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optimLanduse: A package for multiobjective land-cover composition optimization under uncertainty

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Abstract

1. How to simultaneously combat biodiversity loss and maintain ecosystem functioning while improving human welfare remains an open question. Optimization approaches have proven helpful in revealing the trade-offs between multiple functions and goals provided by land-cover configurations. The *R* package *optimLanduse* provides tools for easy and systematic applications of the robust multiobjective land-cover composition optimization approach of Knoke et al. (2016).

2. The package includes tools to determine the land-cover composition that best balances the multiple functions a landscape can provide, and tools for understanding and visualizing the reasoning behind these compromises. A tutorial based on a published dataset guides users through the application and highlights possible use-cases.

3. Illustrating the consequences of alternative ecosystem functions on the theoretically optimal landscape composition provides easily interpretable information for landscape modelling and decision-making.

4. The package opens the approach of Knoke et al. (2016) to the community of landscape modellers and planners and provides opportunities for straightforward systematic or batch applications.

KEYWORDS
land-cover composition optimization, landscape modelling, multiobjective optimization, reference point optimization, robust optimization

1 | INTRODUCTION

The management of ecosystems is a 'wicked' problem (DeFries & Nagendra, 2017). The question of how to simultaneously combat biodiversity loss and maintain ecosystem functioning while improving human welfare remains open. 'Multifunctional landscapes' have evolved as a key concept for addressing multiple goals in the selection of land-cover alternatives (Sayer et al., 2013). These goals can be quantified as ecosystem services (Manning et al., 2018), or more generally, as indicators. These may also include non-use ecosystem functions and biodiversity indicators, as well as social preferences (Knoke et al., 2016). Designing multifunctional landscapes means

deciding upon the composition and configuration of land-cover types, given that landscape patterns drive the landscape's ecological value (Duarte et al., 2018) and its ability to satisfy societal demands (Biber et al., 2015; Grass et al., 2020; Kremen & Merenlender, 2018).

Land-cover allocation models have proven helpful in revealing trade-offs between multiple objectives and services provided by different land-cover compositions (e.g. Cavender-Bares et al., 2015). They allow for the exploration of theoretically optimal land-cover compositions, which satisfy specific sets of requirements on a landscape (Bateman et al., 2013). Optimization procedures, among these particularly Goal Programming and Reference Point approaches, have shown great potential in solving these questions of 'where to put what', (Kaim et al., 2018; Yousefpour et al., 2012), with the land-cover shares being the decision variables in the objective function (e.g. Bateman et al., 2013). In landscape planning and environmental modelling, each land-cover type is assigned a set of ecosystem functions, which are predictions that are subject to uncertainties and risks. This is, for example, due to observable natural variability, measuring errors, estimation errors, gaps in knowledge or disturbances (Messerer et al., 2017; Yousefpour et al., 2012).

Incorporating uncertainty into the objective function has a long tradition in landscape modelling. One prominent approach is based on risk reduction through diversification (Markowitz, 1952), which has been applied to landscape portfolios by Flora (1964) and Macmillan (1992), for example. The contributions of land-cover types to ecosystem functions or services are interpreted as asset returns with continuous probability distributions. A risk-reduction effect is achieved if those asset returns are not perfectly correlated. This has also become an important argument for diversified landscape patterns. A common property of all Markowitz approaches is that they require information about the expectations, uncertainties and also the dependencies between the parameters: that is, any co-variances between ecosystem functions across different land-cover types need to be considered. As those parameters are often gathered through Monte Carlo simulations, data requirements in classic Markowitz portfolio optimizations are usually very high, and finding solutions is computationally demanding since only nonlinear solvers are applicable (Knoke et al., 2015).

Recently, robust optimization procedures have become popular for solving portfolio-based land-cover composition problems (Knoke et al., 2015; Yousefpour et al., 2012). Robust approaches do not require any distributional or stochastic information, as the indicator's individual uncertainty spaces are solely defined by their individual best- and worst-case contributions to the land-cover types. The average effect that a land-cover option has on the indicators and one measure of uncertainty are sufficient to construct a range of contribution that a land-cover type may have on an indicator. The optimization program's state space is then constructed by all possible combinations of all best- and worst-case indicator contributions. Robust solutions guarantee the feasibility of the land allocation over the uncertainty space. The so defined allocation problem is solvable by linear programming, making the solution unique, exact and reproducible. The solver requires no arguments for convergence, and

the demands on computational time and resources are very low (Messerer et al., 2017). This formulation also allows for deriving a robust solution that reduces underperformance across a range of multiple indicators. This could be an important attempt towards exploring multifunctional landscapes.

We here present an adaptation of the successfully established and applied robust land-cover optimization approach for multiple objectives by Knoke et al. (2016) for the statistical programming language *R* (R Core Team, 2022). With this package, we aim to *open the method to the community of landscape modellers and planners*, and to *enhance the possibilities for systematic applications, such as sensitivity analysis*, for that approach. We introduce the theoretical optimization framework, sketch the package structure, and explain its functionality using example data from a recently published scientific study.

2 | METHODOLOGICAL BACKGROUND

The core concept of the robust optimization approach presented here is to find the land-cover composition that minimizes the distance of the worst-performing indicator to its own theoretically best-achievable contribution out of the set of all indicators. We use indicators to describe the relevant functions or services of the land-cover types. The best-case contributions and worst-case contributions of an indicator construct individual uncertainty spaces around each indicator and span a broad state space of the optimization program in comparison to approaches without a consideration of uncertainty. The indicators' possible contributions of a land-cover type are bounded by the worst- and best-case outcomes. The robust uncertainty spaces of the indicators are therefore each defined by two parameters. The entire robust uncertainty space of the optimization problem is then framed by all resulting combinations of all indicator contributions. The corners of the state space of the optimization program are determined by all possible combinations of the indicators' worst- and best-case contributions (Knoke et al., 2016).

For each indicator, the number of possible combinations with all indicators' worst- and best-case contributions, also called uncertainty scenarios, is calculated by $N_U = 2^{N_L}$ with N_L being the number of decision alternatives, that is, land-cover options. For a number of N_I indicators, this results in a total number of uncertainty scenarios N_S of $N_S = N_U \cdot N_I$.

The solution is the land-cover composition that minimizes the relative distance of the worst-case scenario, for the worst-performing indicator, to its (hypothetical) maximum achievable level. The solution of the program is thus solely determined by the worst-case scenario, that is, the indicator combination that shows under a given land-cover allocation the highest distance to its individually achievable level. Unlike in ordinary goal-programming approaches, the indicators or scenarios with higher performances do not compensate for the worse performing indicators (Knoke, Paul, et al., 2020). The program searches the minimum out of the set of maximum distances d_{iu}. d_{iu} are the distances of each indicator to its best-achievable level

out of all possible combinations of indicator contributions. Or in other words, the only variable to be minimized is the distance of the worst-performing scenario to its individual maximum achievable level, which we called β, thus

$$\min \beta. \tag{1}$$

β is not only the objective variable to be minimized, but also determines the maximum threshold of the distances that each indicator in each scenario is allowed to have. This ensures that β represents the worst-case scenario. It builds the right-hand side limitations for the constraints of the performances of all indicators (Knoke, Paul, et al., 2020), which makes the right-hand side of the optimization program dynamically dependent on the objective.

$$\beta = \max(d_{iu}), \text{with}$$
$$i \in I, \text{being the set of indicators and} \tag{2}$$
$$u \in U_i \text{being the set of individual uncertainty scenarios for } i.$$

β can be interpreted as the maximum relative distance of the worst-performing scenario to its scenario-individual achievable level out of the set of all scenarios and thus the worst-case scenario of all possible consequences. We thus minimize the worst possible combination of indicators, reflected by the maximum distance. The vector with the scenarios' distances d_{iu} has the length of the number of scenarios N_S. It contains the relative differences of each scenario to its theoretically best-achievable level. The distances are calculated as the differences between the maximum achievable level in that scenario, reflected by the most desired indicator contribution for R_{liu}, and the performance of the scenario under a given land-cover composition. Dividing the distances by the range of the lowest and highest uncertainty adjusted indicator $\delta_{\min,\max_{iu}}$ normalizes the distances.[1] As the d_{iu} are calculated by their individual, theoretical best-possible contribution for each indicator i within scenario u as

$$d_{iu} = \begin{cases} \dfrac{\max(R_{liu}) - R_{iu}}{\delta_{\min,\max_{iu}}} & \text{if more is better,} \\[2ex] \dfrac{R_{iu} - \min(R_{liu})}{\delta_{\min,\max_{iu}}} & \text{if less is better,} \end{cases} \tag{3}$$

the approach can also be referred to as a Reference Point approach. The R_{liu} are the uncertainty adjusted indicators, which depend on whether the indicator is considered as best case or worst case. As an example, the calculation for indicators where *more is better* is:

$$R_{liu} = \begin{cases} R_{li} + f_u \cdot SD_{li} & \text{if in scenario } u \text{ the indicator } i \text{ is denoted as best-case,} \\ R_{li} - f_u \cdot SD_{li} & \text{otherwise,} \end{cases} \tag{4}$$

with R_{li} being the expectations, and SD_{li} being the uncertainty of the indicators i for the distinct land-cover options l, delivered by the

user. f_u enables changing uncertainty levels, for example, for sensitivity analysis of the risk attitude of the stakeholders. Figure 3 illustrates the distances d_{iu} for all indicators and uncertainty scenarios (circles) for an explicit example. The maximum of d_{iu} is the relative distance of the worst-performing scenario u of the worst-performing indicator i and thus the worst-case consequence of a land-cover decision under all possible combinations. The difference between the highest and the lowest uncertainty adjusted indicator $\delta_{\min,\max_{iu}}$ builds the best-achievable level of the scenario iu and, accordingly, can be interpreted as the reference of this scenario. $\max(R_{liu}) - R_{iu}$, or $R_{iu} - \min(R_{liu})$ if *less is better*, in the enumerator expresses to which level this reference is not achieved in the respective scenario iu. The normalization makes all scenarios comparable, independent of their units or scales. The actual distances of a certain land-cover composition R_{iu} are the averaged means in the scenarios

$$R_{iu} = \sum_{l \in L} R_{liu} \cdot a_l, \tag{5}$$

with L being the set of land-cover options and a_l being the proportion of land-cover option l. Thus, R_{iu} is the only component that contains the proportions of the land-cover composition. The two technical constraints

$$\sum_{l \in L} a_l = 1, \text{ and} \tag{6}$$

$$a_l \geq 0, \forall l \in L \tag{7}$$

restrict the parameter spaces of the land-cover alternatives. The third constraint

$$d_{iu} \leq \beta, \forall i \in I, \text{and } \forall u \in U_i, \tag{8}$$

implements the connection of the constraints to the objective and reveals the compromise nature of the approach. All distances to the references d_{iu} must in all scenarios at least hold the performance of the worst-performing scenario of the worst-performing indicator, expressed by β (Equation 2). The best-possible compromise between the land-cover options is achieved by minimizing the underperformance of the indicators provided.

In most recent applications of the approach (e.g. Gosling et al., 2021; Rössert et al., 2022), the distances to the maximum achievable level (the reference) d_{iu} (Equation 3) and the actual distances under a certain land-cover composition R_{iu} (Equation 5) are calculated with different levels of uncertainties f_u^*. The aim is to stretch the uncertainty space, such that the state space of the actual distances is not limited by an overly restrictive uncertainty space. While the calculation of R_{iu} (Equation 5) remains unchanged on the basis of R_{liu} with uncertainty level f_u (Equation 4), the distances d_{iu}^* are calculated with different uncertainty level R_{liu}^* as

$$R_{liu}^* = \begin{cases} R_{li} + f_u^* \cdot SD_{li} & \text{if more is better,} \\ R_{li} - f_u^* \cdot SD_{li} & \text{if less is better,} \end{cases} \tag{9}$$

which also means that the $\delta_{\min,\max_{iu}}$ is calculated with the different uncertainty level f_u^*.

The optimization program can be straightforwardly solved by linear programming. We nevertheless split the solving procedure into a two-stage, nested approach to enable more flexibility for possible further developments. β is minimized in the outer optimization (Equation 1). The inner optimization maximizes the distances d_{iu} (Equation 2) regarding the land-cover allocation a_l under the known β. In its current version, the outer optimization is solved by a self-programmed grid search. The inner optimization is solved by linear programming using the *R*-package *lpSolveAPI* (Konis & Schwendinger, 2020).

3 | *OPTIMLANDUSE* FUNCTIONS AND WORKFLOW

The functions of the package are structured into three successive working steps: *initialization*, *solving* and *post-processing*. The distinct functions network provides higher flexibility and possibly saves calculation time in batch analyses. An initialized object could, for example, be recycled for multiple optimizations. The functions of the third working step contain tools for reappraisal and interpretation of the results (Figure 1).

3.1 | Initialization

The *initScenario()* function integrates the user settings into the data and returns an *optimLanduse*-object ready for solving. It is capable of processing a long-oriented type of data structure (cf. Gosling et al., 2020; Reith et al., 2020). A detailed example of the data structure required is provided in Chapter 2 in the README of Husmann et al. (2022). The function *exampleData()* provides an example with the required input structure to be passed as argument *coefTable*. In the data table, all indicators are vertically listed with

their average expectations (*indicatorValue*) R_{li} and uncertainties SD_{li} (*indicatorUncertainty*) for the different land-cover alternatives. Our approach allows for one uncertainty measure per indicator and land-cover alternative. The actual entry for uncertainty chosen by the user crucially influences the result and the result's interpretation. Natural variability is usually reflected by the standard deviation, whereas the standard error of the mean usually reflects model confidence. Choosing extreme values, as for example, applied in Knoke et al. (2022), ensures that the entire space of possibilities is covered. *coefTable* further contains a column with the *direction* for each indicator to indicate whether more or less of the indicator is desirable (see Equation 3). Three optional arguments can be used to specify the optimization program further:

- *uValue* is the argument for the uncertainty level f_u (Equation 4). A higher *uValue* reflects a higher risk aversion of the decision-maker.
- *optimisticRule* specifies whether the best-case contributions of each indicator R_{liu} (Equation 3) should be defined either (a) directly by its average, or (b) by its average plus their uncertainty (if *more is better*) or minus its uncertainty (if *less is better*). The former option is most frequently used in recent literature (e.g. Gosling et al., 2020; Knoke, Gosling, & Paul, 2020; Knoke, Paul, et al., 2020) and therefore acts as the default.
- *fixDistance* allows the user to define an uncertainty level f_u^* (Equation 9) for the calculation of the uncertainty space independently of f_u of the averaged distances of a certain land-cover composition R_{iu}. The *fixDistance* argument is enabled when the user provides a numeric value. If *NA* is provided, *fixDistance* equals the *uValue*. *fixDistance* is set to 3 per default.

3.2 | Solver

solveScenario() requires the initialized *optimLanduse* object and only a few optional solver-specific arguments. The function allows the optimization precision to be defined and the shares allocated to each
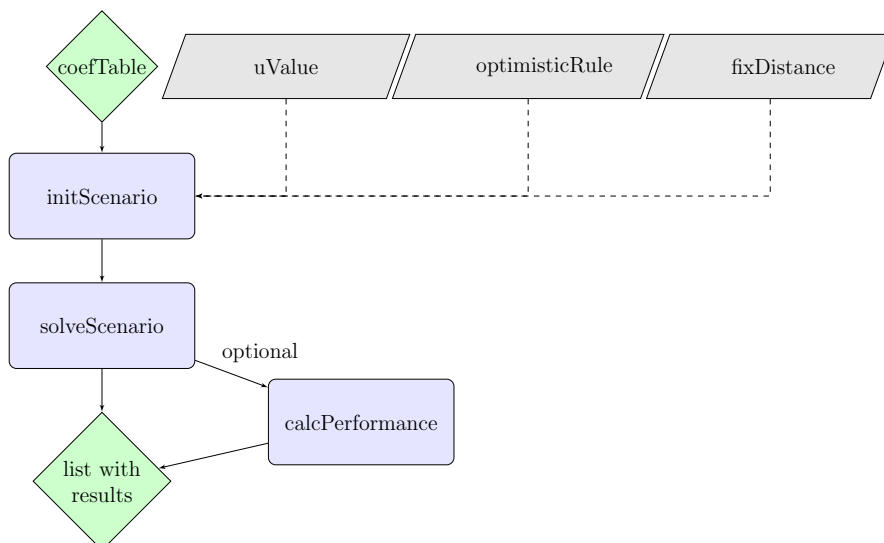

FIGURE 1 Overview of the functions of the *optimLanduse* package. Green diamonds: input and output data; blue rectangles: functions; grey parallelograms: optional function settings

land-cover option to be restricted. As the solving process has no sto-
chastic element, the calculation time depends almost entirely on the
number of digits calculated. *digits Precision* therefore provides the
only possibility for the user to influence the calculation time. *solveS-
cenario()* returns an updated *optimLanduse* object with the optimized
land-cover composition and the distance of the worst-performing
scenario to its individual maximum achievable level (β, Equation 1).
Also, a *scenarioTable* with all scenarios and all calculated interim vari-
ables (Equations 3 to 5) is provided.

3.3 | Post-processing

The *calcPerformance()* function calculates and attaches the port-
folio performances to the solved *optimLanduse* object. The perfor-
mances are calculated by subtracting the scenario distances d_{iu} from
1. They can be interpreted as the degree of fulfilment of an indica-
tor in the solution and enable a graphical interpretation and detailed
data analysis of d_{iu} and β. They also reveal which indicators perform
poorly and thereby define the solution.

4 | EXAMPLE APPLICATION: AGROFORESTRY SYSTEMS

This section illustrates applications of *optimLanduse* based on the
data and results of Gosling et al. (2020). The study took place in a
forest frontier region in Eastern Panama and used data from inter-
views with local farmers. The farmers ranked the performances of
different conventional land-cover types and two agroforestry land-
cover types against various socio-economic and ecological indica-
tors. From the farmer's rankings of each indicator, a mean score and
the corresponding standard error of the mean were then calculated
for every land-cover type (Table 1).

4.1 | Optimizing the land-cover composition with *optimLanduse*

We applied the *optimLanduse* functions step-by-step to determine
the optimal farm land-cover composition, which minimizes the
trade-offs between the different indicators. We imported the ex-
ample dataset (*exampleData()*) and initialized an *optimLanduse* ob-
ject using *initScenario()* (Listing 1). This initial object is the basis for
the following optimization. We set the uncertainty level (f_u, *uValue*)
to 2 and the *optimisticRule* to 'expectation'. This setting is appropri-
ate to define a risk-averse decision-maker following the philosophy
of down-side risk measures; that is, the decision-maker wishes to
only account for risk in the form of potential undesirable deviations
from expected values. We use the set of indicators to represent
the stakeholders' preferences and perceptions, using linear 'disu-
tility' functions, where distances to the best-achievable indicator
levels represent 'dissatisfaction'. We thus do not apply a utility
maximization, but rather a satisficing approach. The comparison
of optimal land-cover compositions under differing indicator com-
binations may help to understand how the preferences of stake-
holders design the land-cover compositions. Examples of how to
calculate and interpret the differences in the performances of the
here presented multifunctional objective to subsets of objectives
are given in Chapter 4.2 of the README (Husmann et al., 2022). A
pay-off matrix is suitable to reveal the synergies and the conflicts
between individual indicators. We provide a respective example in
(README Chapter 4.3).

```
install.packages ("optimLanduse")
library (optimLanduse)
library (readxl)

temp_path <- exampleData ("exampleGosling.xlsx")
dat <- read_excel (path = temp_path)
```

TABLE 1 Expected values and their uncertainties (standard error of the mean) for each land-cover alternative and indicator of the
example application. The superscript letters after the indicator names indicate the direction for the optimization, so whether it is better to
have more of the indicator = ([a]) or less = ([b]). N = number of participants in the farmer interviews in the original study (Gosling et al., 2020).
The data in the format required for the *optimLanduse* package can be accessed via the *exampleData( )* function

[1]	N	Cropland	Pasture	Alleycropping	Silvopasture	Plantation	Forest
Long-term income[a]	32	6.3 ± 0.40	7.9 ± 0.40	7.1 ± 0.32	7.8 ± 0.31	8.3 ± 0.42	3.0 ± 0.47
Labour demand[b]	32	8.3 ± 0.37	7.2 ± 0.36	7.8 ± 0.33	6.9 ± 0.30	6.5 ± 0.47	1.6 ± 0.38
Meeting household needs[a]	32	9.6 ± 0.22	8.4 ± 0.23	6.8 ± 0.36	8.0 ± 0.22	4.3 ± 0.40	3.9 ± 0.51
Financial stability[a]	32	5.7 ± 0.45	7.0 ± 0.53	6.4 ± 0.35	7.8 ± 0.42	7.8 ± 0.42	5.7 ± 0.67
Liquidity[a]	32	7.5 ± 0.33	9.9 ± 0.07	5.9 ± 0.38	8.7 ± 0.28	5.2 ± 0.40	2.9 ± 0.47
Investment costs[b]	32	7.3 ± 0.37	8.1 ± 0.37	7.4 ± 0.43	7.6 ± 0.36	7.3 ± 0.48	1.3 ± 0.33
Management complexity[b]	32	8.1 ± 0.40	6.8 ± 0.36	8.6 ± 0.31	7.6 ± 0.32	7.0 ± 0.47	1.9 ± 0.38
Protecting water[a]	32	4.0 ± 0.43	4.7 ± 0.41	6.8 ± 0.26	7.6 ± 0.21	7.2 ± 0.44	9.9 ± 0.09
Protecting soil[a]	32	5.5 ± 0.46	5.0 ± 0.32	6.5 ± 0.40	6.9 ± 0.32	6.6 ± 0.46	9.1 ± 0.38
General preferences[a]	35	15 ± 3.44	21 ± 3.85	11 ± 3.05	23 ± 3.94	0 ± 0.00	1 ± 0.99

```
init <- initScenario (coefTable = dat,
                      uValue = 2,
                      optimisticRule = "expectation",
                      fixDistance = NA)
```

Listing 1 Installing the package, loading the example data and defining an initial *optimLanduse*-object (*init*). The *coefTable* passed needs to be strictly formatted in the expected *optimLanduse* format. More information about this format is given in the help of the *initScenario()* function and in Chapter 2 of the README (Husmann et al., 2022).

In the next step, we use the *solveScenario()* function to solve the initialized *optimLanduse* object (*init*) (Listing 2). The resulting land-cover composition is shown in Figure 2. By choosing 0 and 1 (the defaults) as boundaries for all decision variables, we do not force any land-cover alternative into the farm portfolio, nor do we constrain the maximum share of any option. *result* includes all settings and solutions. It can be passed to the built-in post-processing functions or accessed directly by the user. To further analyse the performance of each indicator, the post-processing function *calcPerformance()* attaches the portfolio performances of all scenarios (Figure 3). The performance is defined as 1—the distance to the maximum achievable level for each indicator and uncertainty scenario (Equation 3). The performances reveal trade-offs among different indicators and their likely effects on land-cover decisions.

```
result <- solveScenario (x = init,
                         digitsPrecision = 4,
                         lowerBound = 0,
                         upperBound = 1)
performance <- calcPerformance(x = result)
```
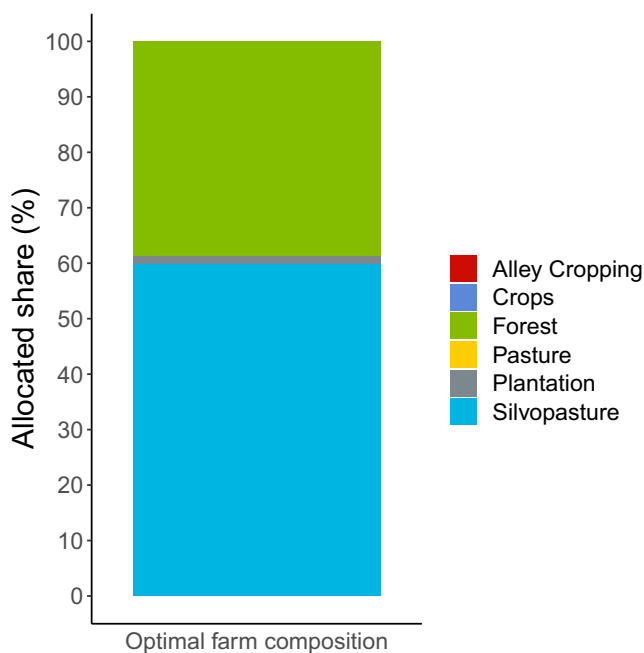

FIGURE 2 Composition of the optimized farm (based on data shown in Table 1, including all indicators). Each land-cover option is shown in an allocated share (%).

Listing 2 Executing the optimization process and calculating the portfolio's performance.

To analyse how sensitive the optimal land-cover configuration reacts towards increasing risk aversion of the stakeholder, we calculated optimal land-cover portfolios for increasing *uValues* (Listing 3). The resulting data frame can be used to compile standard graphics, such as in Figure 4. A more detailed interpretation of the risk attitude is attached in Chapter 4.1 of the README (Husmann et al., 2022). As a tendency, higher levels of uncertainty lead to more diverse portfolios, since the uncertainty spaces of all indicators increase with increasing uncertainty levels. These broadened individual uncertainty spaces then lead to a broader state space with a higher number of possible candidates for lowest-performing scenarios.

```
# define sequence for uValue argument
u <- seq(0, 3, 0.5)

applyDf <- data.frame(u = u)

applyFun <- function(x) {
   init <- initScenario (coefTable= dat,
                         uValue = x,
                         optimisticRule = "expectation",
                         fixDistance = NA)
   result <- solveScenario(x = init)
   return(c(result$beta, as.matrix(result$landUse)))
}

applyDf <- cbind(applyDf,
                 t(apply(applyDf, 1, applyFun)))

names(applyDf) <- c("u", "beta", names(result$landUse))
```

Listing 3 Creating a wrapper for *optimLanduse* to perform batch optimization for a sequence of uncertainty values. We use the base *R* function *apply()* to repetitively execute the wrapper.

5 | DISCUSSION AND CONCLUSIONS

The robust land-cover optimization approach developed by Knoke et al. (2016) is innovative in that it allows for the consideration of uncertainty in ecosystem function provisioning in a multicriteria land-cover allocation model. At the same time, the formulation as a linear programming problem meets the calls for parsimonious models (e.g. Antle et al., 2014). However, so far this approach has been implemented exclusively in *Microsoft Excel* (e.g. Gosling et al., 2020; Knoke, Kindu, et al., 2020). These implementations have been technically complex, requiring many problem-specific settings and very close-to-data spreadsheet designs, which are time-consuming and prone to errors. As a result, analyses that required model repetitions (e.g. sensitivity analyses) were not feasible. *optimLanduse* was designed to overcome these limitations, enable fast and systematic parameterizations, and thus make

FIGURE 3 The performance of each of the 10 indicators for the result of the ideal farm composition. The coloured points are the achieved levels of the indicators of all scenarios *s*. The dotted, horizontal red line illustrates the guaranteed performance $(1 - \beta)$, thus the robust feasible solution of the program (Equation 1).
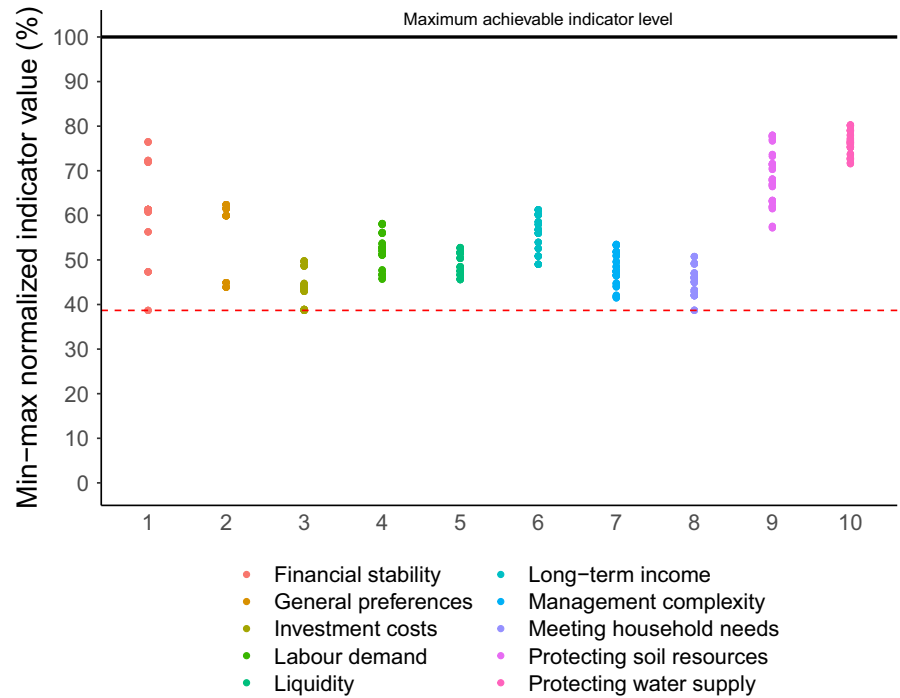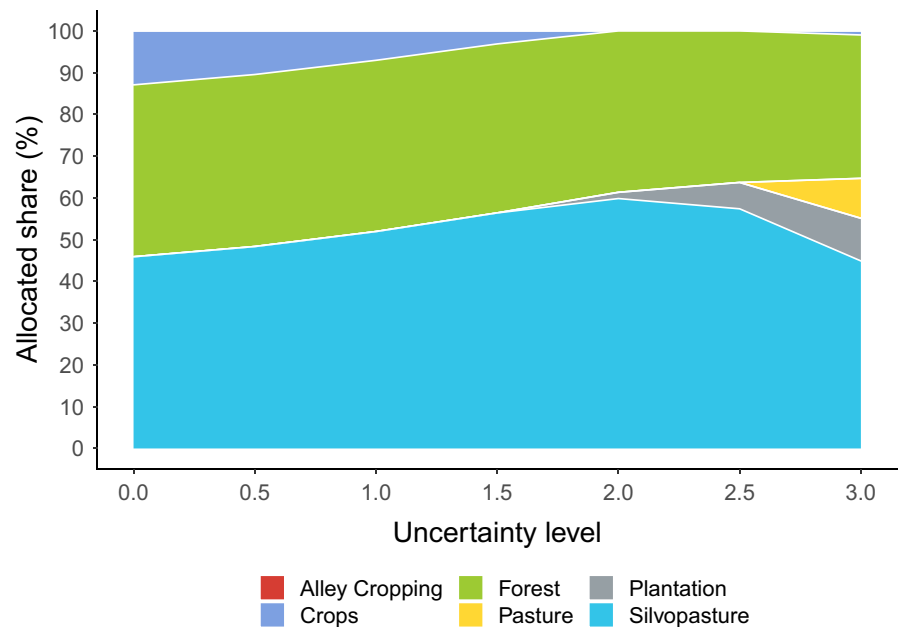

FIGURE 4 Theoretically ideal farm compositions under increasing levels of uncertainty.

robust optimizations accessible to a broad community of landscape modellers and decision-makers.

optimLanduse provides access to one optimization approach. Incorporating alternative approaches would, however, certainly be advantageous as it would allow users to choose from a set of approaches or to straightforwardly analyse the differences between these approaches. The package is therefore also meant to serve as a platform for seamless cooperation in the development of landscape modelling approaches. Programmers are invited to copy our code or to fork our project on GitHub as a basis for own landscape-modelling approaches, or to jointly integrate their approaches into *optimLanduse*.

The robust approach provides one single best land-cover composition under the specific set of preferences out of the entire frontier, using equally weighted decision criteria and uncertainty scenarios. For example, Kaim et al. (2020) show the advantages of illustrating the effect of variable stakeholder preferences in the form of Pareto frontiers. The reference point nature of our model allows for identifying land-cover compositions for which one indicator cannot be improved without compromising another indicator (see e.g. Seppelt et al., 2013). Reith et al. (2022, Appendix A) show that a robust pendant of such a Pareto frontier may be achieved with our method by assigning different weights to different indicators.

In the current version, all indicators have equal weights. The consideration of differing indicator combinations can still reflect stakeholder preferences. Upcoming versions shall provide the possibility to weigh the indicators so as to reflect the stakeholder's preferences better. These weights could be derived, for example, by an analytical hierarchy process or similar methods as a hybrid multi-criteria approach as, for example, shown by Kaim et al. (2020).

The performances of the indicators give an indication of the indicators to which the result reacts sensitive. See Figure 3 and Chapter 4.2 of the README (Husmann et al., 2022). The sensitivity towards the risk assumption can be analysed by calculating portfolios with different *uValues* (f_u, Chapter 4.1 of the README). Necessary parameterizations to calculate the sensitivities have to be conducted by the user. We plan to add a built-in sensitivity report that provides a set of standard sensitivity measures on demand for the indicator expectations, the indicator uncertainties and the *uValues*. In addition, it may be interesting to analyse how much an indicator can be changed without changing the optimal land-cover composition.

optimLanduse is capable of studying the effects of compositional diversity. With only minor changes, the model could also be used to elaborate the influences of structural diversity on the optimal land-cover composition. User-definable restrictions would enable defining groups with different expectations or uncertainty entries of the indicators, which could then be interpreted as spatial regions or any other systematic group.

Our adaptation as an *R* package has four main advantages: (1) The horizontal and vertical dimensions of the optimization problem are solely limited by the hardware. Larger problems are not usually solvable in *Microsoft Excel* without the use of potentially expensive proprietary plugins. (2) The entire optimization process is relatively fast since the core solving procedure is a simple Simplex approach and the surrounding data processing consists of only a few necessary operations. (3) The package enables straightforward conduction of repetitive applications. By summarizing all relevant information of the optimization in an S3-list object, more in-depth analyses, such as systematic scenario comparisons, can be easily performed. (4) The *R* universe opens the door to a further streamlining of our approach. Not only does it allow experienced *R* users to reproduce the same workflow on different machines, it also allows less technically trained users to apply this method through an interface created using the *R* package *Shiny*. This enables collaboration between various interest groups and stakeholders. The composition of land-cover options has a crucial influence on many ecosystem functions. Our package helps to analyse the potential of different land-cover alternatives and contributes to the understanding of the trade-offs between the different essential ecological and socio-economic functions.

AUTHOR CONTRIBUTIONS

Thomas Knoke and Carola Paul conceived the idea of the robust optimization approach; Carola Paul and Kai Husmann conceived the idea of the *R* package; Thomas Knoke and Carola Paul programmed the original robust optimization approach; Kai Husmann, Volker von Groß, Jasper M. Fuchs and Kai Bödeker programmed the *R* package; Volker von Groß and Kai Bödeker analysed the data; Kai Husmann, Volker von Groß and Kai Bödeker led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

optimLanduse (1.1.0) has been released on CRAN (https://cran.r-project.org/package=optimLanduse) and version 1.1.3 on Zenodo (https://zenodo.org/record/7115933). It can also be accessed via the project page https://github.com/Forest-Economics-Goettingen/optimLanduse. The example dataset taken from Gosling et al. (2020) can be loaded in the *R* package with *optimLanduse::exampleData*("*exampleGosling.xlsx*"). The shiny dashboard can be accessed via http://rshiny.gwdg.de/apps/optimLanduse/.

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ENDNOTE

1 The package returns a table with all scenarios containing all calculated interim results. See Section 3 for more details.

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