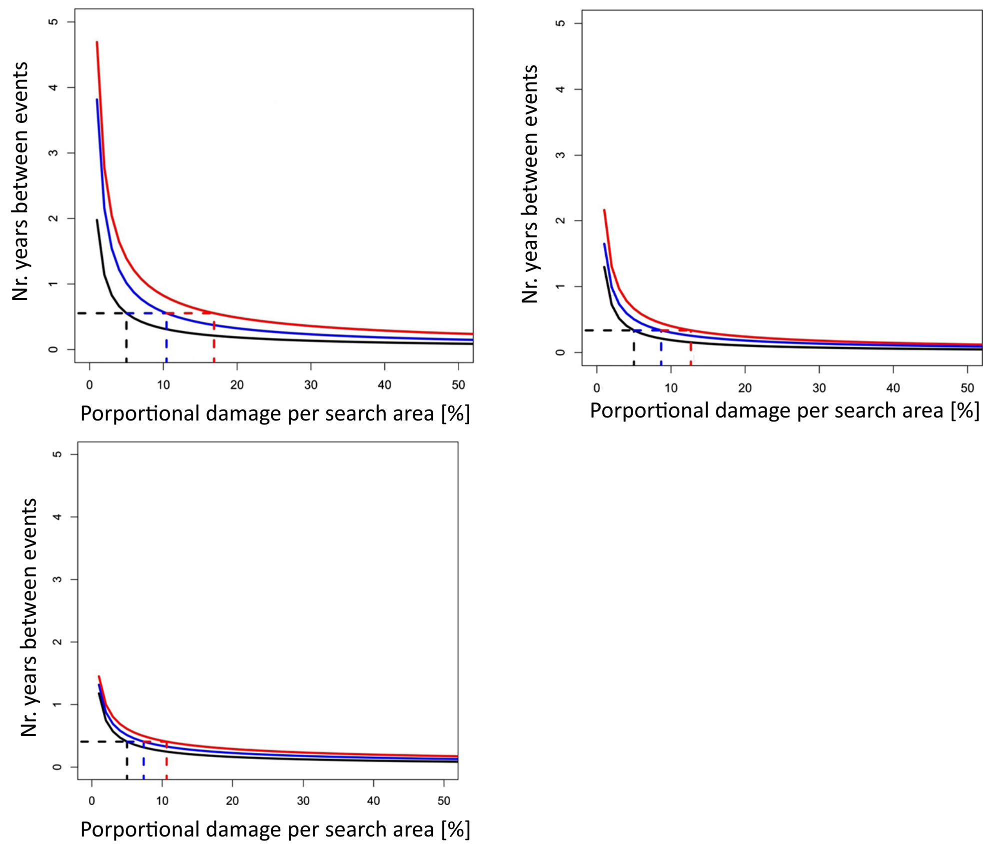

Fig. 7 Nonlinear relationships between proportional burned areas damaged and average time between events in Brazil (*top-left*), Ecuador (*top-right*), and Colombia (*bottom-left*) for different spatial-intensity regions: $\hat{\Lambda}_{low}$ (*black solid line*), $\hat{\Lambda}_{med}$ (*blue solid line*), and $\hat{\Lambda}_{high}$ (*red solid line*). Here, the *farm's proportional damage* at low spatial-intensity was fixed to 5 %, (vertical and horizontal *dashed lines*)

average time between events $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$ and the proportion of damage $\rho_t(\varphi|\hat{\Lambda}_{subreg})$ (Eq. 6), when compared against Brazil, $R^2 = 0.93$, Fig. 6. This could be also the reason for the low spatial intensity values of Ecuador, which present fires mostly in its high mountain range, with a maximum of 0.03 events/km^2 (Fig. 3). In MODIS, every pixel identified as a burned area is classified with a number from 1 to 4, representing most to least confidence, respectively [9]; for our study, we used all pixels classified as burned area. A potential improvement, though this might also yield a more conservative risk model, could be obtained by using only pixels classified with the highest degree of confidence. In spite of the relative lower correlation values in Ecuador and Colombia between the average time between events and the proportion of damage, the relationship is still statistically significant in all three countries and at every spatial intensity. Future research of such a relationship could yield a better assessment of hazard and risk at landscape level. Another alternative is the use of Unmanned Aerial Vehicles (UAVs) or Remote Piloted Vehicles (RPVs) which can be equipped with sensors similar to the ones used by satellites. Due to the fact that UAVs and RPVs flight at lower hight, compared to satellites, they could flight below clouds level as well and thus spot environmental damage. A drawback, however, is that they can cover less area per image than sat ellite imagery.

In order to model the spatial intensity, we assumed that fire events were independent. According to Peng et al.

Table 3 Comparison of constant average time between events $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$ at different spatial-intensities regions $\hat{\Lambda}_{subreg}$

Land	Environmental Risk[a]				
	$\hat{\delta}_{t\varphi}$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t
	0.56	Low	5.0	23	0.22
Brazil	0.56	Med	10.4	11	0.94
	0.56	High	16.4	7	2.34
	0.41	Low	5.0	24	0.21
Colombia	0.41	Med	7.4	19	0.39
	0.41	High	10.6	11	0.96
	0.33	Low	5.0	22	0.23
Ecuador	0.33	Med	8.7	18	0.50
	0.33	High	12.7	10	1.27

[a]The value of $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$ used corresponds to a damage of $f_{t_{inv}} = 5.0$ % at low spatial-intensity level. ρ_t is the proportional burned area damage, $\hat{N}_{BA}$ the estimated number of events near location φ and ξ_t is the proportional damage per event

[39], and for the case of California wildfires, if a particular location burns in 1 year, then it is perhaps less likely to burn the next year, thus the processes are not independent. However, Nichols [37] studying the same region, found that year to year dependence was rather a weak factor. In our particular case of wildfire activities in tropical forests, once an area is deforested there is a high likelihood that highly frequent management fires, which may become uncontrolled, will follow particularly in pastures [6]. Thus, there is a high likelihood that repeated fires, including slash-and-burn fires, take place over a multi-year period after forest felling [6].

In the present study, there was on average a greater burned area per event in regions with higher spatial density than in lower ones for all three countries studied. This observation may be taken into account when designing ex-ante risk management strategies. Policies encouraging the use of adequate agricultural techniques and promoting forest protection may strongly reduce the risk due to wildfires. Slash-and-burn is a common agricultural technique widely used in South America to clear the land after harvests. Other use of fire involves the conversion of original forest lands to other land uses. The high spatial intensity values, found in the this study, of up to 1.4 and 2.2 burned areas per kilometer squared in Colombia and Brazil, respectively, reflect not only the extended use of such techniques but that many of the fires become uncontrolled, even in humid tropical regions where fires were largely absent since the last glacial maximum [38]. According to [2], fire-free land-management can substantially reduce fire incidence by as much as 69 %.

Policy makers could also consider relocating rural households operating in high-risk regions as a governmental ex-ante management strategy that could be less expensive than, as usual, coping with the damage in the aftermath, an approach that has proven vastly ineffective [8]. Former UN Secretary General Kofi Annan reported in October 2005 that flash appeals had generated on average only 16 % of the requested funds [8]. In fact, rural migration is currently used by rural smallholders as one of the informal means of self-insurance. However, the implied risk premium for self-insurance strategies is usually paid by the farmers with few or no governmental support in developing countries [8]. So far, governments in such economies have shown support and are active in the promotion of market-based risk management (e.g., insurance), as this approach can reduce the needs and scope for government interventions and thereby decrease the costs incurred by governments in ex-post coping activities [52]. However, traditional insurance is out of reach for most rural households, and the relatively new microinsurance is still under development and has focused more on drought and floods. We think that our risk assessment approach can contribute to better insight into the understanding of environmental risks and their potential impacts at farm level.

The methodology for the assessment of fire environmental damage developed in the present study can be easily adapted to other kinds of environmental risk. In the case of floods, the spectral reflection of water can be captured using multi-spectral cameras on board of satellites or aircrafts. Although more difficult to detect, droughts can be recognized using proxy values like the Normalized Difference Vegetation Index NDVI, that can be computed as well from multi-spectral cameras and compared to existing spectral libraries in order to know whether the plants are under water stress. Thermo cameras can be used to spot some types of water or soil pollution. As long as a particular environmental damage is recognized, the presented methodology in this study can be used to assess its spatiotemporal impact.

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Integration of environmental and market risks in the analysis of land-use portfolios*

A case study of REDD+ compensations in South America

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Abstract Current approaches to computing optimal land-use investments involve the analysis of portfolio returns mostly within a market-risk perspective. However, such investments are also vulnerable to environmental hazards such as fire, floods and droughts, that might put at risk the whole investment. In developing countries, where family-farmers play an important role in the production of staple food and dairy products for national consumption, such hazards become even more relevant because many live under the poverty line with few alternatives to transfer risks. The present study integrates environmental risk assessment methodology with current approaches optimizing land-use portfolios. The methodology is implemented for the particular case of financial compensations to be paid to family-farmers in order to avoid further deforestation within the REDD+ framework. The results highlight the importance of such approaches for understanding the spatial dimension that environmental risk modeling generates and, for the particular case of REDD+, for identifying areas of low environmental risks where such projects can reach sustainability.

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Keywords Environmental and market risk assessment · land use portfolios · REDD+ · higher-order moments · fat tails · fire risk · family farmers

1 Introduction

Agriculture is one of the riskiest sectors of economic activity, and effective risk-reducing instruments are severely lacking in rural areas [86]. With respect to market risk, farmers are subject to low prices that threaten their long term viability, when income is too low to provide for the operational needs of the farm [50], as well as high food-price variability, which out of all non-fuel commodities, shows the highest ever historical volatility over a decade (1971-1980 [51], with the second highest peak between 2008 and 2009 [52]). Land-use related activities are also subject to environmental risks, mostly in the form of hazards, such as fires, droughts, floods and frosts. These are among the most frequent, costly and impactful kinds of shock that lead to poverty in the first place, and that make escape from it so difficult [32]. Yet, about 75% of the world's poor people live in rural areas, and most of them are involved in farming [63].

In developing countries with abundance of land, the most relevant stakeholders are family-farmers and corporations [25]. In the case of Latin America, the FAO/BID [38] conducted a survey in Brazil, Chile, Colombia, Ecuador, Mexico and Nicaragua, and found that, on average, family-farmers hold 12 hectares per family, while the average farm held by corporations is 141 hectares. In spite of the relatively small share of agricultural land they hold, South American family-farmers produce large shares of the national consumption totals for many staple food products in the region, *e.g.*, 49% of maize and 52% of milk in Brazil, 70% of maize in Bolivia and Ecuador, and more than 40% of maize and milk in Chile [38], [80]. Notwithstanding their substantial involvement in national markets, the number of rural households in the region living below the poverty line is 53% [28], with an estimated income of US $1.25 per day per capita [50].

Farmers in developing countries also face constraints that prohibit them from either leveraging their productivity or transferring risks, resulting in fewer opportunities for increasing their production and revenues. Limited access to financial and insurance services, dislocation from markets, poor access to inputs, lack of advisory services or information, and poor infrastructure [87] are common constraints to farm economies, especially in developing countries due to low governmental investment at the rural level. The main problem is that such constraints, shown in Table 1, lead to higher uninsured risk exposure, forcing rural households to adopt the low-risk and low-return farming activities, shown in Table 2. This in turn reduces the farmers' likelihood to accumulate the assets needed to escape poverty through savings and investment [6]. Losses in agriculture associated with such types of risk exposure are not

Table 1 Constraints faced by family-farmer agriculture [83].

Investment Barriers	Social/Institutional Barriers	Technological Barriers
Lack of assets and savings	Poorly functioning markets	Lack of technical expertise
No or little access to credit or extension services	No or limited market access	Existing resource degradation (for example soil/water)
No or little access to insurance	Limited market information and understanding	Lack of baseline data (for example forest or soil carbon) content
Lack of infrastructure and equipment	Weak land tenure security	

Table 2 Risk management techniques of family-farmers. Based on [2], [67] and [83].

Type of risk management	Examples	Available to small farmers
Technical	Low-risk production	yes
	Irrigation	not always
	Pest prevention (pesticides, herbicides)	not always
	Livestock disease prevention (vaccination)	not always
	On-farm diversification	yes
	Off-farm diversification	not always
Financial	Insurance	seldom
	Hedging	seldom
	Precautionary savings	seldom
	Contingent borrowing	seldom

exclusive to farmers, but also shared by agribusiness entities, financial and insurance providers, governments and all actors involved throughout the supply chain.

In spite of the risks and constraints mentioned above, the amount of land available for agricultural purposes in Latin America has been increasing in the last decades. Commercial agriculture and, to a lesser extent, family-farming have benefited from weak tenure land rights and specific national policies fostering deforestation [84]. As a result, land used for commercial agriculture has expanded significantly in recent decades. Typical products such as soybeans, palm oil and sugarcane, have altogether shown a 12% annual growth of arable land between 1990 and 2010 [75]. According to Kissinger *et al.* [56], commercial agriculture has become the most important driver of deforestation in Latin America, contributing to around 66% of the total deforested area, followed by agriculture of subsistence (family-farming) at almost 27%.

According to the State of the World's Forests [37], South America had an estimated 864 million hectares covered by forest. These abundant forest resources account for 21% of the world's forest areas and 57% of its primary forests. Yet, South America lost more than 8 million hectares of its total forest area between 1990 and 2010, at a rate three times higher than the world's forest loss rate during the same period [37]. Due to higher returns on investments in certain high productive agricultural commodities, the conversion of forest land to agriculture has become the leading cause of the regional deforestation [37]. It is performed primarily through illegal logging and intentionally-ignited fires. According to Uriarte *et al.* [89], policies to promote low-fire land use systems and access to education, as well as the improvement of early warning systems and other mechanisms, could reduce fire damage in the region [89].

1.1 Payment for ecosystem services (PES) to family-farmers

Halting global deforestation is inherently linked to economic considerations at both the national and household levels because most endangered primary forests are located in developing countries where the forest is an important economic commodity [71], [59]. From a macroeconomic perspective, the immediate reduction of carbon emissions achieved by halting deforestation is highly cost-effective [30]. Thus, two types of regimes have emerged: a policy and a voluntary-driven one. The former is currently being established under the United Nations Framework Convention on Climate Change (UNFCC). The second regime is a market for the voluntary compensation of carbon footprints, for example, carbon credits generated by companies via various project types [26]. Among the possible project types, there are forest-related activities in different countries which are aimed at REDD+ (Reducing Emissions from Deforestation and forest Degradation). According to FAO [37], several countries have recognized the potential impact of REDD+ and have provided financial resources to establish pilot activities. Yet, the sustainability of such projects is dependent not only on stable financial sources, but also on effective forest governance, secure forest carbon tenure and equitable benefit sharing, among other things [37], and must also consider food production [61]. Although REDD+ is still a relatively new mechanism, a review of initial outcomes of 41 REDD+ projects in 22 countries in Africa, Asia, and Latin America recently [64] revealed PES as the most common strategy intervention (39%). To date up to $134 per project per year has been paid to individuals and households as part of these projects.

According to Stern [82], in order to reverse emissions from land use change, compensation from the international community should be provided and the opportunity costs of alternative uses of the land should be taken into account. But this is perhaps the greatest challenge that mechanisms like REDD+ face. Indeed, Fisher *et al* [40] and Pacheco *et al.* [75] argue that such incentives to keep forest standing can not compete with, for example, palm oil, soy, sugar cane and other products of commercial agriculture, as the net present value of such plantations ranges between US $6000 - US $9000 per hectare per year. In such cases alternative strategies may be much more effective. Indeed, Brickell and Elias [16] present an interesting example of how international publicity campaigns from environmentalists who reported the wrongdoing of some multinational companies linked to the soybean supply have helped reduce deforestation rates in some regions of Brazil.

Despite that PES may have a rather limited influence on commercial agriculture, it may be relevant for family-farming as a means for ameliorating poverty and reducing deforestation and forest degradation. For these reasons REDD+ has sparked renewed hope in the ability of conservation programs to deliver win-wins by saving the environment and reducing rural poverty [64].

1.2 Environmental risk in land-use portfolios for family-farmers

Despite that land use investments (*e.g.* pasture, forest, crops) by family-farmers are vulnerable to several hazards including environmental risks, commodity price vulnerability and changes in agricultural/forestry policies, most studies ([62], [46], [19]) have focused on fair compensations of PES and REDD+ within the market risk perspective. However, environmental hazards, such as fires (specially in forests due to long lasting damage) can have enormous economic consequences demonstrated in an analysis of social capital and fire contagion by Simmons *et al.* [81]. Therefore, a thorough understanding not only of market but also of environmental risks affecting family-farmers land use is of particular importance for the sustainability of mechanisms such as REDD+ [79].

In this study we focus on the financial benefits that South American family-farmers may receive if they decide to protect their own forests within the REDD+ framework. After reviewing current methodologies for optimizing portfolios, we present a methodology for integrating the assessment of environmental risks (introduced in [1]) into the portfolio analysis in order to obtain more realistic results and fair payments.

2 Materials and methods

2.1 Selected South American countries

According to the World Bank [88], South America experienced an average growth in GDP per capita from USD 3258 in 2000 to USD 7483 in 2010, and the region is expected to grow more during upcoming years [52]. Past growth was partially attributable to additional agricultural output during the period, which increased 35% in the case of industrial roundwood, 43% in cow milk, and 66%, 92% and 132% in maize, sugar cane and soybeans, respectively; see Table 3.

Some of the most heavily forested countries in South America are Brazil (520 mill ha), Colombia (60 mill ha) and Ecuador (10 mill ha), which combined represent 70% of the total South American forest [36]. In terms of GDP (nominal) the three countries rank in a similar fashion, with Brazil as the largest South American economy, Colombia the third largest, and Ecuador one of the smallest [88]. For this study, data from these three countries were used to analyze necessary financial compensations in order to stop deforestation at the family-farm level.

2.2 Selected agricultural and forest products

In terms of agricultural output, South America's top crops are sugar cane, soybeans and maize [39], see Table 3; the top livestock product is cow milk; and industrial roundwood is the main forest product. This ranking of commodities is observed as well when looking only at the countries with the most abundant forest resources, with the exception that soybean in Colombia is not a top crop and it is replaced by oil palm fruit.
According to FAO/BID [38], "sensitive crops" are products thought by regional policy makers to have a higher potential impact on family-farmers due to frequent changes in productivity and prices, or because they are considered relevant as staple foods. Example of staple foods include livestock products: cattle (dairy and meat) and grains, such as maize, wheat, beans and rice. When compared with the list of the most productive agricultural commodities in South America (Table 3) only maize and cow milk become relevant at national and South American levels. Therefore, in the portfolio analysis of family-farmers the commodities included were maize as representative of croplands, cow milk of pastures and tropical industrial timber of natural forest. These are the most likely land-uses that a family-farmer would choose to replace forest with in the absence of financial compensations. Other commodities with higher agricultural output such as sugarcane, soybeans and oil palm fruits are typical products of corporations and therefore not within the scope of the family-farmer portfolio analysis.

2.3 Market risk data for portfolio analysis of family-farmers

Costs of production ($\frac{US\$}{ha \cdot yr}$) and productivity values ($\frac{ton}{ha \cdot yr}$) were obtained from existing studies along with our own calculations (Table 4). In order to compare REDD+ financial compensations with different approaches, models were constrained to produce land-use portfolios having at least the same proportion of forest as current national levels. Fixed proportions for all countries are shown in Table 5. Yearly time series data for commodity prices and marketed product

Table 3 Most productive agricultural commodities.

Top crops	**Ecuador**		**Colombia**		**Brazil**		**S.America**	
	$\times 10^6$ton	%	$\times 10^6$ton	%	$\times 10^6$ton	%	$\times 10^6$ton	%
Sugar cane	8.3	55	20.3	-42	717.5	119	811.7	97
Soybeans	⊗	⊗	0.04	40	68.8	110	132.3	131
Maize	1.0	61	1.5	27	56.0	76	92.2	66
Oil palm fruit	1.8	34	3.2	30	1.3	>200	⊗	⊗
Top livestock product								
Cow milk	5.7	184	7.5	22	31.6	55	64.4	43
Top forest	$\times 10^6$ m^3	%	$\times 10^6$ m^3	%	$\times 10^6$ m^3	%	$\times 10^6$ton	%
Ind. roundwood	1.8	8	2.4	10	128.4	25	196.1	35

Source: [39]. Production during 2010, along with change in % compared to 2000. ⊗ means that the commodity is not a top productive one for the particular country or region.

quantities within the time frame 1990-2011 for Brazil, Colombia and Ecuador were obtained from "FAOSTAT" (FAO Statistic Division [39]). However, price and quantity data representing forest land use were scarce therefore only data on exported timber, extracted from Knoke *et al.* [62], were used.

2.4 Land-use portfolio under market risk

When considering the risks of land-use investments, farmers are most concerned with low prices, when income is too low to provide for the operational needs of the farm [50]. Another source of risk for producers is the high food-price variability that, out of all non-fuel commodities, shows the highest ever historical volatility over a decade (1971-1980) [51], with the second highest peak between 2008 and 2009 [52]. Those peaks from the last forty years benefited neither consumers, nor small to medium producers, as input prices for agriculture increased at the same time, thus canceling out any potential for higher returns for producers [35]. Final consumers, however, have an advantage thanks to a greater geographical diversification of production which has reduced the sensitivity of consumer prices to supply shocks [34]. Although more limited, family-farmers can partially hedge their investments against market risk through land-use diversification. The first authors to study the diversification effects when using commodities were Mills and Hoover [72], who used portfolio theory to explain the use of forest as a risk diversifier in spite of its comparatively low economic-yield. Other authors ([12], [59], [62]) have also studied the benefits of land-use diversification in developing economies. In this section, the approach of choosing land-use portfolio weights that max-

Table 4 Productivity and cost data for the land-uses and commodities investigated.

Land-use	Commodity	Land	Productivity† $\frac{ton}{ha \cdot yr}$	Efficiency* $\frac{animal}{ha \cdot yr}$	Costs* $\frac{US\$}{ha \cdot yr}$	Sources for *
Cropland	Maize	Ecuador	2.0	—	217.4	[29]
		Brazil	3.0	—	232.0	[21], [78]
		Colombia	2.0	—	255.0	[18], [85]
Pasture	Cow milk	Ecuador	1.10	0.56	142.9	[90], [66]
		Brazil	0.95	0.86	118.2	[49], [11], [22]
		Colombia	1.02	0.97	153.0	[48], [23]
Nat. forest	Ind. timber	All	$0.7 \frac{m^3}{ha \cdot yr}$	—	27.5	[12], [62]

† Productivity values are taken from FAOSTAT [39].

Table 5 Land cover proportions in 2010

	Ecuador %	**Colombia** %	**Brazil** %	**S.America** %
Forest	39.0	55.0	62.0	48.0
Pasture*	19.4	35.0	23.0	27.0
Crop**	5.5	3.0	8.0	6.0
Others	36.1	7.0	7.0	19.0

Source: FAOSTAT [39].

*Pastures and permanent meadows. **Permanent crop and arable land.

imize returns and minimize risk is followed, but using a model that departs from previous ones by capturing asymmetry and heavy tails in the distribution of commodity prices, *i.e.* a model that represents more accurately the real market risk situation of developing countries.

Let's consider n risky commodities that a family-farmer is considering to produce, every commodity return is defined as

$$r_{i,t} = \frac{price_{i,t}}{ton} \times prod_{i,t} - \frac{cost_{i,t}}{ha}, \tag{1}$$

where $prod_{i,t}$ is the productivity of the commodity in $\frac{ton}{ha}$ and $cost_{i,t}$ its production costs. Thus, the return column vector of all commodities considered is $\mathbf{r_t} = (r_{1,t}, ..., r_{n,t})'$ and it is assumed to be governed by a joint continuous cumulative, although not necessarily Gaussian, probability distribution function $F(\cdot)$. Further, let's the column vector $\boldsymbol{\alpha_t} = (\alpha_{1,t}, ..., \alpha_{n,t})'$ be defined as the farmer's land proportions (portfolio weights) allocated to the considered commodities, with the constraint that the weights at any moment sum to one.

The concept of ordinal utility has been widely used as the basis on which portfolio theory is built, thus an investment can be ordered by an individual as better than, equal to, or worse than other alternative. In order to reflect this behavior several authors have used the approach of stochastic dominance, where a probability distribution over possible outcomes of an investment can be ranked as superior to the distribution of another investment. Moments are used to compare probability distributions in order to determine "dominance" and thus rank investments. Although portfolio theory has widely used the first two moments (mean and variance) several authors argue about the advantages of using the first fourth moments, such as capturing asymmetry and heavy tails in the distribution of returns. Therefore, conditional on the assumption that higher moments exist, the expected utility can then be represented as an increasing function of the mean and the skewness, and a decreasing function of the variance and the kurtosis of the portfolio return distribution [55].
Let W_t be the initial wealth of a family-farmer who is willing to allocate his land-use portfolio. Denote by $U(\cdot)$ a von Neumann-Morgenstern utility function, defined over his next-period wealth W_{t+1}, and assume it belongs to the family of fourth-order stochastic dominance D_4, [55], satisfying[1]:

$$D_4 = \{U | U^{(1)}(\cdot) > 0, U^{(2)}(\cdot) < 0, U^{(3)}(\cdot) > 0, U^{(4)}(\cdot) < 0\}$$

where $U^{(i)}(\cdot)$ is a derivative of order i of $U(\cdot)$. Without loss of generality, the beginning-of-period wealth W_t is set equal to one [53] and the next-period family-farmer's wealth is defined as $W_{t+1} := (\boldsymbol{\alpha_t'}\mathbf{r_{t+1}})W_t = \boldsymbol{\alpha_t'}\mathbf{r_{t+1}}$, where, in the most general case, a utility function is used as a proxy for an investor's

[1] There is no clear economic justification concerning the link between the expected utility function and moments higher than the fourth-order of the investment return distribution [55]

expected payoff preferences $E[U(W_{t+1})] = \int_{-\infty}^{\infty} U(W_{t+1})\, dF(W_{t+1})$. Specifically, a family-farmer allocates his next period portfolio by maximizing the expected utility of his wealth return:

$$\begin{aligned} \max_{\boldsymbol{\alpha}} \;\; & E[U(\boldsymbol{\alpha}_{\mathbf{t}}^{'}\mathbf{r}_{\mathbf{t+1}})] \\ s.t. \;\; & \boldsymbol{\alpha}'\boldsymbol{e} = 1 \end{aligned} \tag{2}$$

Where e is a $(n, 1)$ vector of ones. Finally, the gross return of the farmer's optimal land-use portfolio is determined by

$$\mathbf{r}_{\mathbf{p},\mathbf{t+1}}(\boldsymbol{\alpha}_{\mathbf{t}}) = \boldsymbol{\alpha}_{\mathbf{t}}^{'}\mathbf{r}_{\mathbf{t+1}}. \tag{3}$$

2.5 Mean-Variance (MV) approach

Based on stochastic dominance of second order, the utility in MV starts with an exponential transformation of wealth, also known as Constant Absolute Risk Aversion (CARA):

$$U(W_{t+1}) = 1 - e^{-\lambda W_{t+1}} = 1 - e^{-\lambda(\boldsymbol{\alpha}_{\mathbf{t}}^{'}\mathbf{r}_{\mathbf{t+1}})}, \tag{4}$$

where $\lambda \geq 0$ is the coefficient of absolute risk aversion and W_{t+1}, therefore $U(W_{t+1})$, is the value that the decision-maker wants to maximize. Risk-neutral investors are usually assumed to have a $\lambda \approx 0$, whereas risk-averse investors have $\lambda > 0$. Whenever a random variable X follows a normal distribution with mean m and variance v^2, the transformation e^X follows a log-normal distribution with expected value $E[e^X] = \int_{-\infty}^{\infty} e^X\, dF(X) = e^{m+\frac{1}{2}v^2}$. Hence, if the returns $\mathbf{r}_{\mathbf{t}}$ are assumed to be normally distributed, equation (4) can be rewritten[2] as

$$E[-e^{-\lambda(\boldsymbol{\alpha}_{\mathbf{t}}^{'}\mathbf{r}_{\mathbf{t+1}})}] = -e^{-\lambda(\mu_{p,t+1} - \frac{1}{2}\lambda\sigma^2_{p,t+1})}. \tag{5}$$

where $\mu_{p,t+1} = E[\mathbf{r}_{\mathbf{p},\mathbf{t+1}}(\boldsymbol{\alpha}_{\mathbf{t}})] = E[\boldsymbol{\alpha}_{\mathbf{t}}^{'}\mathbf{r}_{\mathbf{t+1}}] = \boldsymbol{\alpha}_{\mathbf{t}}^{'}E[\mathbf{r}_{\mathbf{t+1}}] = \boldsymbol{\alpha}_{\boldsymbol{t}}'\boldsymbol{\mu}_{\boldsymbol{t+1}}$ is the land-use portfolio's expected gross return and the covariance $\sigma^2_{p,t+1} = E\big[\boldsymbol{\alpha}_{\boldsymbol{t}}^{'}\boldsymbol{r}_{\boldsymbol{t+1}} - E[\boldsymbol{\alpha}_{\boldsymbol{t}}^{'}\boldsymbol{r}_{\boldsymbol{t+1}}]\big]^2 = E[\boldsymbol{\alpha}_{\boldsymbol{t}}'(\mathbf{r}_{\mathbf{t+1}} - \boldsymbol{\mu}_{\boldsymbol{t+1}})]^2 = \boldsymbol{\alpha}_{\boldsymbol{t}}'E[\mathbf{r}_{\mathbf{t+1}} - \boldsymbol{\mu}_{\boldsymbol{t+1}}]^2\boldsymbol{\alpha}_{\boldsymbol{t}} = \boldsymbol{\alpha}_{\boldsymbol{t}}'cov_{t+1}\big(\mathbf{r}_{\mathbf{t+1}}, \mathbf{r}_{\mathbf{t+1}}\big) = \boldsymbol{\alpha}_{\boldsymbol{t}}' \cdot \boldsymbol{\Sigma}_{\boldsymbol{t+1}} \cdot \boldsymbol{\alpha}_{\boldsymbol{t}}$ is used as a measure of the commodities' market risk. Thus, maximizing $E[U(W_{t+1})]$ is equivalent to the optimization problem [53]

$$\begin{aligned} \max_{\boldsymbol{\alpha}} \;\; & \boldsymbol{\alpha}_{\boldsymbol{t}}' \cdot \boldsymbol{\mu}_{\boldsymbol{t+1}} - \frac{1}{2}\lambda\big[\boldsymbol{\alpha}_{\boldsymbol{t}}' \cdot \boldsymbol{\Sigma}_{\boldsymbol{t+1}} \cdot \boldsymbol{\alpha}_{\boldsymbol{t}}\big] \\ s.t. \;\; & \boldsymbol{\alpha}'\boldsymbol{e} = 1 \end{aligned} \tag{6}$$

[2] Notice that maximizing the expected value of eq.(4) gives the same result as maximizing the expected value of $U(W_{t+1}) = -e^{-\lambda W_{t+1}}$ since the expected values of utility, contrary to the utility function itself, are to be interpreted as ordinal utility instead of cardinal utility. Thus, the sign of the expected utility values are of no significance

However, Mandelbrot [68] showed that the frequency distribution of prices of typical commodities, hence of returns, does not follow a normal distribution. In addition to this Fama [33] demonstrated that variance is not an appropriate measure of risk, because it penalizes profits and losses symmetrically, and in the case of heavy tails or skewed distributions, undervalues market risk. Thus, in cases where prices are not normally distributed, wrong portfolio selection may occur when using the MV approach [69].

2.6 Alternative market risk measures

Market, credit and operational risk are three measures nowadays acknowledged by the Basel Committee on Banking Supervision (BCBS). With respect to market risk, the BCBS [8] encourages financial institutions to use the comprehensive *Value-at-Risk (VaR)* measure. VaR is defined as the minimum potential loss that an investment portfolio could obtain over a given time horizon with a preset probability level α. One popular parametric approach for computing the next period VaR is presented by J.P. Morgans *RiskMetrics* Group [73], it applies to a multivariate portfolio under the assumption of normality [41], and uses historical return data for computation:

$$VaR_{\theta,t+1} = \mu_{p,t+1} - z_\theta \times \sigma_{p,t+1},$$

where $\mu_{p,t+1}$ is the land-use portfolio's expected gross return, $\sigma^2_{p,t+1}$ is the variance used as a measure of the commodities' market risk, and where $z_\theta = \Phi^{-1}(\theta)$ is the quantile for a probability of loss equal to θ. A common criticism is that VaR is not subadditive [27], meaning that the VaR of a multivariate portfolio can be larger than the sum of the VaRs of its components. Moreover, in spite of VaR being a BCBS standard measure, some authors ([13], [7]) argue that it fails to account for the risk of extreme losses. After all, VaR defines only the spread "to the left" of the mean as a measure of risk [45], and most practitioners use either the historical simulation approach or the normal distribution function to compute VaR [15]. However, the huge and non-expected losses of financial institutions during the 2007-2008 global crisis provided first-hand evidence that standard VaR calculations seriously underestimate true market risk. In response, the BCBS ([9], [10]) supplemented the measure with a new requirement, the *Stressed VaR*, computed using a one-year observation period containing the worst-ever recorded losses. The Stressed VaR is now provided in addition to the most recent one-year observation period VaR. Although no particular approach for computing the VaR is favored, the BCBS requests model validation and backtesting to demonstrate that any assumptions made do not underestimate risk [10], such us the assumption that returns follow symmetric distributions without heavy tails.

Out of several approaches for computing VaR, three categories are recognized as the most representative: historical simulation, semi-parametric and parametric models [53]. Historical simulation is perhaps the simplest and most common approach for calculating VaR. As it makes no particular assumption about the distribution of returns, it is considered non-parametric, its extension for multivariate assets requires minimal additional work. Because a step function is used as an empirical distribution, its main drawback is that it may cause biased results, particularly in the tails of the distribution. As risk management is especially concerned with extreme observations, these limitations might be serious ([42], [15]).

The leading alternative to historical simulation makes assumptions about how returns are distributed. The best known semi-parametric approach is based on Extreme Value Theory (EVT) and involves modeling the lower tail of the return's distribution [31]. The method is more accurate than historical simulation, but requires large sample sizes, high-frequency data and filtering to obtain independent and identically distributed observations [20]. It is also highly sensitive to the chosen threshold; selection of an optimal one remains a current research topic [57]. Extension to the multivariate case is much more complex, [57], making it less popular than other methods.

With respect to parametric approaches, the most popular are *Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH)*. GARCH comprise time series analyses that have been extensively studied and from which several models have been developed [14]. For the univariate case it is assumed that returns might be autocorrelated, that volatility follows a GARCH(1,1) model and that standardized returns $z_t = \frac{r_t - \mu_t(\theta)}{\sigma_t(\theta)}$ are governed by $g(z_t \mid \eta)$, where the shape vector η captures asymmetry and heavy tails of z_t [54]. If g is not normal, a Student-t or a variation of it may be used instead [70]. For multivariate portfolios where a normal distribution is suitable, variations including Factor-GARCH, Orthogonal-GARCH and Flexible-GARCH apply. Outside of the normality assumption, however, several difficulties arise [65].

2.7 Multivariate portfolios incorporating higher-moments (HM)

In order to cope with the shortcomings of MV and VaR, while at the same time maintaining their intuitive optimization framework (6), significant efforts have been made to build model extensions that use alternative risk measures. These relax the normality assumption. Jurczenko and Maillet [55] propose that if $U(\cdot)$ is arbitrarily continuously differentiable, then it can be expressed as a Taylor series expansion of order K evaluated around the expected wealth:

$$U(W_{t+1}) = \sum_{j=0}^{K} \frac{U^{(j)}\left[E[U(W_{t+1})]\right]\left[W_{t+1} - E[U(W_{t+1})]\right]^j}{j!} + \xi_{j+1}, \qquad (7)$$

where $U^{(j)}$ is the jth derivative for $j = 0, ..., K$ and ξ_{j+1} is the Taylor series remainder. Following Jondeau *et al.*, [53], by assuming that $\lim_{K\to\infty} \xi_{k+1} = 0$

and truncating the Taylor series expansion at the 4th order, the expected utility is approximated by

$$E\big[U(W_{t+1})\big] \approx U\big[E[U(W_{t+1})]\big] + \frac{U^{(2)}\big[E[U(W_{t+1})]\big]cov_p}{2} \\ + \frac{U^{(3)}\big[E[U(W_{t+1})]\big]skw_p}{3!} + \frac{U^{(4)}\big[E[U(W_{t+1})]\big]kur_p}{4!}, \tag{8}$$

where $\mu_p = E[U(W_{t+1})]$, $cov_p = E\big[W_{t+1} - E[U(W_{t+1})]\big]^2$, $skw_p = E\big[W_{t+1} - E[U(W_{t+1})]\big]^3$ and $kur_p = E\big[W_{t+1} - E[U(W_{t+1})]\big]^4$ are respectively the mean, covariance, skewness and kurtosis of the family-farmers's portfolio return distribution. Without loss of generality, a utility function such as CARA (4) is substituted into (8) obtaining:

$$E\big[U(W_{t+1})\big] \approx -e^{-\lambda\mu_p}\left[1 + \frac{\lambda^2 cov_p}{2} - \frac{\lambda^3 skw_p}{6} + \frac{\lambda^4 kur_p}{24}\right]. \tag{9}$$

Equation (9) requires the computation of a portfolio's first four moments out of a sample of commodities' returns. Defining moments as functions of tensor products, [5] and [54], has the advantage that no particular distribution function must be considered. For n risky commodities and $\boldsymbol{\alpha}$ weight vector, the *q-th* central portfolio moment is $m_q = E[(r_p - \boldsymbol{\alpha'} \cdot \boldsymbol{\mu})^q]$. Thus, the first four moments are calculated as:

$$\begin{aligned} \mu_p &= E[r_p] = \boldsymbol{\alpha'} \cdot \boldsymbol{\mu} \\ cov_p &= m_2 = \boldsymbol{\alpha'} \cdot \mathbf{M_2} \cdot \boldsymbol{\alpha} \\ skw_p &= m_3 = \boldsymbol{\alpha'} \cdot \mathbf{M_3} \cdot (\boldsymbol{\alpha} \otimes \boldsymbol{\alpha}) \\ kur_p &= m_4 = \boldsymbol{\alpha'} \cdot \mathbf{M_4} \cdot (\boldsymbol{\alpha} \otimes \boldsymbol{\alpha} \otimes \boldsymbol{\alpha}) \end{aligned}$$

where $\otimes$ is the tensor product of two vector spaces. The above definitions of skewness and kurtosis as central higher moments depart slightly from the traditional statistical definition of standardized central higher moments [54]. As an example, for a multivariate portfolio with $n = 3$ risky commodities, $\mathbf{M_3}$ becomes a 3×9 matrix,

$$\mathbf{M_3} = \left[\begin{array}{ccc|ccc|ccc} s_{111} & s_{112} & s_{113} & s_{211} & s_{212} & s_{213} & s_{311} & s_{312} & s_{313} \\ s_{121} & s_{122} & s_{123} & s_{221} & s_{222} & s_{223} & s_{321} & s_{322} & s_{323} \\ s_{131} & s_{132} & s_{133} & s_{231} & s_{232} & s_{233} & s_{331} & s_{332} & s_{333} \end{array}\right], \tag{10}$$

with $s_{ijk} = E\left[(r_i - \mu_i)(r_j - \mu_j)(r_k - \mu_k)\right]$, calculated as

$$s_{ijk} = \frac{T}{(T-1)(T-2)} \sum_{t=1}^{T} (r_i - \mu_i)(r_j - \mu_j)(r_k - \mu_k) \tag{11}$$

where $\frac{T}{(T-1)(T-2)}$ is a factor that produces an unbiased estimator of coskewness [45] and time $t = 1, ..., T$, for this particular case, years. The matrix $\mathbf{M_4}$ is 3×27 with

$$\mathbf{M_4} = \left[\begin{array}{ccc|ccc|c} k_{1111} & k_{1121} & k_{1131} & k_{1112} & k_{1122} & k_{1132} & k_{3133} \\ k_{1211} & k_{1221} & k_{1231} & k_{1212} & k_{1222} & k_{1232} & \cdots\; k_{3233} \\ k_{1311} & k_{1321} & k_{1331} & k_{1312} & k_{1322} & k_{1332} & k_{3333} \end{array} \right], \tag{12}$$

and $k_{ijkl} = E\left[(r_i - \mu_i)(r_j - \mu_j)(r_k - \mu_k)(r_l - \mu_l)\right]$, calculated as

$$k_{ijkl} = \frac{T(T+1)}{(T-1)(T-2)(T-3)} \sum_{t=1}^{T} (r_i - \mu_i)(r_j - \mu_j)(r_k - \mu_k)(r_l - \mu_l). \tag{13}$$

In order to find the weights $\boldsymbol{\alpha_t} = (\alpha_{1,t}, ..., \alpha_{n,t})'$ that maximize the next-period family-farmer's wealth W_{t+1}, allocated to the considered commodities, the approximation (9) is maximized:

$$\begin{aligned} \max_{\boldsymbol{\alpha}} \quad & -e^{-\lambda \boldsymbol{\alpha}' \cdot \boldsymbol{\mu}} \Bigg[1 + \frac{\lambda^2 \boldsymbol{\alpha}' \cdot \mathbf{M_2} \cdot \boldsymbol{\alpha}}{2} - \frac{\lambda^3 \boldsymbol{\alpha}' \cdot \mathbf{M_3} \cdot (\boldsymbol{\alpha} \otimes \boldsymbol{\alpha})}{6} \\ & + \frac{\lambda^4 \boldsymbol{\alpha}' \cdot \mathbf{M_4} \cdot (\boldsymbol{\alpha} \otimes \boldsymbol{\alpha} \otimes \boldsymbol{\alpha})}{24} \Bigg] \\ s.t. \quad & \boldsymbol{\alpha}' \boldsymbol{e} = 1, \end{aligned} \tag{14}$$

where e is a $(n, 1)$ vector of ones. The maximization was accomplished using the optimization package "DEoptim" [4] in the statistical software R [77]. The optimization is based on the Differential Evolution (DE) search algorithm, which is similar to classic genetic algorithms [76]. DE has the advantage of finding global optimal portfolios subject to non-linear constraints, and in cases where the objective function is a non-linear proxy of risk and return [3].

2.8 Environmental risk assessment approach

Acevedo-Cabra *et al.* [1] recently provided an approach for assessing environmental hazards affecting land productivity. Using historical Terra-satellite data [74] of burned areas in South America, they found a non-linear relationship between average time of events and damage per hectare at three different spatial intensities of events, $\hat{\Lambda}_{low}, \hat{\Lambda}_{med}$ and $\hat{\Lambda}_{high}$, in Brazil, Colombia, and Ecuador for the years 2000 to 2012. Thus, they were able to evaluate how much a farmer could lose at particular regions in terms of productivity per hectare due to fires. In order to assess the potential damage per hectare at a particular location φ, the authors defined the *farm's proportional damage* $f_{t_{inv}} = 5\%$ as a threshold value of the proportion of land that a farm could lose due to damage caused by fire during the period of investment $(0, t_{inv}]$. Setting an arbitrary low threshold value helped identify locations with low record of fire activity where land use investment could still be contemplated [1].

Specifically, with $\rho_t(\varphi|\hat{\Lambda}_{subreg})$ denoting the *proportional damage* ρ_t at location φ restricted to the spatial intensity $\hat{\Lambda}_{subreg}$, and $\hat{\delta}_{t\varphi}(u|\,\hat{\Lambda}_{subreg})$ the average time between burned areas up to time t, the following non-linear relationship, see Fig. 1, was estimated:

$$\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg}) = e^{\varrho} \cdot \left[\rho_t(\varphi|\hat{\Lambda}_{subreg})\right]^{\omega}, \tag{15}$$

where ϱ and ω are regression parameters to be estimated.

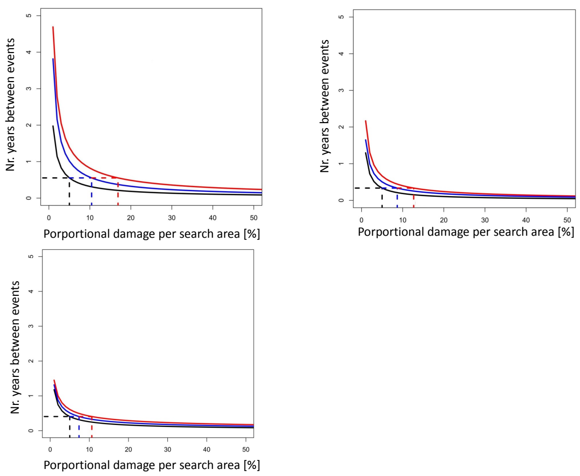

Fig. 1 Source [1]. Nonlinear relationships between proportional burned-areas damaged and average time between events in Brazil (top-left), Ecuador (top-right) and Colombia (bottom-left) for different spatial-intensity regions: $\hat{\Lambda}_{low}$ (black solid line), $\hat{\Lambda}_{med}$ (blue solid line) and $\hat{\Lambda}_{high}$ (red solid line). Here the *farm's proportional damage* at low spatial-intensity was fixed to 5%, (vertical and horizontal dashed lines)

With $\hat{N}_{BA}$ the number of burned area events to be found in the surroundings of φ during the time period $t = 0, ..., T$, in years, the proportional damage per event up to time t was calculated as

$$\xi_t(\varphi|\hat{\Lambda}_{subreg}) = \rho_t(\varphi|\hat{\Lambda}_{subreg})/\hat{N}_{BA}, \tag{16}$$

and the total damage (%) per year as

$$\hat{\psi}_t(\varphi|\hat{\Lambda}_{subreg}) = \frac{\rho_t(\varphi|\hat{\Lambda}_{subreg})}{\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg}) \cdot \hat{N}_{BA}}. \tag{17}$$

On setting $\rho_t(\varphi|\hat{\Lambda}_{subreg}) = f_{t_{inv}}$ in (15), the authors estimated the average time between events $\hat{\delta}_{t\varphi}(u|\hat{\Lambda}_{subreg})$ for a given *farm's proportional damage*; see [1] for details.

2.9 Integration of Market and Environmental Risk

As considered in section 2.4, W_t is the initial wealth of a family-farmer willing to allocate his land-use portfolio in n risky commodities. Returns $\mathbf{r_t} = (r_{1,t}, ..., r_{n,t})'$ of any land use investment are subject to market prices at which commodities can be sold, as well as subject to changes in productivity per hectare due to environmental hazards. Changes in productivity are modeled with the approaches explained in section 2.8. To be consistent with the additional incorporation of environmental risk assessment, as in (1): Returns are computed

$$r_{i,t} = \frac{price_{i,t}}{ton} \times prod_{i,t,\hat{\psi}_t} - \frac{cost_{i,t}}{hectare}, \tag{18}$$

where i represents a commodity (maize, cow milk or wood) to be included in the portfolio analysis and $r_{i,t}$ is the return value in $US\$/ha$ of commodity i at time t. All return values at time t are included in the total return column vector $\mathbf{r_t} = (r_{1,t}, ..., r_{n,t})'$. Productivity of a commodity i at time $t \in (0, t_{inv}]$ is defined as

$$prod_{i,t,\hat{\psi}_t} = prod_{i,t} \times (1 - \hat{\psi}_t), \tag{19}$$

where $prod_{i,t}$ is computed from national or regional productivity in ton/ha for agricultural commodities and m^3/ha for forestry products, and ψ_t is the total damage (%) per year. In locations with few or without previous records of environmental damage for example, locations in regions with low spatial intensity of events, the total damage per year is defined as $\psi_t = 0$. In regions where the land has been under hazard such as with a historical record of burned areas, the productivity is affected by the damage per year, $\hat{\psi}_t$, and computed with equation (17). To compare potential damage between different spatial intensities, a threshold of $f_{t_{inv}} = 5\%$ is used; see [1] for details. After productivity values per hectare were computed, new portfolios were obtained by maximizing the utility function with both the method MV (5) and HM (6), which became the optimization problems (9) and (14), respectively.

2.10 Market and environmental risk scenarios

Gray *et al.* [43] showed how regular payments, such as the Agricultural Market Transition Act, shift the distribution of returns without changing the variability. On the other hand, irregular payments, for example the Marketing Loan Program and the Subsidized Crop Revenue Coverage Insurance, increase the mean, reduce variability and change skewness because only certain market conditions or crop failures trigger payments. For their study, a yearly and constant financial compensation paid to farmers was analyzed, so that the expected returns increased without changing vulnerability to market risk. This facilitated the comparison of models under regular conditions for family-farmers in developing economies.

In order to obtain fair financial compensations within the REDD+ program, previous results on land-use portfolios, [12] and [62], were compared with the above-mentioned methodology incorporating environmental risk assessment and accommodating asymmetrical and heavy tailed distributions. To determine fair values, payments in US$ per hectare of forest per year (without including transaction costs) were increased stepwise and the portfolio was optimized with both the MV (6) and higher-order moment (14) approaches. The models were compared in Brazil, Colombia and Ecuador, with and without financial compensation, under both market-risk aversion and neutrality.
When analyzing agricultural commodities, Holt and Laury [47] and Benítez *et al.* [12] proposed a coefficient of relative risk aversion $\gamma = 1.2$ that represents a risk-averse land-use investor. This corresponds to an absolute risk aversion of $\lambda = 0.016$, given that $\lambda = \frac{\gamma}{x}$, and using $x = 75$ as the average net revenue for all land uses while for a risk-neutral investor $\lambda = 0$ is assigned, [62].

Yearly time series data for product prices and marketed product quantities within the time frame 1995-2010 for Brazil, Colombia and Ecuador were obtained from "FAOSTAT" [37] and other sources; see Table 4.

3 Results

3.1 Non-Gaussian distributed commodity-prices

None of the three commodities used as representative of the land uses, crop, pasture and forest, in any of the countries studied followed a Gaussian distribution; see Table 6. The skewness and kurtosis depart from zero indicating

Table 6 Moments of the return distribution and Kolmogorov-Smirnov Normality test

Land	Land-use	μ $\frac{US\$}{ha \cdot yr}$	var	skw	kur	Kolmogorov $p - value$
Brazil	Crop	114	10554.5	2.26	7.35	$<$ 2.2e-16
	Pasture	74.2	1083.3	0.04	-0.27	$<$ 2.2e-16
	Forest	8.2	71.6	-1.05	2.72	8.796e-10
Colombia	Crop	147.8	8684.3	1.16	2.00	2.22e-16
	Pasture	105.5	7448.4	2.09	6.96	2.22e-16
	Forest	55.9	494.5	-0.4	-0.72	3.442e-15
Ecuador	Crop	122.2	4924.6	0.3	1.7	$<$2.2e-16
	Pasture	65.7	1352.8	-0.2	0.1	$<$2.2e-16
	Forest	20.7	182.2	-0.9	0.6	0.001493

that none of the returns from the individual land-uses are symmetrically distributed. The non-normality is confirmed in all cases by the p-values of the Kolmogorov-Smirnov test of normality. All null-hypothesis are rejected even after adjustment for 9 multiple comparisons at the $0.5/9 \approx 0.01$ level (using a Bonferroni adjustment). Visual inspection of empirical distributions of returns for Brazil, shows the non-normal distribution; similar histograms where obtained for Colombia and Ecuador.

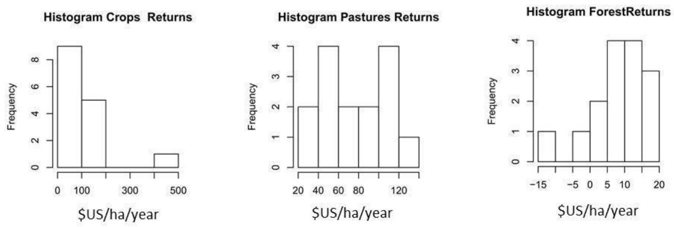

Fig. 2 Histograms of returns for Brazil from 1995 to 2010

4 Commodity returns and higher moments

Based on yearly time-series for commodity prices and productivity over 1995 - 2010, crop produced the highest mean return of all land-uses studied for each of the three countries, with values ranging from 122 in Ecuador to 148 $\frac{US\$}{ha \cdot yr}$ in Colombia (Table 6). In all three countries pasture yielded the second highest returns, ranging from 66 in Ecuador to 105 $\frac{US\$}{ha \cdot yr}$ in Colombia. Forestry showed the lowest returns in all three countries, with values ranging from 8 in Brazil to 56 $\frac{US\$}{ha \cdot yr}$ in Colombia. In Brazil, forest generated 14 times less returns per hectare than crop and 9 times less than pasture. In Colombia pasture's return was just 1.8 times higher than forest's.

Crop and pasture represent not only the highest and second highest mean returns, respectively, but the highest and second highest variance of the three commodities studied in all three countries. Unlike risk-neutral family-farmers, risk-averse ones consider market price risk when deciding what portfolio suits them best. In the case of Modern Portfolio Theory with the MV approach, variance is used as proxy for risk, which is minimized for a given return value. Thus a high variance is penalized even if the variability is due to high positive returns. In the case of the higher-order moment approach, a high variance is penalized only if it has a negative skewness.

Skewness determines whether the distribution of returns is symmetrical, right-tailed or left-tailed. A skewness greater than zero reflects whether the variance is made up of positive increments in returns. Interestingly, Table 6, shows that, except for pasture in Ecuador, crop and pasture exhibit positive skewness in all countries. Forest, on the contrary, has negative skewness in all three countries, implying that its variance is dominated by drops in returns. Thus, family-farmers may expect sporadic decrements in returns when investments are made in this particular commodity. The higher the negative value from skewness and the larger the variance, the greater the decrement in returns from the particular land use. This result is relevant because it may force a higher compensation in order to avoid conversion from forest to more profitable land uses, in this case crop or pasture.

Positive kurtosis is observed in Colombian crop and pasture, Brazilian crop and forest and in all land uses studied in Ecuador (Table 6). Positive kurtosis roughly means that the variance is more influenced by infrequent extreme deviations than when kurtosis is less than or equal to zero. This may be beneficial as long as the skewness remains positive as both aspects are linked to positive returns.

5 Land-use portfolio scenarios

All results presented in this and the following sections were obtained using the utility function with either the method of MV (5) or HM (9). A total of 10500 iterations were used for each computed portfolio and traceplots for every commodity of the column vector of the optimal land-use proportions $\boldsymbol{\alpha_t} = (crop,\ pasture,\ forest)'$ are shown in figure 3.

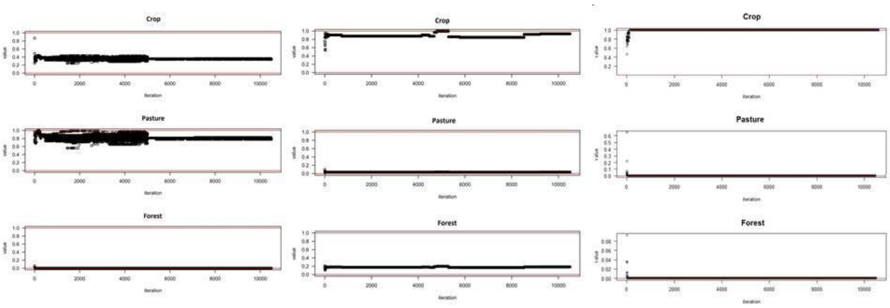

Fig. 3 Optimal portfolio weights $\boldsymbol{\alpha_t} = (crop,\ pasture,\ forest)'$ obtained after 10500 iterations with the optimization package "DEoptim" [4] in the statistical software R [77], for Brazil (left), Colombia (center) and Ecuador (right).

Five scenarios were generated in order to compare both models under different circumstances of risk-aversion and compensation:

- Scenario I: Market risk: risk-neutral farmer ($\lambda = 0$) without compensation for avoided deforestation
- Scenario II: Market risk: risk-neutral farmer with compensation for avoided deforestation.

– Scenario III: Market risk: risk-averse farmer ($\lambda > 0$) without compensation for avoided deforestation.
– Scenario IV: Market risk: risk-averse farmer with compensation for avoided deforestation.
– Scenario V: Environmental and Market risk: for farmers with risk-aversion ($\lambda > 0$) and with compensation for avoided deforestation.

Results, including scenarios I to IV, for Brazil, Colombia and Ecuador are presented in Tables 7, 8 and 9 respectively, and scenarios IV and V are presented in Tables 10, 11 and 12. For scenarios with financial compensation the amount compensated ($US\$$ per hectare per year) was increased stepwise from 0 up to an amount that would keep the proportion of forest, in the family farmer land-use portfolio, at least equal to the current country forest levels: Brazil 62%, Colombia 55% and Ecuador 39%; see Table 5.

5.1 Scenario I: Risk-neutrality ($\lambda \approx 0$) without compensation

When considering a risk-neutral attitude towards investments in the absence of compensation, MV and HM behaved similarly in all of the countries studied. Both chose a 100% crop portfolio, which represents the highest financial yield: 114, 148 and 122$\frac{US\$}{ha \cdot yr}$ for Brazil, Colombia and Ecuador, respectively. HM behaved similar to MV because when $\lambda \approx 0$ the variance, skewness and kurtosis have almost no relevance, and in both methods the only relevant variable to maximize is the mean return μ_p.

Table 7 Brazil, representative of a large South American economy.

Scenario	Method	Market Risk λ	FC $\frac{US\$}{ha \cdot yr}$	Portfolio % Cr	Pa	Fo	μ_p	cov_p	skw_p	kur_p
I	Both	≈ 0	0	100	0	0	114	10554.5	2.3	7.3
II	Both	≈ 0	106	0	0	100	114.2	71.5	-1	2.7
III	MV	0.016	0	24	76	0	83.7	1769.1	0.8	2.5
III	HM	0.016	0	30	70	0	86.1	2097.2	1.1	3.5
IV	MV	0.016	59.2	25	13	62	79.9	901.9	1.7	5.7
IV	HM	0.016	59.5	33	5	62	83.2	1352.2	2	6.3

– MV and HM stand for portfolio optimization with the method MV and HM.
– λ is the Coefficient of Absolute Risk Aversion, two scenarios are presented: $\lambda \approx 0$ (risk-indifferent) and $\lambda = 0.016$ (risk-averse) investor.
– FC is the financial compensation given to a family-farmer in $US\$$ per hectare per year in order to stop deforestation.
– Cr, Pa and Fo are the portfolio weights of crop, pasture and forest respectively.
– μ_p, cov_p, skw_p, kur_p are the portfolio higher moments mean, variance, skewness and kurtosis.

5.2 Scenario II: Risk-neutrality ($\lambda \approx 0$) with compensation

When compensations were added for the risk-neutrality case, the results obtained from both models changed dramatically in all three countries from a 100% crop to a 100% forest portfolio. This occurs when the mean of crop return μ_{crop} is surpassed by forest-returns plus the added compensation of 106, 91 and 102 $\frac{US\$}{ha \cdot yr}$ ($\mu_{forest}+\mathbf{FC}$) for Brazil, Colombia and Ecuador respectively. Similarly to scenario I and because $\lambda \approx 0$, only the mean return is relevant for the maximization process.

5.3 Scenario III: Risk-aversion ($\lambda = 0.016$) without compensation

Risk-averse farmers will consider not only the mean return of a commodity as a decisive factor, but a risk measure that will inform them which commodities offer greater but less stable returns. In all countries, HM chose portfolio weights that produced slightly higher returns (Tables 7 to 9). In Brazil and Ecuador both models chose similar portfolio weights with a zero proportion of forest, a situation that clearly fosters transition from forest to more attractive land-uses. In Brazil and Ecuador forest not only had low returns (compared to crop or pasture) but it also exhibited negative skewness and positive kurtosis. This implies that the variance was influenced by drops in forest returns (skewness < 0) and by frequent extreme deviations (kurtosis > 0). This situation was avoided by the HM approach since it generated a portfolio with no proportion for forests. In MV, a zero forest portfolio was chosen due to the low returns of forest compared to crop and pasture.
Colombia not only showed the highest returns of forest (56 $\frac{US\$}{ha \cdot yr}$), but the highest forest skewness of all this countries. This combined with a negative kurtosis meant that the variance was less influenced by infrequent negative extreme deviations in returns. This allowed both models, MV and HM, to chose a portfolio with a proportion of forest of 23% and 16% respectively. Thus, a higher compensation was necessary in Colombia to stop deforestation and transition from forest to other land-use.

For portfolios where risk is proxied by MV (6) variance becomes the only measure of risk included in the optimization. Thus, in the case of portfolios departing from a Gaussian distribution, high covariance will be avoided by the MV approach even if these values are due to positive increments in returns (skewness > 0). As a result, not only the mean portfolio return μ_p but also the variance of the MV portfolios are smaller than those obtained with HM; see Brazil (Table 7, scenario III and IV), Colombia (Table 8, scenario I, III and IV) and Ecuador (Table 9, scenario III).

Under risk-aversion without compensation (scenario III), both MV and HM produced diversified portfolios in Brazil and Colombia, but chose an almost 100% crop portfolio in Ecuador. This might be due to the fact that crop in

Ecuador not only offered the highest value in mean returns when compared to other land-uses, but also had positive skewness, which means that the returns were expected to be positive. In Brazil, both models produced $crop + pasture$ portfolios but with different weights. Colombia was the only country where under scenario III both models chose a diversified portfolio that included forest without the need to compensate. Interestingly in all countries the weight of crop portfolios was higher with the HM than the MV model. The opposite held for forest and pasture.

5.4 Scenario IV: Risk-aversion ($\lambda = 0.016$) with compensation

When compensation was added, both models produced diversified portfolios that met the required forest proportion: Brazil 62%, Colombia 55% and Ecuador 39% (Table 5). In all countries, higher compensation was needed when the portfolio optimization included skewness and kurtosis to measure risk, in other words, when HM was used. In Ecuador, the HM required a compensation of $57\frac{US\$}{ha\cdot yr}$, while MV needed $54\frac{US\$}{ha\cdot yr}$; in Brazil, $59.5\frac{US\$}{ha\cdot yr}$ and $59.2\frac{US\$}{ha\cdot yr}$ were needed respectively; and in Colombia, $44\frac{US\$}{ha\cdot yr}$ and $32\frac{US\$}{ha\cdot yr}$ respectively. This seems to confirm the idea that the method of HM is less optimistic than the MV approach when returns depart from a normal distribution. Of all the scenarios studied, scenario IV presented the highest compensations (with both models) overall, *i.e.* this scenario represented the highest land-use opportunity cost for forest, a value that must be compensated if forest is to be retained.

Table 8 Colombia, representative of a medium-sized South American economy.

Scenario	Method	Market Risk	FC	Portfolio %			μ_p	cov_p	skw_p	kur_p
		λ	$\frac{US\$}{ha\cdot yr}$	Cr	Pa	Fo				
I	Both	≈ 0	0	100	0	0	147.9	8689.6	1.2	2
II	Both	≈ 0	91.2	0	0	100	148.3	483.1	-0.6	-0.5
III	MV	0.016	0	63	14	23	121.0	4473.1	1.6	3.9
III	HM	0.016	0	81	3	16	132.1	6059.2	1.2	2.2
IV	MV	0.016	31.8	45	0	55	115.4	2190.7	0.9	0.9
IV	HM	0.016	44.5	45	0	55	122.4	2191.2	0.9	0.9

Abbreviations used here explained in Table 7.

Table 9 Ecuador, representative of a small South American economy.

Scenario	Method	Market Risk	FC	Portfolio %			μ_p	cov_p	skw_p	kur_p
		λ	$\frac{US\$}{ha\cdot yr}$	Cr	Pa	Fo				
I	Both	≈ 0	0	100	0	0	122.2	4924.6	0.3	1.7
II	Both	≈ 0	102	0	0	100	122.6	182.8	-0.9	0.6
III	MV	0.016	0	97	3	0	120.5	4709.8	0.3	1.8
III	HM	0.016	0	100	0	0	122.2	4924.6	0.3	1.7
IV	MV	0.016	54	61	0	39	103.6	1755.9	0.5	1.9
IV	HM	0.016	56.7	61	0	39	103.6	1755.9	0.5	1.9

Abbreviations used here explained in Table 7.

5.5 Integration of fire risk assessment in land-use portfolio modeling

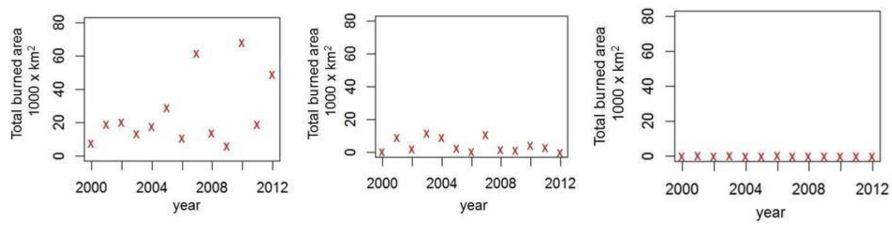

Fig. 4 Record of burned areas in thousands of square kilometers, for Brazil (left), Colombia (center) and Ecuador (right)

When environmental risk is included and all other factors kept constant (scenario V), both MV and HM produced portfolios with less amount of forest share than portfolios optimized only for market risk conditions (scenario IV); see tables 10, 11 and 12. Brazil presented the highest values of decrement (27% of forest share) from 62% (scenario IV) to 35% (scenario V with MV), followed by Colombia and Ecuador with a maximum decrement of 4%.

As mentioned before, the purpose of this study was not to increment the value of current compensations due to losses from environmental risks, but rather to recognize locations where projects including payments for ecosystem services should be avoided in order to keep sustainable the REDD+ initiative, at least until changes in national or regional policies manage to stop the expansion of fire and burned areas. Brazil showed the greatest decrement of forest share in the optimal portfolios at all spatial intensities. The lowest decrement in Brazil was shown in regions of low spatial intensities, with decrements of 6% (MV) and 7% (HM), followed by medium spatial intensities, with decrements of 13% and 12%, respectively. Colombia and Ecuador showed a relatively small decrement in forest share of 1% and 2%, respectively, at low spatial intensity and a maximum decrement of 4% at high spatial intensities.
According to Kissinger *et al.* [56], since the peak year of deforestation in 2004, the rate of forest clearing in Brazil has fallen by almost 75%. Unfortunately, and according to our analysis based on the satellite information from NASA's Terra-satellite [74], the size of burned areas in the northern part of Brazil has actually increased since 2004; see Figure 4. The affected regions corresponded primarily to the Amazon's rain forest, thus highlighting the importance of strengthening policies to control environmental damage of forests in developing countries and the sustainability of all projects involved to halt deforestation.

6 Discussion and conclusions

6.1 Land-use portfolios under market risk

When considering land-use portfolios exclusively under market risk we found that the necessary financial compensations obtained with the HM model do not depart significantly from the MV model. Both models showed also similarities in the weights of the optimal portfolios founded and therefore in the land-use diversification. An explanation for these similarities is the frequency of input data used, because the values from FAO data are averaged yearly. Thus, intra-month peaks that could have provided valuable information for HM are reduced to a merely yearly average. Another problem is the use of national data, here again for FAO purposes regional data are averaged to a national value repeating the reduction to average above mentioned. In theory when mean values are used both models should behave very similar, because when data tends to be Gaussian HM converges to MV as the skewness and kurtosis approaches zero and the effect of higher moments disappear. For this

Table 10 Optimal land-use portfolio weights for Brazil under market risk with and without integration of environmental risk.

Scenario	Method	FC	Market Risk	Environmental Risk*					Portfolio %		
		$\frac{US\$}{ha \cdot yr}$	λ	$\hat{\delta}_t$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t	Cr	Pa	Fo
IV	MV	59.2	0.016	-	-	-	-	-	25	13	62
				0.56	Low	5	23	0.22	25	18	56
V	MV	59.2	0.016	0.56	Med	10.4	11	0.94	26	25	49
				0.56	High	16.4	7	2.34	25	40	35
IV	HM	59.5	0.016	-	-	-	-	-	33	5	62
				0.56	Low	5	23	0.22	33	10	57
V	HM	59.5	0.016	0.56	Med	10.4	11	0.94	33	17	50
				0.56	High	16.4	7	2.34	33	29	38

- $\hat{\delta}_t$ is the average time between events, the value used corresponds to a damage $f_{t_{inv}} = 5\%$ at low spatial-intensity level, see section 2.8 and [1]
- $\hat{\Lambda}_{subreg}$ represents the subregion of spatial intensity low ($\hat{\Lambda}_{low}$), medium ($\hat{\Lambda}_{med}$) and high ($\hat{\Lambda}_{high}$) computed using the record of burned areas.
- ρ_t is the *proportional damage*.
- $\hat{N}_{BA}$ is the average number of burned area events found in the surroundings of φ.
- ξ_t is the proportional damage per event.

Table 11 Optimal land-use portfolio weights for Colombia under market risk with and without integration of environmental risk.

Scenario	Method	FC	Market Risk	Environmental Risk*					Portfolio %		
		$\frac{US\$}{ha \cdot yr}$	λ	$\hat{\delta}_t$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t	Cr	Pa	Fo
IV	MV	31.8	0.016	-	-	-	-	-	45	0	55
				0.41	Low	5	24	0.21	46	0	54
V	MV	31.8	0.016	0.41	Med	7.4	19	0.39	46	0	54
				0.41	High	10.6	11	0.96	47	0	53
IV	HM	44.5	0.016	-	-	-	-	-	45	0	55
				0.41	Low	5	24	0.21	47	0	53
V	HM	44.5	0.016	0.41	Med	7.4	19	0.39	48	0	52
				0.41	High	10.6	11	0.96	49	0	51

Abbreviations used here explained in Table 10.

research it was not possible to get historical records of daily or monthly official prices for the commodities and countries studied. FAO data used in all cases is a yearly national estimates of historical records.

Since 2014 some regions of Colombia are starting to collect data of prices and productivity at a monthly and even weekly base [24], this information together with the use of models like HM could improve the results obtained with the portfolio analysis here presented. In any case, when considering the potential land-use investments of family-farmers in developing markets, close attention should be paid to the "non-normal" behavior of the price distribution of commodities. Many financial or statistical approaches used as decision support tools assume a Gaussian distribution in direct or indirect form. More often than not, however, the statistical evidence shows that prices of commodities in such markets tend to have skewed and heavy tailed distributions; these translate to an underestimation of market risk and therefore of expected returns. In regions with a significant proportion of farmers living under the poverty line, and with a strong tendency for such rural households to abandon agriculture in favor of rural-urban migration, an overestimation of returns by policy makers, financial analysts, or any other players involved in the process might only worsen the situation. In the case of South America, the incorporation of compensation payments in exchange for keeping land forested has, at least, two potential positive effects - mitigation of global climate change [82] and a positive shift in the annual income of family-farmers.

6.2 Integration of Market and Environmental Risk

As was expected, the inclusion of the environmental risk assessment (here in the form of fire) in the portfolio produced a decrement in the share of forest in all countries. This was obtained by dividing every country into spatial regions of high, medium and low activity (number of burned areas per hectare). For all regions the recurrence of events (number of years between fires) was computed. In order to compare damage between regions the recurrence of events, of an

Table 12 Optimal land-use portfolio weights for Ecuador under market risk with and without integration of environmental risk.

Scenario	Method	FC	Market Risk	Environmental Risk*					Portfolio %		
		$\frac{US\$}{ha \cdot yr}$	λ	$\hat{\delta}_t$	$\hat{\Lambda}_{subreg}$	ρ_t	$\hat{N}_{BA}$	ξ_t	Cr	Pa	Fo
IV	MV	54.5	0.016	-	-	-	-	-	61	0	39
				0.33	Low	5	22	0.23	62	0	38
V	MV	54.5	0.016	0.33	Med	8.7	18	0.50	63	0	37
				0.33	High	12.7	10	1.27	65	0	35
IV	HM	56.7	0.016	-	-	-	-	-	61	0	39
			0.016	0.33	Low	5	22	0.23	62	0	38
V	HM	56.7	0.016	0.33	Med	8.7	18	0.50	63	0	37
			0.016	0.33	High	12.7	10	1.27	65	0	35

Abbreviations used here explained in Table 10.

arbitrarily low threshold of damage of 5% per hectare at low activity region, was computed. The same recurrence of event was used to find the spatial characteristics of events at higher spatial intensities. Thus, the recurrence of events in Brazil that generate a 5% damage per hectare at low spatial intensity correspond to a 10.4% and 16.4% at medium and high spatial intensities; see Table 10.

Keeping constant the financial compensation found for portfolios exclusively with market-risk, it was observed how much the forest share in the portfolios decreased at low, medium and high spatial intensities. It was also observed that the higher the spatial intensity of environmental risk, the less the share of forest in the portfolio in all countries. This highlights the importance of finding regions with a historical low record of fires in order to establish sustainable REDD+ projects.

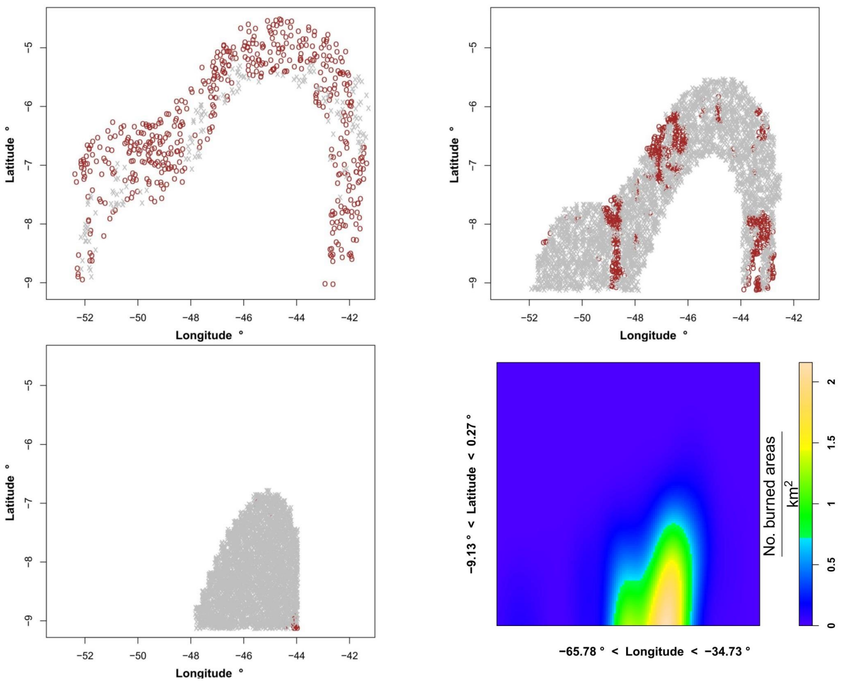

Fig. 5 Hazard maps of Brazil to determine locations where REDD+ projects could take place. The bottom-right figure shows the actual record of fires from 2000 to 2012. The blue region is the low spatial intensity, whereas green and yellow represent medium and high spatial intensity regions. Random sample maps of locations with total burned area damage of less than = $5\%/ha$ (brown circles) and more than $5\%/ha$ (grey crosses) is shown for low (top-left) medium (top-right) and high (bottom-left) spatial intensity regions. Source [1].

Brazil presents the highest decrement of forest when environmental risk is integrated into the portfolios. For this particular case the arbitrarily fixed 5%

threshold used was not meant to determine the worst possible damage at different intensities, but rather to determine regions where land-use investments including forest could be contemplated, gray crosses in Figure 5. The methodology thus reports not only about optimal returns of a diversified investment but the sustainability of such at different locations. This allowed us to observe that, while forest share of a portfolio decreases at higher intensities, pasture and crop increase at similar proportions. This reflects the actual situation in South America where forest are replaced by other land-uses with higher returns on investment. Forest thus not only becomes less interesting because a farmer receives less per hectare, but it has a much longer recovery period (decades) in the aftermath of uncontrolled fire events compared to other land-uses.

6.3 REDD+ and land-use portfolios

Within the forest and global warming perspective REDD+ has evolved as one of the most promising PES at the global level. REDD+ compensates monetarily family-farmers for every hectare of forest that they avoid to replace with other land-uses such as crop or pasture. In addition to its primary goal, although not originally thought as such, REDD+ may also become an instrument to partially alleviate poverty of family-farmers in developing regions by generating an alternative income out of forestry, an activity that otherwise has been seen as of secondary importance in a region where many governments still foment the expansionism of agriculture. In the particular case of South America, 53% of rural households live below the poverty line [28]. Thus REDD+ could find several family-farmers willing to cooperate with this new alternative. One important step towards reaching sustainable PES (particularly REDD+) is to find fair and competitive prices where actors involved benefit.

Several authors have studied the topic of fair financial prices to be paid to family-farmers due to PES, either by comparing two mutually exclusive land uses [44] [58], [17] and [60] or including more than two land uses [12], [19], [46] and [62] with values of financial compensation ranging from US$ 40 to US$ 170 per hectare per year for different countries in South America, confirming thus that our results within a purely market-risk perspective are plausible. However, none of the authors mentioned included potential changes in compensations due to environmental risks. Inclusion of such risks should be contemplated to get a more realistic overview of the situation and to determine the sustainability of projects at particular regions. Our study reveals how relevant is the inclusion of such assessment even in areas of low risk. In the case of regions with record of environmental risk, either much higher compensation payments should be paid, a rather unrealistic assumption, or all parts involved in such projects should be aware that the sustainability of such projects could be seriously compromised.

For the special case of forest as a land-use activity, fire is one of the most devastating environmental hazards affecting stands as decades may pass before a forest stand recovers to its original conditions. In the case of South American countries, this becomes even more important since, either through intentional or unintentional fires, the region has the highest global rates of deforestation through fires and illegal login. Thus, environmental risk assessment of hazards such as fire becomes particularly relevant for the sustainability of initiatives such as REDD+ in the region. Another relevant factor to take into account is the fact that family-farmers are usually ill-prepared to face risks. Family-farmers are constrained to low effective risk-mitigation strategies which costs are usually entirely paid by themselves with little or non-governmental or private sector support. Thus, any attempt to establish sustainable approaches to halt deforestation should take into account not only the market but also the environmental risk that family-farmers and other actors might face if they decide to cooperate with such initiatives. Full understanding of the risks to which family-farmers may be subject to will allow better planning and sustainability of initiatives like REDD+ to halt deforestation.

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Assessment of the Voluntary Carbon Standard Tool to compute the Non-Permanence Risk Analysis of forestry projects in fire prone regions of South America.

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Abstract

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1. Introduction

The need to provide food for an ever-growing human population has generated enormous pressure on resources resulting in a significant expansion of agricultural land at the expense of forest cover. This is particularly relevant in several South American countries where, until recently, farmers could only maintain their land tenure rights if they kept their land free of forest (Streck and Zurek, 2013, p.7). In spite of this apparent low value that developing countries place on forests, scientific evidence has shown that forest plays a critical role in limiting and slowing-down the impact of global warming. The international community has therefore created mechanisms that compensate farmers who actively stop deforesting their land. However, since the early days of the Kyoto Protocol there has been debate about the permanence of forest carbon related

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emission reductions and greenhouse gas GHG removals (Trines 2008, Murray *et al.*, 2007). Forest carbon is considered particularly vulnerable because emission reductions and removals could be reversed, either by natural events (fires, droughts, floods) or due to failure of a project or policy to control the drivers, underlying causes and agents of deforestation (Seifert-Granzin, 2011). The discussion has led to a situation in which GHG removals due to afforestation and reforestation (AR) activities under the Kyoto Protocol's Clean Development Mechanism (CDM) can only generate temporary credits or are excluded from compliance markets altogether, as in the case of the European Union Emissions Trading System. However, voluntary carbon markets accept the credits generated by a country's efforts to reduce emissions from deforestation and forest degradation (REDD) and by AR activities generated within a comprehensive risk accounting and monitoring framework (Seifert-Granzin, 2011). Since its initial introduction to the agenda of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992, REDD has gained increasing recognition. A review of initial outcomes of 41 REDD projects in 22 countries of Africa, Asia, and Latin America (Lawlor *et al.* 2013) revealed that Payment for Ecosystem Services (PES) is the most common strategy intervention, with 39% of projects using this method, see Fig. 1.

Carbon projects are a smaller but rapidly growing group of PES programs (Pagiola *et al.*, 2013). Attention has particularly focused on forestry projects because a significant proportion of carbon emissions worldwide come from deforestation (17% according to IPCC, 2007). Thus, to assist developing countries to implement such activities, the Forest Carbon Partnership Facility (FCPF) was launched through the World Bank in 2008 to engage countries and direct funds to successfully initiate REDD projects (Fortmann, 2014). Activities such as planting trees, changing agricultural tillage and cropping practices, or re-establishing grasslands help to increase carbon sinks by sequestering carbon (Pearson *et al.*, 2005). The Voluntary Carbon Standard (VCS, 2010) presents some examples of land management activities for carbon sequestration and/or emissions reduction that can form the basis of PES schemes, see Fig. 2. The

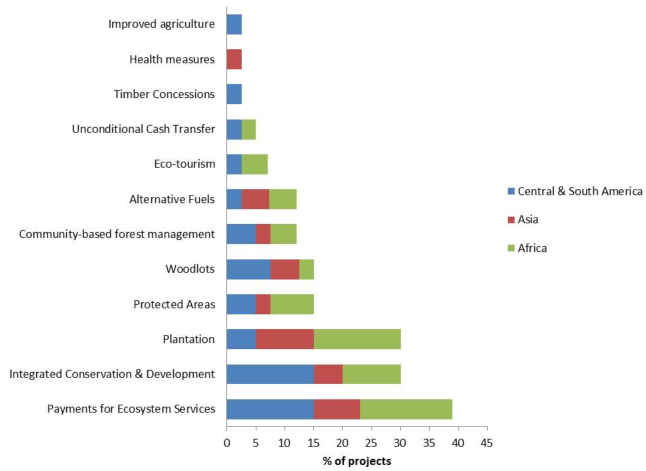

Figure 1: Intervention strategies of 41 REDD projects in Africa, Asia, and Latin America (Lawlor *et al.* 2013)

resulting emissions reductions are then sold either in regulated carbon markets, such as that established under the Kyoto Protocols Clean Development Mechanism (CDM), or in voluntary markets (Pagiola, 2013). According to Diaz *et al.* (2011), about 75 million metric tonnes of CO_2 have contracted in projects covering 8 million ha in 49 countries. From these, voluntary markets dominate accounting for about 83 % of total carbon transacted (Diaz *et al.* 2011).

While the discussion about REDD has been driven mainly by the UNFCCC, the World Bank created the FCPF to implement REDD activities mainly in tropical countries. It is funded by 16 financial contributors, including various countries and environmental organizations, who have pledged an estimated US$447 million. Of this, approximately US$230 million goes towards the Readiness Fund and US$205 million to the Carbon Fund (FCPF, 2012). The Carbon Fund, which became operational in May 2011, is the main mechanism for payments for verified emissions reductions in REDD countries (Fortmann *et al.* 2014). At present, there are essentially no ongoing annual financial streams from countries or the private sector for payments to avoid deforestation. Some

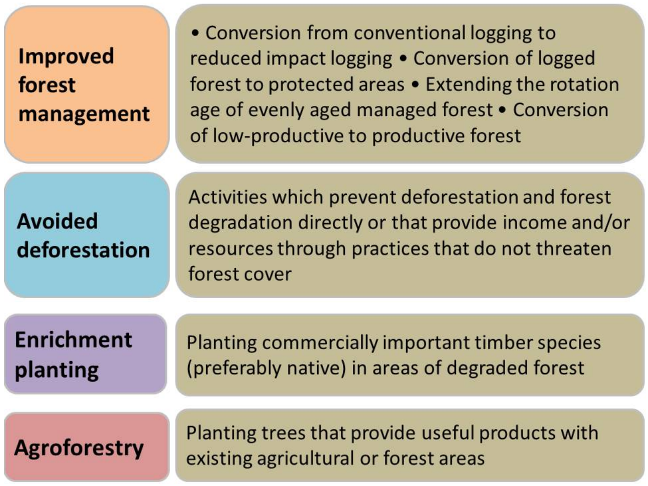

Figure 2: Examples of land management activities for carbon sequestration and/or emissions reduction. Sources VCS, 2010 and WWF, 2010

countries have provided funds to the World Bank FCPF, or other institutions, but these resources are typically one-time donations, not annual funding (Fortmann *et al.* 2014). However, there are already examples of private voluntary initiatives for carbon sequestration that allow the purchase of carbon credits generated through REDD activities (UNEP 2011), such as the Verified Carbon Standard (VCS) or the efforts of individual Non-Governmental Organizations (NGOs), like The Nature Conservancy. It is worth noting that efforts to operationalize REDD accounting, such as those by the Verified Carbon Standard, may ultimately enable REDD credits to be included in compliance schemes (Fortmann *et al.* 2014).

While all PES programs worldwide monitor compliance of participants with contract conditions, few adequately monitor actual environmental benefits. Given the incipient experience with PES in countries like Brazil and the innovative nature of many of the programs, it is unfortunate that few programs, not even those which are explicitly intended as pilots, have put in place arrangements for rigorous impact evaluation (Pagiola *et al.* 2013). If in the near future such projects suffer damages that could have been avoided or mitigated, the reputation and sustainability of PES may also be at risk. In Cancun in 2010, the UNFCCC decided that developing countries should develop and provide robust and transparent national forest monitoring systems for the reporting of REDD activities (FONAFIFO *et al.* 2012; UNFCCC, 2011). Unfortunately, the implementation of risk monitoring systems for carbon projects has been the exception and not the rule. From the few standards that offer a coherent risk assessment, the Voluntary Carbon Standard has become a very popular tool to validate projects. Market surveys clearly point to a preference among buyers and investors for projects validated under the VCS, as it offers the most comprehensive standard, covering all relevant Agriculture, Forestry and Other Land Use (AFOLU) activities, and is based on the Intergovernmental Panel on Climate Change (IPCC) guidelines (Seifert-Granzin, 2011; Merger *et al.* 2011). However as it is shown in following sections, the VCS tool to compute the Non-Permanence Risk Analysis lacks very relevant information necessary for risk assessment (like the probability of occurrence of a damaging event) that may help to classify projects as being sustainable, that is a project that has a high likelihood of reaching the target results within the project time, or not sustainable. This difference in turn may help all actors involved in PES or REDD projects to avoid incurring in unnecessary costs.

2. Materials and methods

According to the State of the Worlds Forests report (FAO, 2011, p118), South America had an estimated 864 million hectares covered by forest, which represented almost half of its total land cover by 2011. These abundant forest resources account for 21% of the worlds forest areas and 57% of its primary forests. Yet South America lost more than 164 million hectares of its total forest area between 1990 and 2010 (8,2 million hectares per year), at a rate three times higher than the rate of global forest loss during the same period (FAO, 2011, p.118). Due to higher returns on investments of some highly productive agricultural commodities, the conversion of forest land to agriculture has become the leading cause of the regional deforestation (FAO, 2011), which is performed mainly through illegal logging and intentionally-ignited fires. According to Uriarte *et al.* (2012) this effect is magnified in regions with severe droughts, that are close to roads and rivers, and that have extensive use of pastures and agricultural crops. The authors further argue that policies to promote low-fire land use systems and access to education, as well as the improvement of early warning systems and other mechanisms, could reduce fire in the region (Uriarte *et al.* 2012).

2.1. VCS methodology to compute the non-permanence risk assessment of AFOLU projects

A very interesting example of how risk analysis of forest carbon projects is carried out is the popular[1] Voluntary Carbon Standard (VCS), which was used for more than a third of all credits traded in the voluntary market in 2009 (Hamilton *et al.* 2010, Jagger *et al.* 2010) and is used to compute the non-permanence risk[2] and monitoring analysis of potential projects. The methodology is used to determine which AFOLU project proposals fulfill the minimum risk assessment and mitigation requirements, and to compute the number of buffer credits to be set aside to cover such risks during the lifetime of the project(VCS, 2008, 2010). AFOLU projects considered by VCS are: afforestation, reforestation and revegetation (ARR); agricultural land manage-

[1] Recent market surveys clearly point to a preference among buyers and investors for projects validated under the VCS, as it offers the most comprehensive standard, covering all relevant AFOLU activities, and is based on the IPCC guidelines (Seifert-Granzin, 2011; Merger *et al.* 2011)

[2] In AFOLU projects, the permanence of emission reductions can be at risk due to various factors. These factors determine the level of buffer credits needed to be set aside to mitigate risks (WCS, 2012)

ment (ALM); improved forest management (IFM) and reducing emissions from deforestation (RED).

In general, the VCS non-permanence risk assessment of all AFOLU projects must be conducted in two steps:

- Risk factor analysis (project, economic, regulatory, social and natural disturbance risks), see Fig. 3. Each factor is classified as either unacceptably high/fail, high, medium or low.
- Overall non-permanence risk rating and buffer determination.

Figure 3: Non-permanence risk factors that shall be assessed for all AFOLU project types. Source: VCS (2008)

Calculating the natural disturbance risk in VCS is based on likelihood[3], *i.e.* the inverse of the average historical number of events occurring in the project area over the past (VCS, 2012 p.14), and significance (*i.e.* the average loss of carbon stocks of such events). All project proposals with evidence of significant natural risks, *i.e.* risk affecting more than 5% of the project area occurring

[3]The likelihood and significance of events is estimated based on historical records, probabilities, remote sensing data, peer-reviewed scientific literature, and/or documented local knowledge, such as survey data from the project (VCS, 2012; Shoch *et al.* 2011)

Table 1: Non-Permanence Risk Rating Table for all AFOLU Projects. Source: VCS (2012, p.14)

Natural Risks					
	$< 10yr$	$10yr \leq TI < 25yr$	$25yr \leq TI < 50yr$	$50yr \leq TI < 100yr$	$100yr \leq$
Significance	Score				
Catastrophic $70\% \leq$ loss of carbon stocks	F	30	20	5	0
Devastating $50\% \leq$ loss of carbon stocks $< 70\%$	30	20	5	2	0
Major $25\% \leq$ loss of carbon stocks $< 50\%$	20	5	2	1	0
Minor $5\% \leq$ loss of carbon stocks $< 25\%$	5	2	1	1	0
Insignificant loss of carbon stocks $< 5\%$	2	1	1	0	0
No loss	0	0	0	0	0
LS Score					
Mitigation (M)					
Prevention measures applicable to the risk factor are implemented					0.50
Project proponent has proven history of effectively containing natural risk					0.50
Both of the above = 0.50 x 0.50					0.25
None of the above					1
Score for each natural risk applicable to the project = LS x M					
Fire (F)					
Pest and disease outbreaks (PD)					
Extreme weather (W)					
Geological risk (G)					
Other natural risks (ON)					
Total Natural Risk Score = F + PD + W + G + ON					

Where yr means year, TI is time interval between damaging events and F means that the project has an unacceptable high risk and therefore fails, see section 2.1.

*Instead of *time interval between events*, the word *Likelihood* is used by VCS (2012. Table 10) although likelihood should not have units of time as it is a probability value.

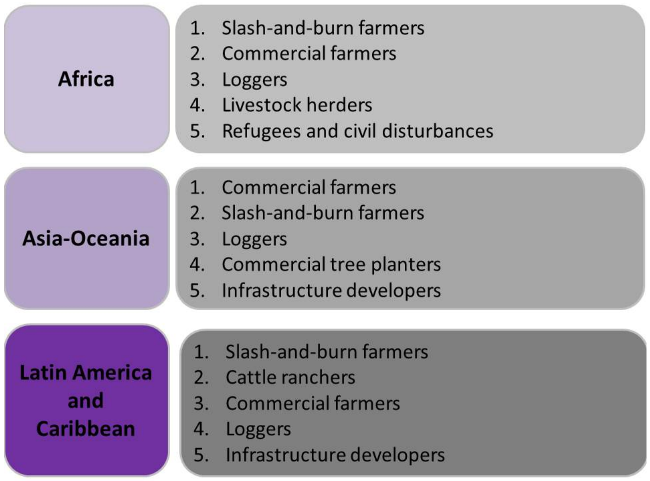

Figure 4: Most important agents of deforestation, degradation and fragmentation. Source; FAO Forestry Department, 2007.

over the past, are considered for further overall Non-Permanence Risk Analysis, except for those proposals with evidence of catastrophic loss (70% to 100% loss of carbon stocks) with a time interval of one destructive event in less than 10 years (see VCS, 2012, classification Table 1), which would be classified as unacceptably high/fail. However, if the time interval of such a catastrophic event was greater than 10 years, the project could still be considered for further risk analysis (VCS, 2008, 2012). In the original VCS document the word *likelihood* (VCS, 2012. Table 10) is used instead of the here used *time interval between events*. The term *likelihood* is misleading because it is defined by VCS as the historical average number of times the event has occurred in the project area VCS (2012 p.14), so according to their own terminology likelihood should not be expressed in units of years as it is done in their Table 10. Additionally, in risk analysis the likelihood is usually defined as the hypothetical probability that an event that has already occurred would yield a specific outcome (Weisstein, E.W. 2015), so likelihood has no units. Therefore, for this study, the term *time interval between events* is used instead of *likelihood*, and the later is only used when a probability outcome is discussed.

As already mentioned, validation and verification of non-permanence risk are almost totally absent in PES and conservation incentive programs (FONAFIFO *et al.* p.36, 2012). Therefore, a deeper analysis of the VCS non-permanence risk classification methodology becomes relevant because it is popular, *i.e.* it was used by more than a third of all credits traded in the voluntary market in 2009 (Hamilton *et al.* 2010, Jagger *et al.* 2010), and because other programs may use VCS methodology as a reference starting point to make their own analyses. Thus, potential changes proposed in the following sections of this study may hopefully improve VCS and other methodologies as well.

Although the VCS classification in Table 1 offers a structured classification of risks, it misses valuable information (like the probability of occurrence). Because it is clearly not the same to have a risk of 70% farm damage from fire in the next 25 years, with a 1% probability of occurrence than to have a risk of the same level of damage in the same time-frame with 95% occurrence probability. Although not included in the VCS non-permanence risk methodology of AFOLU projects, fat-tailed risks (Extreme Value Analysis) are also important to consider, particularly for cases with forest fires where the occurrence of a low probability but highly destructive event might result in more forest area being destroyed in one event, than in the previous hundred events (Fortmann *et al.* 2014). Because these types of risks are not usually accounted for, Cooley et al. (2012) claim that non-permanence risks of such projects maybe be substantially underestimated. Although several distribution functions may be used to compute the occurrence probability, such as the Generalized Extreme Value or the Generalized Pareto (Klüppelberg *et al.* 2014b), binomial and Poisson distribution are the basis for extreme value statistics (Fasen *et al.* 2014). Without loss of generality let us use the binomial probability as an example to compute occurrence probability due to its simple and intuitive approach.

To compute the occurrence probability of damages caused by fires in farms, let D be the percentage of farm damage due to fire, and X be a Bernoulli random variable which takes value 1 with success probability p (if the next fire damage is $\geq D$) and value 0 with failure probability $q = 1 - p$ (if the damage is $< D$). Thus, the probability function can be expressed as

$$P(X = k) = f(k; p) = p^k (1 - p)^{1-k}, \quad k \in \{0, 1\} \tag{1}$$

If $X_1, ..., X_n$ are independent and identically distributed Bernoulli random variables with success probability p, then $Y = \sum_{i=1}^{n} X_i$ follows a Binomial distribution $\sim B(n, p)$. In this case, the probability of getting exactly k successes in n trials is given by the probability of occurrence:

$$P(Y = k) = f(k; n, p) = \binom{n}{k} p^k (1 - p)^{n-k}, \tag{2}$$

where $k = 0, 1, 2, ..., n$ and $\binom{n}{k} = \frac{n!}{k!(n-k)!}$.

Following the VCS classification (see Table 1) to determine the risk of for example an AFOLU project in a farm that in the last 100 years had 10 catastrophic fires, each with 70% or more loss of carbon stocks *i.e.* $70 \leq D$, we find that the project is viable and it is classified as having a total score of 30 if no mitigation strategy is put in place, see Table 1. However, in the VCS' table and in their methodology the occurrence of catastrophic events is not mentioned. Let us suppose that we want our farm to be part of an AFOLU project for the next 10 years[4]. Therefore we can compute the probability of occurrence of a catastrophic fire damaging more than 70% of our farm within the next 10 years by using eq. 2. Out of historical records we compute that $p = 10/100 = 0.1$ and that

$$P(Y = 1) = f(1; 10, 0.1) = \binom{10}{1} 0.1^1 (0.9)^9 = 0.387 \approx 39\%.$$

[4]VCS certified projects have a lifespan between 10 to 100 years (VCS, 2008; Fortmann *et al.* 2014).

Thus, there is a 39% probability that before the projects ends an area of 70% or more has irreparable damage[5] and even the buffer risk zone might be damaged due to fire.

For further analysis, let us consider a complete example of a proposed AFOLU project located in Brazil, in a region with a recent history of fire events, *e.g.* at the border of the Amazonas rain forest. Historically, this region shows evidence of low fire activity, but in recent years due to the conversion of forests to more profitable land uses and the extended use of agricultural techniques like slash-and-burn, see Fig. 4, the region shows signs of deforestation and forest degradation (FAO Forestry Department, 2007). Statistical evidence obtained from satellite imagery (Acevedo-Cabra *et al.* 2014) shows that there is a high likelihood of finding areas in this region having up to 8 devastating fires, each having burned approx 60% of the area within the last 12 years. Following the VCS risk rating system and terminology, the project has an average number of events $\frac{8\ events}{12\ years} = 0.66$ and a likelihood of $\frac{1}{0.66} = 1.5$ years between events. According to the VCS rating table, see Table 1, the project is classified as having a likelihood-and-significance LS of 30. Let us further assume that the project has no mitigation strategy at all (*i.e.* Mitigation M = 1). Thus, the score for fire risk applicable to the project (determined by LS M) is 30. Without loss of generality, let us further assume that other natural risks (pest, extreme weather, geological risk, etc) present "no loss". Therefore the project has a "Total Natural Risk" of 30, which is still acceptable within the VCS framework because the single Total Natural Risk is less than 35 (VCS p.15-17, 2012).

[5]For destructive events, the carbon benefits generated by the destroyed part of the project are assumed to be completely lost. In this case, the number of years that loss continues equates to the remaining lifespan of the project (VCS, 2008).

In case of *force majeure*[6] in REDD projects, additional rules for adjusting the baseline and the risk buffer apply, forcing the project to compensate the risks and losses caused by force majeure (Seifert-Granzin, 2011). However, as in the example above of catastrophic events (60% loss of carbon stocks) not only the project but also the buffer credits set aside to mitigate hazards may easily be at risk of total loss. In case of force majeure in PES projects, typically the agreement will be terminated and neither party is liable to the other party for non-performance (FONAFIFO *et al.* 2012). Thus, in the best case, the landowner (or whoever is responsible for the project) will be left with a terminated contract, the partial or non-covered project costs and serious natural-hazard damages to deal with. Moreover, not only the project may suffer irreparable damage, according to FAO Forestry Department (2007) it is thought that about 25% of the total global carbon dioxide emissions result from deforestation and forest fires. Such fires are a key threat that could undermine attempts to implement restoration initiatives underway in the world's deforested or degraded forest regions (WWF, 2004). Even worse, the reputation of PES and REDD projects is at risk and the low effectiveness of forest carbon sequestration could force the international community to avoid financing forest carbon projects at all. Thus, a thorough environmental risk assessment, especially for fire, is extremely important because the post-fire recovery processes in a forest can be extremely slow and may take several decades, which puts the sustainability and success of such projects at high risk.

2.2. Mitigation strategies for fire hazard

When mitigation strategies (*e.g.* best-practice fire prevention measures) such as fuel removal, suppression systems, prescribed-fires, fire breaks, fire detection

[6] A *force majeure* event, also known as "an act of God" and "risk of innocent loss", is something that is out of the control of either party, such as a storm, wildfire, or war (Greiber, 2009; FONAFIFO *et al.* 2012)

systems and fire fighting equipment are implemented in the project, (VCS, 2010, 2012), VCS penalizes less strongly the "Natural Risk", see Table 1. In the above mentioned example, the score for fire risk applicable to the project will be reduced from 30 to $0.50 \times 30 = 15$ if such measures are implemented, increasing thus the overall chances for the project proposal to be accepted.

While mitigation strategies such as fire detection technology (aerial and/or satellite spotting, robot towers, communication technology) and fuel removal techniques have shown to improve early detection and effective mitigation (Moghaddas and Craggs 2007), fire suppression techniques have had mixed results and have been accused of leading to greater fire outbreaks in Europe (Moreira *et al.* 2011) and USA (Stephens and Ruth 2005; Keane *et al.* 2008). Moreover, planed or unplanned fires especially under extreme weather conditions (Gould *et al.* 2007; Moritz *et al.* 2010) can reach substantial sizes despite sophisticated suppression systems (Gill *et al.* 2013). If fire crews are available, fire-fighters may arrive when fire is already too intense, the perimeter too extensive, and its rate of growth too great for immediate containment (Gill 2008: chapter 1). Other common technique is the use of prescribed-fires, but this technique is largely debated because of the interactions between prescribed burns and unplanned fires. Thus, prescribed burning is forbidden in Greece (Williams *et al.*. 2011) and Namibia (Goldammer *et al.* 2002) while Gillon (1983) discussed choosing the most adequate burning regime in tropical savannas. Therefore, the effectiveness of prescribed burning in minimizing wildfire is contingent on land use. For example, it would be inappropriate in a farmers improved pastures or crops, useful in some forests for protecting wood products and biodiversity and impossible to carry out in some environments (Gill, 2005; Gill *et al.* 2013). Another popular technique to mitigate forest fires is the use of fuel-free breaks (fire breaks), however determination of effective width is a serious question given that spot fires from lofted firebrands can be a problem (Gill and Stephens 2009).

Biodiversity is another mitigation strategy that has shown a hedge effect against natural hazards (Griess *et al.* 2012; Gill *et al.* 2013). Griess *et al.*

(2012) present statistical evidence supporting the theory that short-term benefits achieved by the homogenization of ecosystems, as in mono-culture plantations, and the resulting loss of biodiversity are overshadowed by the consequent reduction in the ability of forest stands to cope with natural risks. Although biodiversity is not included in the VCS rating system of "Natural risks", it is contemplated indirectly in the risk of management failure ("project risk factor", see Table 3) if the project manager decides to afforest or reforest with tree species not resistant to regional natural hazards. Some project guidelines establish that a maximum of 25% of the tree varieties can be foreign. In many cases, managers could opt for fast-growing and highly productive (and therefore high takers of carbon emissions) foreign species like *Pinus radiata* and *Eucalyptus*. The establishment of fast-growing non-native tree species is an often-cited example, because they might not only replace more biodiversity-rich habitat but could also have implications for the water table, thus increasing the sensitivity of the system to drought and contribute to wider problems such as acidification, disease transmission or fire risk (Van de Sand, 2012; Smith *et al.* 2013). The experience of Chile with such species is negative, as fires have increased in such plantations since their introduction and currently devastating fires are the rule and not the exception (Acevedo and Knoke, 2011). According to Pena-Fernandez and Valenzuela-Palma (2005) the occurrence of forest fires has increased almost exponentially in Chile from 1973 to present. This increase is closely related to the increase in surface area planted with highly flammable species: Pinus radiata and Eucalyptus globulus. Indeed, the National Forestry Corporation of Chile (CONAF) has detailed statistics of wildfires greater than 200 hectares since 1973 until today (CONAF, 2014), analysis of the data shows that 25% of all historical devastating forest fires (including natural forest and plantations) were in Pinus and Eucalyptus plantations, despite the total area of such monoculture plantations representing less than 10% of the total forest cover in Chile. It is not rare for Eucalyptus plantations to be registered in PES schemes (Rival, 2013), which must be adequately addressed to avoid greater ecological damage.

Our knowledge of the wildfires and how to minimize them is growing, but is also limited. Scientifically, the ability to predict fire properties and their interrelationships is partial; quantifying the probability of asset-negative events and regimes is still very difficult, yet critical, and assessing the efficacy of minimizing actions is usually relative rather than absolute (Gill *et al.* 2013). Furthermore, there is a residual probability of disastrous fire events even after a variety of measures have been introduced to counter it. Thus, even if best-practice fire prevention measures are included in AFOLU projects, the scientific evidence shows that a high risk of devastating forest fires may remain high, contrary to what VCS assesses in its risk ranking system when mitigation strategies are included (VCS, 2008, 2010).

Although the example mentioned above highlights weak points of the VCS risk system that could be improved, at least the system involves rigorous validation and verification according to Kyoto (CDM standards). This is unfortunately not the case for national PES and conservation incentive programs, where such validation and verification is almost totally absent (FONAFIFO *et al.* p.36, 2012). Therefore, based on the results of this study a proposed improvement for the VCS risk rating system (Table 1) is presented and discussed in following sections.

2.3. Proposed changes of the VCS Non-Permanence Risk Analysis tool

In order to overcome the drawbacks of the VCS Non-Permanence Risk analysis mentioned in previous sections, the methodology presented by Acevedo-Cabra *et al.* (2014) can be used. The authors present a spatial-temporal approach that ranks regions according to historical burn damages spotted with satellite imagery and recorded during the last 12 years. The results for particular locations are then compared to the behavior of random locations of interest (for example a location where a PES or REDD project may take place) to establish hazard maps at local and at regional levels. The methodology introduced can be used to improve the Natural Risk Rating System (see Table 1) proposed by VCS (2012) by adding the probability of occurrence of an event with a particular damage per hectare at a location where a PES or REDD project may take place. Additionally, the generation of hazard maps, also part of the methodology proposed by Acevedo-Cabra *et al.* (2014), is useful to determine whether a location may have low local historical risk but it is situated in a high risk region, incrementing thus its likelihood in the long term of having much greater damages than the ones already observed.

The statistical model proposed by Acevedo-Cabra *et al.* (2014) uses historical remote sensing information, which shows burned areas detected by the NASA Terra satellite (NASA, 2012 and 2013b) from year 2000 onwards for the northern part of South America, including all Amazon rainforest and it surroundings. The authors compute the polygon and the centroid coordinates $u_i := (x_i, y_i)$ of every single burned area spotted with the Moderate Resolution Imaging Spectroradiometer (MODIS) on board of Terra satellite. Every event recorded is uniquely determined by the triple (u_i, b_i, t_i), where $\{u_i \in A| \ i = 1, \dots, n\}$ is the set of locations of burned areas which occurred in a region $A \subset \mathbb{R}^2$; $b_i \in \mathbb{R}$ corresponds to the burned area in km^2, and $t_i \in [01.01.2000, T]$ is the date at which MODIS first spotted the burned area. Defining $\varphi \in A$, as the coordinates of a location where a PES or REDD project may take place, and assuming $u_i, ..., u_n$ to be a partial realization of a point process, the authors estimate its spatial intensity function $\hat{\lambda}_h(\varphi)$ with a kernel smoother. For every country, minimum $\min_{\varphi\in A} \hat{\lambda}_h(\varphi) := 0$, and maximum values $\omega := \max_{\varphi\in A} \hat{\lambda}_h(\varphi)$, are used as limits of an interval partitioned into three equal-length subintervals in order to generate three subsets $\hat{\Lambda}_{low}, \hat{\Lambda}_{med}$ and $\hat{\Lambda}_{high}$ which are depicted in Figure 5 with blue, green and yellow pixels respectively.

According to VCS (2012, p. 14) project proposals with evidence of significant natural risk, *i.e.* affecting more than 5% of the project area over the past,

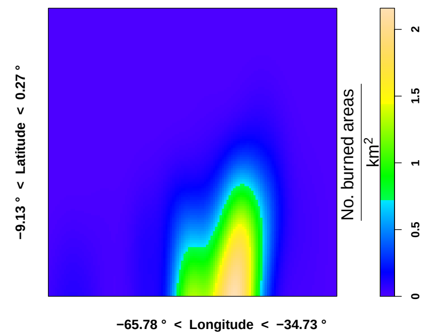

Figure 5: Kernel smoothed spatial intesity of fires in Brazil respectively from 2000 to 2012. $\hat{\Lambda}_{low}$ (blue pixels), $\hat{\Lambda}_{med}$ (green) and $\hat{\Lambda}_{high}$ (yellow), source Acevedo-Cabra *et al.* 2014

shall be considered for further Non-Permanence Risk Analysis. Using the same threshold value to determine locations without ($\leq 5\%$) and with fire risk ($> 5\%$), Acevedo-Cabra *et al.* (2014) built hazard maps based on binomial proportions and confidence intervals that estimate the likelihood of finding damaged areas at given levels of spatial intensity. For every intensity region $\hat{\Lambda}_{low}$, $\hat{\Lambda}_{med}$ and $\hat{\Lambda}_{high}$, the historical locations of burned areas $u_i, ..., u_n$ are assumed to be independent and identically distributed Bernoulli random variables with success probability p, *i.e.* locations where the cumulative burned area over the past is $\leq 5\%$; and with $(1 - p)$ failure probability, *i.e.* locations where the burned area is $> 5\%$. Thus, eq. (2) can be used to build binomial proportions and confidence intervals, see Table 2.

The sample of random location points used to generate the binomial proportions can also be used to generate maps of risk for a specific threshold of damage, see for example the case of Brazil (Fig. 6) where every location has either a cumulative damage of $\leq 5\%$ (depicted with brown circle) or $> 5\%$ (grey cross). Of course the value of the threshold can be changed to estimate any damage and its probability of occurrence for a location of interest. Independently of the approach to compute the estimated damage and its probability of occurrence,

Table 2: Damage per hectare: binomial proportions and confidence intervals

Land	Spatial intensity	Locations with any damage $Low_{CI}(\%)$	$\hat{q}$ (%)	$Up_{CI}(\%)$	Locations with damages $\leq 5\%$ $Low_{CI}(\%)$	$\hat{q}_{5\%}$ (%)	$Up_{CI}(\%)$
	Low	6.1	6.4	6.7	57.5	60.2	62.8
Brazil	Med	98.6	98.8	99.0	14.8	15.5	16.2
	High	99.9	100.0	100.0	0.6	0.8	0.9

$Low_{CI}\%$, $Up_{CI}\%$ correspond to lower and upper values of the confidence intervals for $\hat{q}$, source Acevedo-Cabra *et al.* (2014)

their value should be added to the VCS Non-Permanence Risk Analysis (Table 3) in order to improve the overall accuracy of the system so that project related actors can take more adequate decisions.

Table 3 present an improved version of the VCS risk rating system, the main changes are the introduction of the probability of occurrence for different time intervals between events and a revaluation of when project proposal should fail or not. Thus for example, events damaging more than 50% of the project area shall fail in all cases, whereas an event damaging between 25 to 50% of the project area within the next 10 years shall only be considered if its probability of occurrence is less than 10%. Although the score values of Table 3 are only suggested values that may be adjusted to national or international requirements, the methodology proposed here integrates valuable information provided by the probability of occurrence that may be computed using the methodology presented by Acevedo-Cabra *et al.* (2014).

3. Discussion and conclusions

Agriculture is one of the riskiest sectors of economic activity, and effective risk-reducing instruments are severely lacking in rural areas (The World Bank, 2008, p89). For the particular case of forest as land-use activity, fire is one of the most devastating environmental risks that affects stands as it may pass decades before a forest stand recovers to its original conditions. In the case of South American countries, this becomes even more important when it is known

Table 3: Proposed improvement for the Non-Permanence Risk Rating Table presented in VCS (2012, p.14), see Table 1

Score for natural risks (LS)												
	$< 10yr$			$10yr \le TI < 25yr$			$25yr \le TI < 50yr$			$50yr \le TI < 100yr$		
	$P_c \le 10$	$10 < P_c \le 50$	$50 \le P_c$	$P_c \le 10$	$10 < P_c \le 50$	$50 \le P_c$	$P_c \le 10$	$10 < P_c \le 50$	$50 \le P_c$	$P_c \le 10$	$10 < P_c \le 50$	$50 \le P_c$
Catastrophic $70\% \le$ loss of carbon stocks	F	F	F	F	F	F	F	F	F	F	F	F
Devastating $50\% \le$ loss of carbon stocks $< 70\%$	F	F	F	F	F	F	F	F	F	F	F	F
Major $25\% \le$ loss of carbon stocks $< 50\%$	30	F	F	20	30	F	10	20	30	5	10	20
Minor $5\% \le$ loss of carbon stocks $< 25\%$	20	30	F	10	20	30	5	10	20	0	5	10
Insignificant loss of carbon stocks $< 5\%$	1	2	5	0	1	2	0	0	1	0	0	0
No loss loss of carbon stocks $= 0\%$	0	0	0	0	0	0	0	0	0	0	0	0
Mitigation (M)												
Prevention measures applicable to the risk factor are implemented												0.75
Project proponent has proven history of effectively containing natural risk												0.50
Both of the above = 0.75 x 0.50												0.38
None of the above												1
Score for each natural risk applicable to the project = LS x M												
Fire (F)												
Pest and disease outbreaks (PD)												
Extreme weather (W)												
Geological risk (G)												
Other natural risks (ON)												
Total Natural Risk = F + PD + W + G + ON												

Where yr means year, TI is the time interval between damaging events, P_c is the probability of occurrence in % and F means that the project has unacceptable high risk and therefore fails, see section 2.1.

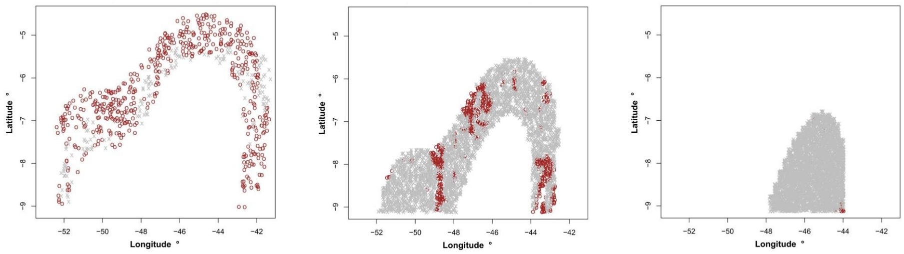

Figure 6: Hazard maps of Brazil for the spatial intensity regions: $\hat{\Lambda}_{low}$ (left), $\hat{\Lambda}_{med}$ (center) and $\hat{\Lambda}_{high}$ (right). Random sample of locations with cumulative burned area damage since the beginning of satellite imagery recording of $\leq 5\%$ (brown circles) and $> 5\%$ (grey crosses), source Acevedo-Cabra *et al.* (2014)

that, either through intentional or unintentional fires, the region has the highest global rates of deforestation through fires and illegal logging.

The need to stop deforestation has generated a compensation mechanism that needs constant adaptation and improvement. This has triggered an open discussion among policy makers and the scientific community leading to the creation of the first projects that actively protect forests in developing countries. However, since the early days of the Kyoto Protocol there has been debate about the permanence of forest carbon related emission reductions (Trines 2008, Murray *et al.*, 2007). Forest carbon is considered particularly vulnerable because emission reductions and removals could be reversed, either by natural events (fires, droughts, floods) or due to failure of a project or policy to control the drivers, underlying causes and agents of deforestation (Seifert-Granzin, 2011). Currently, voluntary carbon markets accept the credits generated by a project to reduce emissions from deforestation and forest degradation (Seifert-Granzin, 2011). Thus, different methodologies that estimate the non-permanence of forest carbon related emission have evolved. Recent market surveys clearly point to a preference among buyers and investors for projects validated under the Voluntary Carbon Standard (VCS), as it offers the most comprehensive standard, covering all relevant AFOLU activities, and is based on the IPCC guidelines (Seifert-Granzin, 2011; Merger *et al.* 2011). However, as it was shown in the present study, the VCS Non-Permanence Risk Analysis lacks valuable information like the probability of occurrence of a given event during a project lifetime. The absence of such information may generate optimistic results that may not be reached in the event of catastrophic fires. In order to improve VCS Non-Permanence Risk Analysis, the present study uses a statistical model introduced by Acevedo-Cabra *et al.* (2014) that uses burned areas recorded by Terra satellite. In this study it was shown that it is possible to use such methodology to improve substantially the information of risk assessments of natural hazards, particularly for the case of fires.

The use of modeling techniques to improve upon the assessment of natural risk is vital to compute the sustainability not only of any PES and REDD project but also of voluntary carbon markets as a whole. As all projects are intended to obtain long-lasting results, the continuous improvement of current techniques will help achieve project sustainability and hopefully halt deforestation.

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