General Indicator Modeling for Decision Support based on 3D city and landscape models using Model Driven Engineering

Mostafa ELFOULY[1], Tatjana KUTZNER[2] and Thomas H. KOLBE[3]

[1]Chair of Geoinformatics, München/Germany · mostafa.elfouly@tum.de
[2] Chair of Geoinformatics, München/Germany · kutzner@tum.de
[3] Chair of Geoinformatics, München/Germany · thomas.kolbe@tum.de

Abstract

In order to support automated decision-making, landscape and urban planning require the evaluation of alternative scenarios within the context of geodesign. The evaluation is frequently based on indicators, where the decisive ones are typically called key performance indicators (KPIs). These KPIs often are related to physical objects (e.g. buildings or land parcels) which are stored in geoinformation systems (GIS). Several approaches have been introduced for representing KPIs; however, they pose a problem, as stakeholders and domain specialists often are not capable, lack sufficient knowledge, or are not willing to implement these indicators in the language of the underlying GIS. In this paper we propose a framework that assists domain specialists in expressing indicators, indexes, and their dependencies using a model-driven approach. We define an object-oriented data model for an abstract General Indicator Model (GIM) formally specifying concepts like indicators, numeric indicators, and their compositions. Specific indicators/KPIs from different decision contexts, for e.g. energetic, environmental, or financial assessments, are then defined as concrete subclasses of the GIM. The concrete KPI classes are linked to spatial feature classes from digital city and landscape models (like CityGML) using model weaving. This effectively sets the object context or reference frame of the individual indicators and provides means to automatically derive the values of those indicators from characteristics and attributes of the linked spatial objects. We apply this framework to a case study for a real scenario in energy demand estimation as a proof of concept for our framework. However, the concept can also be used for indicators from other indicator domains to cover e.g. environmental and financial aspects of planned scenarios in decision-making as well.

1 Introduction

An important aspect of geodesign is the evaluation of alternative scenarios in landscape and urban planning which does not only help in decision-making, but also in its automation. Evaluations are carried out in different domains like the energy (e.g. energy demand estimation) or environmental sector (e.g. noise dispersion, or assessment of greenhouse gas emissions). The evaluation is often based on key performance indicators (KPIs). Indicator modeling in general refers to KPIs as measures that indicate/assess organizational performance; i.e., it is a metric that evaluates performance with respect to some objective (BARONE et al. 2011), and, thus, measures how far we are from where we want to be (SUSTAINABLE MEASURES 2010). It triggers an alert of what needs to be done or what action needs to be performed in order to enhance the performance (PARMENTER 2007). However, the action to be taken in order to change the current state and improve the performance has to be provided as well, as is e.g. done by SINDRAM & KOLBE (2014) in a complementary concept using a so-called General Action Model.

Nevertheless, as explained by BARONE et al. (2011), indicators can be also composite, consisting of a hierarchy of indicators. In this case, the value of an indicator for an object depends on the values of indicators for objects on lower levels of the hierarchy. The problem hereby is, that in some cases no well-defined mathematical function exists that relates component indicators to a composite one.

As part of a state-of-the-art analysis we identified diverse approaches for representing knowledge about KPIs. WETZSTEIN et al. (2008) introduce a framework for modeling and monitoring KPIs in Semantic Business Process Management aiming to minimize the support needed from the IT staff throughout the business process life cycle. DEL-RÍO-ORTEGA et al. (2010) present an ontology for defining process performance indicators (PPIs) enabling the analysis of PPIs at design time. Furthermore, the relationships between business processes and PPIs are explicitly defined. BARONE et al. (2011) focus on modeling processes, indicators, and business objectives related to one another in order to achieve business intelligence activities in the Business Intelligence Model context. ROJAS & ZAPATA (2013) propose so-called executable pre-conceptual schemas to obtain an appropriate knowledge representation of KPIs.

By taking into account these research concepts we developed a KPI framework which comprises major features for an appropriate KPI representation. The framework is defined as a generic, easily understandable, and extensible conceptual model. Furthermore, the framework follows the ISO 191xx series of geographic information standards and can, thus, be employed and implemented for any application in the context of the geospatial domain. The paper is organized as follows: In section 2 we introduce the theoretical background for our KPI framework. In section 3 we present our proposed KPI framework and apply it to a case study in energy demand estimation. Section 4 covers relevant related work and in section 5 we present the conclusion and some future work.

2 Theoretical Background

2.1 Model Driven Engineering

Model Driven Engineering (MDE) represents a software engineering approach which started to develop in the 1980s. MDE allows for creating links between systems using Model Weaving (FABRO et al. 2005). To do so, the systems are represented by models which conform to metamodels and which can be transformed into other models based on the definitions in the weaving models (BEZIVIN et al. 2005). One well-known model-engineering framework which follows the MDE principles is the Model-Driven Architecture (MDA) developed by the Object Management Group (OMG 2003) (BEZIVIN et al. 2005). In the context of MDA several standards have been developed; the most important one is the modeling language UML (Unified Modeling Language) which is widely employed in the geospatial domain for defining models (OMG 2011) and which we will also use for our KPI framework.

Key points for MDE include simplifying the design process and reusing standardized models and components. Thus, rather than building the variants of each new system from scratch, domain-specific reusable components should be implemented in the domain engineering process (CZARNECKI et al. 2000) as is demonstrated in figure 1. Here, the General Indicator Model (GIM) can be considered as such a reusable component which is used as basis for defining domain-specific indicator models (e.g. Energy-Related Indicator Model, Climate-Related Indicator Model). The individual indicators defined therein can then be related to geospatial elements by linking the domain-specific indicator models with geospatial application models (e.g. CityGML). This process of linking these models together is called model weaving.

CityGML is an international standard of the Open Geospatial Consortium (OGC) (GRÖGER et al. 2012). CityGML specifies both, an application-independent geospatial information model and an XML-based encoding for the representation, storage, and exchange of semantic 3D city and landscape models. CityGML groups geospatial elements into different thematic areas such as buildings, vegetation, water, terrain, traffic, tunnels, and bridges; furthermore, it represents 3D geometry, 3D topology, semantics and appearance of the geospatial elements in five discrete levels of detail (LOD).

The GIM, the domain-specific indicator models, and the CityGML model can be arranged within a hierarchy which is based on the OMG four-layer metamodel hierarchy (OMG 2011), as is shown in figure 1. The layer M0 represents the objects of the real world, such as buildings or land parcels or also the concrete indicator values, in the form of geospatial data. The structure of these data objects is described by models, e.g. using UML, which are located at layer M1. In figure 1 the domain-specific indicator models for energy and climate as well as the CityGML model belong to this layer. At layer M2 reside the metamodels; they define the concepts to be used for creating the models at layer M1. The GIM is such a metamodel as it defines the concepts on which the domain-specific indicator models are based. Similarly, the CityGML model is based on the General Feature Model (see ISO 19109), which is a metamodel defining how to represent geospatial objects in geospatial application models. The fourth layer in this hierarchy is the meta-metamodel layer M3 (not depicted in figure 3). At this layer all the elements which can be used to create metamodels at the layer M2 are defined.

2.2 Indicator Modeling

KPIs as defined by PARMENTER (2010) are sets of measures or metrics that focus on the most critical aspects of current and future success of an organization. Different indicators have been suggested according to studies made by authors like GALLOPIN (1997), BLANCHET & NOVEMBER (1998), and BOTH et al. (2003). According to them, the indicator shall be able to describe the state of a system, evaluate the state of a system, and measure correlations between different indicators or in other words allow for derived measurements (CARNEIRO 2011).

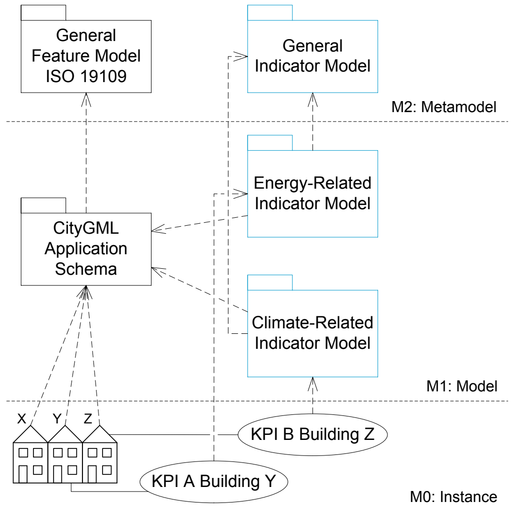

Fig. 1:
General Indicator Model and domain-specific indicator models in the MDE perspective. The dashed arrows indicate an "is-represented-by" relationship.

Two of the approaches proposed for allowing the indicator system to support the decision-making process, is its implementation using the so-called top-down and bottom-up processes (MAYSTRE & BOLLINGER 1999). The top-down process starts from the decision-makers' side. It simply asks the question what has to be evaluated and then breaks up this comprehensive and generic question into descriptive data. On the contrary, the bottom-up process is carried out by organizing data, aggregating them into indicators, and selecting relevant indicators (CARNEIRO 2011). When an indicator is related to a geolocation or to a specific territory, it is referred to as a geographical indicator. In other words, a geographical indicator connects an observation to a spatial or a geo-referenced object (CARNEIRO 2011).

2.3 The Impact of Indicator Modeling on Landscape Architecture

"The design method" (SIMON 1969) does not exist, Herbert Simon a political scientist and economist stated. Since there is not one single design method, there is not one single geodesign method or path (STEINITZ 2012). According to Jack Dangermond (WHEELER 2012), Geodesign shall be "thought of as a systematic process of measuring, modeling, interpreting, designing, evaluating, and making decisions". Hence, in order to support automated decision-making, the evaluation of different geodesign methods became a necessity. In this paper we focus on the development of a KPI framework which can be used to support the evaluation of geodesign methods for landscape and urban planning. Steinitz's study in his book "A Framework for Geodesign: Changing Geography by Design" pointed out, that architects, designers, and scientists count on models, which are abstractions of the real world, modeled from their individual perspectives. Evaluation and assessment of these models is to be considered from the basic usages during the geodesign process by using indicators for determining, monitoring, and detecting the impact of a specified change on a given model (STEINITZ 2012). In a case study conducted by Steinitz back in 1967 for rapidly changing suburban areas, the necessity of the evaluation of attractiveness or vulnerability for each land use in the future was demonstrated. It was also used for determining and measuring the impact of any specific change (STEINITZ 2012).

3 Spatial Object-Related Indicator Modeling

Based on our state-of-the-art analysis, we defined major factors for expressing representative indicators. Thus, a comprehensive KPI model is required which covers the following features: i) clear and accurate semantics with indicators related to one another; ii) a formal language with clear and accurate syntax for describing the indicators; iii) extensiveness when indicators are intended to be present in different application schemas within different domains; iv) data sources and accuracy for ensuring data reliability; v) a link between the KPI model class entities and class entities from relevant ISO191xx standards; vi) the representation of time-dependence as indicators can be time-dependent; and vii) features for aggregation metric, duration metric, passive and active monitoring, and stakeholders' understanding (WETZSTEIN et al. 2008; BARONE et al. 2011; DEL-RÍO-ORTEGA et al. 2010; ROJAS & ZAPATA 2013; CAPUTO et al. 2010; FRANK et al. 2008; FOX 2013; POPOVA & SHARPANSKYKH 2010).

3.1 The General Indicator Model

In order to achieve an appropriate knowledge representation of KPIs we propose a framework, the so-called General Indicator Model (GIM), which allows expressing elementary indicators, complex indicators, and indexes. Elementary indicators are realized/derived directly from raw data, while complex indicators consist of two or more indicators (elementary or complex) and consistently show complex functions on the elementary data (CARNEIRO 2011). Indexes are an aggregation of elementary or complex indicators or a combination of both and represent simple functions for different areas of application. The higher level of aggregation represented in indexes supports the decision-making process because of the simplicity and comprehensiveness which makes them easier communicable to the public (CARNEIRO 2011). Indicators and indexes shall encapsulate, simplify, assess, and measure related information which require an underlying metric of their values, e.g. integer or real values, or a reference to such values, and usually a unit of measure (KRÜGER & KOLBE 2012).

The GIM is represented in figure 2 as a UML class diagram; this makes it easily readable and understandable as well as extensible with constraints formulated in the Object Constraint Language (OCL). Furthermore, the model follows the ISO 191xx series of geographic information standards which enables its linkage to the General Feature Model defined in ISO 19109 and allows for diverse applications in the geospatial domain.

The abstract class Indicator is the base class of the GIM. It defines the attributes which are common to all indicators. This indicator class is specialized to the three abstract subclasses TextIndicator, NumericIndicator, and ClassifierIndicator. TextIndicator represents indicators as arbitrary text, whereas ClassifierIndicator is used for categorizing indicators in the form of discrete values. Our focus in this paper is on NumericIndicator, which represents indicators resulting in real values. NumericIndicator is further specialized to the classes ArithmeticOperation, NumericConstant, NumericAttribute, and NumericAggregationOperation, which is an aggregation of other indicators or values. NumericAttribute represents attribute values through a relation to geospatial elements in geospatial application models using the referenceToObject attribute. ArithmeticOperation represents indicators that result from mathematical formulas; it is classified into

UnaryArithmeticOperation and BinaryArithmeticOperation. UnaryArithmeticOperation comprises formulas which require only one operand and takes its operator from the UnaryOperation enumeration, while BinaryArithmeticOperation represents indicators consisting of two operands taking its operators from the enumeration BinaryOperation.

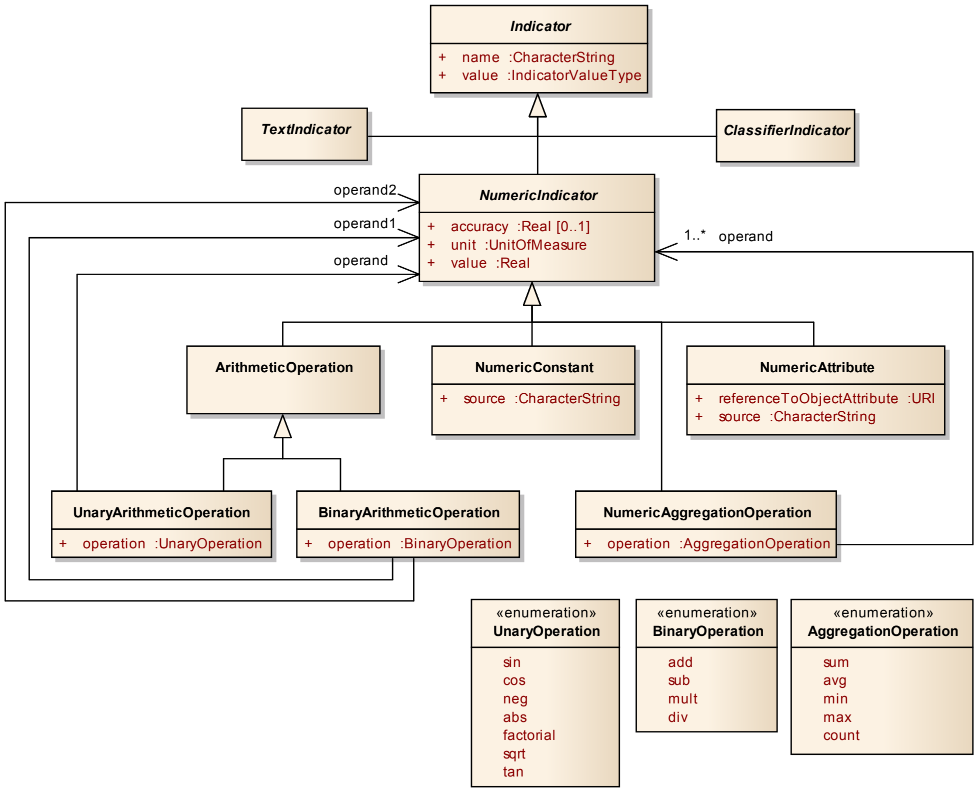

Fig. 2: The General Indicator Model in UML. Names of abstract classes are in italics.

The GIM comprises several of the major features introduced above which allow it to i) augment numeric values with accuracy information to specify the reliability of the data measured, which in figure 2 is represented as an attribute of the abstract class NumericIndicator; this also allows for providing the capabilities for automatic sensitivity analysis which depends on the data accuracy and the computation function; ii) track the data sources, which are provided by attributes in the NumericConstant and NumericAttribute classes, as they allow for verifying the indicator's credibility by storing information about the indicators' origin; iii) compose complex indicators using attribute values from a linked digital city or landscape model, constants (NumericConstant class), and mathematical formulas (unary/binary arithmetic operations); and iv) model aggregations (e.g. summation, average, maximum, etc.) with other indicators, constants or attributes through the NumericAggregationOperation class which allows the representation of indexes. The GIM is defined to be extensible and domain-independent; hence, domain indicator models for different domains can be defined having a generalization relation to the classes of the GIM. Domain-specific indicator classes (e.g. heat energy demand, population change or CO2 emission) can then be defined as specialization of the GIM inheriting the attributes and methods from the abstract indicator classes. This will be explained in more detail in the next section.

3.2 Application of the General Indicator Model to a Case Study

In this section we describe how the GIM framework can be used for automated decision-making. In figure 3 we apply the GIM to a heat energy demand estimation use case in addition to a population growth use case as an example from another domain. In the heat energy demand use case, the buildings of a certain district are to be retrofitted. It is to be evaluated whether after retrofitting the energy demand of the district can be met by using a combined heat and power plant. Thus, we need two important indicators: an indicator representing the heat energy demand for each building before and after retrofitting and an indicator which sums up the energy demand of all buildings within the district. In this way it can be evaluated, if the combined heat and power plant can cover the heat energy demand required by the district.

In domain A, the object-related domain indicators BuildingHeatEnergyDemand and DistrictHeatEnergyDemand, which is an aggregation of the former ones, inherit from the domain indicator HeatDemand. The same concept applies to domain B. The domain indicators for HeatDemand and Population, in turn, inherit from the NumericIndicator which is defined in the GIM. As mentioned in section 2.1, this makes the GIM a reusable component following the MDE approach. Furthermore, an association is established between the object-related domain indicators and the reference objects District and Building. Thus, figure 3 represents abstract GIM classes, concrete indicators from different application domains, object-related indicators, and reference objects which the indicators are related to.

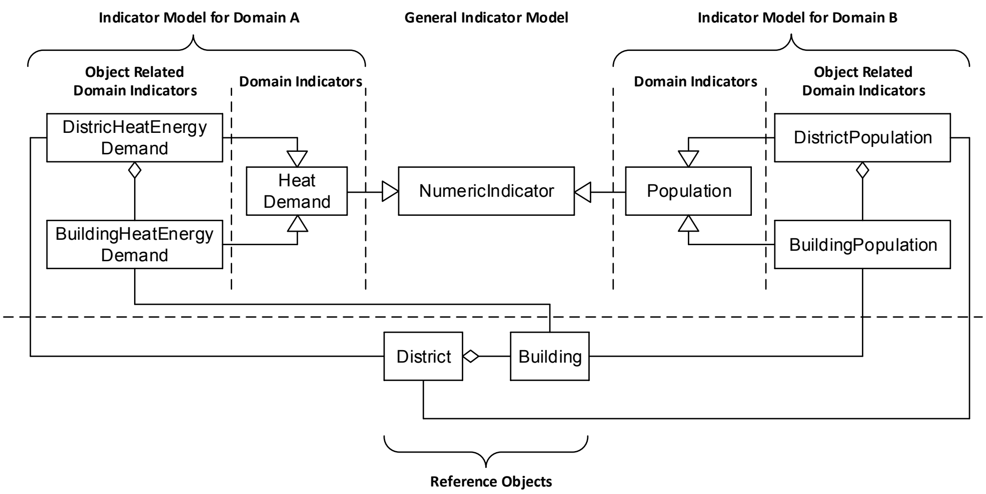

Fig. 3: Indicator Data Model linkage for different application domains.

Figure 4 gives a more detailed view of our approach specifically for the heat energy demand estimation use case. The geospatial application model, representing the geographical context, and the domain indicators are related explicitly using the concept of model weaving. In our use case, the domain indicator HeatDemand, which is derived from NumericIndicator, is specialized to the object-related domain indicators DistrictHeatEnergyDemand and BuildingHeatEnergyDemand, which are then linked to the reference objects District and Building, respectively. The reference objects, in turn, are linked to the classes Building and CityObjectGroup of the geospatial application model (here: CityGML) via the weaving classes BuildingConnector and DistrictConnector, respectively. The value of the indicator is calculated in the compute() method. The computation algorithm of the method is defined using the Object Constraint Language (OCL). For our use case the heat demand for a specific instance of the class Building is computed. OCL rule 1 defines the algorithm for computing the building volume by linking the building object of the geospatial application model with the corresponding reference object. Afterwards, the algorithm provided by OCL rule 2 is used to compute the heat energy demand of the building and store the result in the value attribute of the BuildingHeatEnergyDemand indicator class, which is inherited from NumericIndicator.

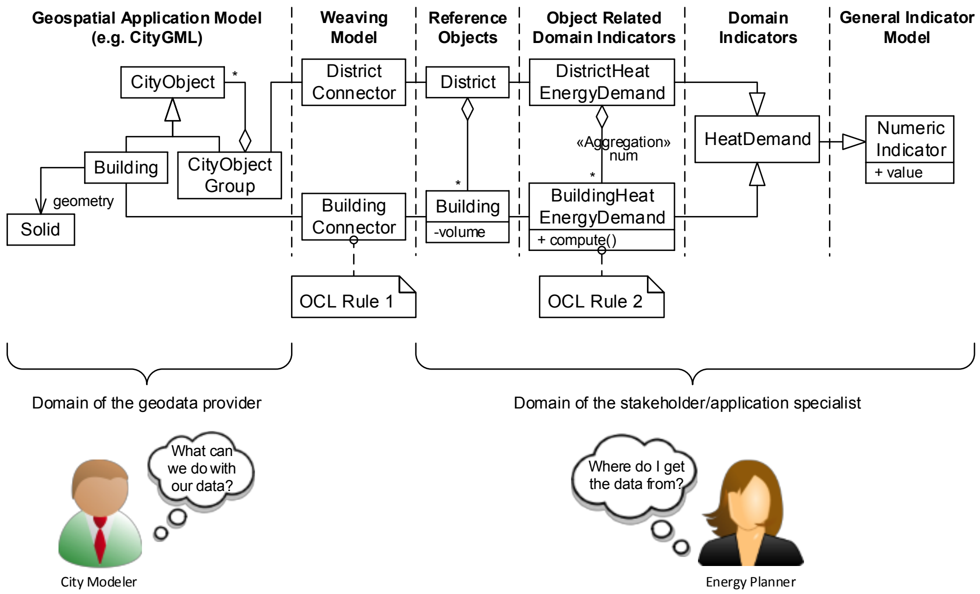

Fig. 4: Model Weaving Concept

Figure 4 furthermore shows that in a real-life scenario there could be on the one side a city modeler who raises the question regarding what to do with the generated geodata and on the other side an energy planner who requires geodata for a specific evaluation task. The city modeler belongs to the domain of the geodata provider, while the energy planner belongs to the domain of the stakeholder/application specialist. The weaving classes fill the gap between these two domains and enable sharing and enrichment of geodata/information.

Figure 5 illustrates another important feature of the model weaving concept. The object-related indicators of domain A and B, as explained in context of figure 3, are connected through the reference object classes to the desired geospatial application models (e.g. CityGML, INSPIRE or Building Information Modeling (BIM)/Industry Foundation Classes (IFC)) via the corresponding weaving classes. This concept of separation allows the representation of the same type of indicator models and reference classes in conjunction with different geospatial data model sources. However, it has to be noted, that it depends on the structure and information richness of the used geospatial application model to which extent the indicator values can be taken, derived, or computed from the linked geospatial feature classes.

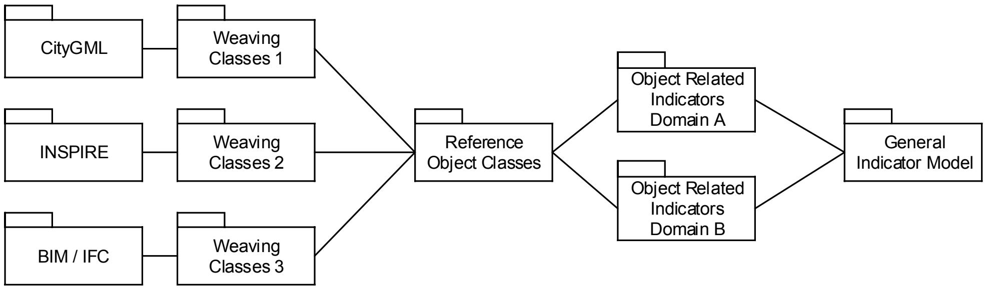

Fig. 5: Weaving Classes between different geospatial application models and the General Indicator Model

4 Related Work

Several approaches for KPI representation that cover some of the previously established dimensions exist. WETZSTEIN et al. (2008) defined a KPI ontology for measuring performance of business processes. The main focus of their research is on KPIs for business processes and how to fill the gap between the business and IT views of business processes which encounter considerable difficulties. They also presented instance metrics, aggregate metrics as well as allowing the calculation of the duration between activities. However, the proposed ontology is domain-specific, covering business aspects; possible relations to geospatial applications have not been investigated. Furthermore, the KPI ontology presented does not define derived measures.

DEL-RÍO-ORTEGA et al. (2010) presented another work that is close to WETZSTEIN et al.'s work. They developed a process performance indicator ontology defining the relationship between the indicators and the elements defined in the business process life cycle from its design to its evaluation. In addition to that, time measure was also introduced which can be used for computing the duration of a certain process. Count measure, which is the number of times that something happens, base, derived and aggregated measures were also covered in this work. It is possible to extend the presented ontology, since it is built upon a formal basis. The ontology is represented using UML, yet the presented indicator model is not related to the geospatial domain.

ZAPATA et al. (2011) used so-called executable pre-conceptual schemas for prescribing convenient knowledge representation of KPIs. Pre-conceptual schemas are shown to be useful as an intermediate step between natural language discourse and UML diagrams. They allow for graphically depicted information in a way that everyone can understand the information they describe (ZAPATA et al. 2011). Nevertheless, pre-conceptual schemas do not specify in detail the different operations or procedures carried out within the domain, because they only refer to the interaction among participants and objects. In other words, this information is not completely clear to the stakeholder, because it reflects the problem structure instead of its functionality. The presented indicator model is not related to the geospatial domain. Moreover, it is not clear if they support sophisticated mathematical calculations, aggregated measures and derived measures, or not.

The above research studies focus on the sectors business, economics, and health and do not apply their work to landscape modelling or the geodesign domain in general. Not all of these research studies represent a data model using a formal modelling language. Also a possible relation to the geospatial domain has not been investigated by them so far.

5 Conclusion and Future Work

Within this paper, we introduced a framework for representing KPIs and demonstrated how to apply this framework to the modelling of specific domain indicators. This is a prerequisite for evaluating alternative scenarios in the context of geodesign. Key aspects for the credibility, reliability, tractability, and accuracy of indicators have been introduced and have been taken into account in the framework development process. Moreover, the framework can be linked to geospatial application models which follow the ISO 191xx series of geographic information standards allowing for its diverse utilization in the geospatial context. Above that, by representing individual indicators as objects we make them first class objects and also make them linkable in this way. Hence, we can model and implement relations between geospatial objects and individual indicators. This is different from previous approaches in GIS where indicators often are represented by attributes of geospatial objects. Thus, in the traditional model we can link to the geospatial object but not to their individual attributes.

Furthermore, a model weaving concept was presented which allows for i) automatically deriving the KPI values from attributes of the geospatial application model and other KPIs – depending on the data available in the geospatial application model, and ii) the enrichment of the geospatial application model by the indicators and indexes. The geospatial application model used in the examples is the international OGC standard CityGML which enables full coverage of city objects of the entire urban area, including geometry, properties, and the topology of buildings (KRÜGER & KOLBE 2012). It facilitates the communication between stakeholders involved in the usage of KPIs (ROJAS & ZAPATA 2013).

Several future research aspects can be identified for the development of indicator modeling. Our next step will be the implementation of our GIM framework, which includes the automatic derivation of computation programs/scripts for the indicators based on the UML and OCL models. Our other future work will focus on dynamic indicator modeling as indicator values can change over time and also error propagation is to be further investigated. Moreover, different geospatial application schemas have to be tested for their compatibility with the GIM and the ability to sustain extensive sophisticated calculations. In parallel to the GIM a complementary concept is developed dealing with urban planning actions. This so-called General Action Model allows for representing complex transactions on geospatial application models (SINDRAM & KOLBE 2014). By linking the GIM with this General Action Model, actions have a direct impact on the indicators, allowing for assessing the impact by using the indicator model.

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