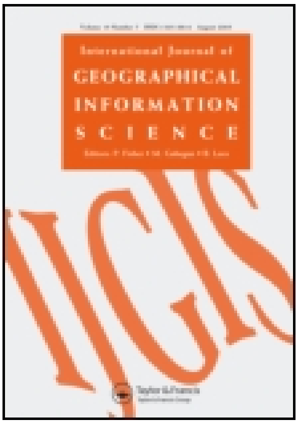

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A framework for uncertainty assessment in simulation models

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In this article, we introduce a conceptual framework for systematic identification and assessment of sources of uncertainty in simulation models. This concept builds on a novel typology of uncertainty in model validation and extends the GIScience research focus on uncertainty in spatial data to uncertainty in simulation modelling. Such a concept helps a modeller to interpret and handle uncertainty in order to efficiently optimise a model and better understand simulation results.

To illustrate our approach, we apply the proposed framework for uncertainty assessment to the *TREE LI*ne *M*odel (TREELIM), an individual-based model that simulates forest succession at the alpine tree line. Using this example, uncertainty is identified in the modelling workflow during conceptualisation, formalisation, parameterisation, analysis and validation. With help of a set of indicators we quantify the emerging uncertainties and assess the overall model uncertainty as a function of all occurring sources of uncertainty.

An understanding of the sources of uncertainty in an ecological model proves beneficial for: (1) developing a structurally valid model in a systematic way; (2) deciding if further refinement of the conceptual model is beneficial for the modelling purpose; and (3) interpreting the overall model uncertainty by understanding its sources. Our approach results in a guideline for assessing uncertainty in the validation of simulation models in a feasible and defensible way, and thus functions as a toolbox for modellers. We consider this work as a contribution towards a general concept of uncertainty in spatially explicit simulation models.

Keywords: model validation; uncertainty; individual based model; tree line

1. Background

Modelling should involve validation and uncertainty assessment as an integral part of the model development process. As spatially explicit simulation models grow in complexity, this fundamental postulation of good academic practice can pose a major challenge. Minor *et al.* (2008) reveal that important factors of uncertainty usually are not considered in the validation of spatially explicit model predictions. Heath *et al.* (2009) found in their review of 279 agent-based models that 65% of these models were incompletely validated and 29% were not validated at all. This unknown amount of uncertainty limits the promising potential of simulation models in contributing to the forecasting of spatial processes and the understanding of process-pattern relationships. Especially simulations using real-world

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data are extremely data-hungry, complex and uncertain (Guisan and Thuiller 2005, Jeltsch *et al*. 2008, Thuiller *et al*. 2008, Ligmann-Zielinska and Sun 2010).

Understanding uncertainty in spatial data and how to handle it adequately has been a serious research challenge over the past two decades (Goodchild 2010). Today, GIScience literature increasingly discusses uncertainty as *not just a flaw that needs to be excised* (Couclelis 2003, p. 166), but an intrinsic property of geographic information (Duckham and Sharp 2005, Roth 2009, Tucci and Giordano 2011), as it is neither possible, nor would it be useful to perfectly represent the real world. Longley *et al.* (2005) define uncertainty as the umbrella term of these imperfections. In the spatio-temporal domain, spatial data quality issues are extended by process quality issues, adding a considerable amount of complexity to traditional approaches for analysing uncertainty. The discussion on model validation has shifted from a mere comparison of model results with empirical data, towards decomposing uncertainty to its contributing sources. For comprehensive model validation, all sources of uncertainty need to be identified and quantified with a set of adequate methods.

For the identification of uncertainties, several approaches of their classification have been discussed in the literature. Uncertainties can originate in the data or in the model itself (Barry and Elith 2006, Turley and Ford 2009). Regan *et al.* (2002) subsumed such uncertainties as 'epistemic' and identify 'linguistic' vagueness as an additional aspect of uncertainty. Foody and Atkinson (2002) used a similar classification of 'measurement' and 'understanding' uncertainty and identified the mixture of these two aspects of uncertainty as challenge in assessing model quality. Renard *et al.* (2011) identified three sources of uncertainty: data uncertainty, uncertainty of model structure, and 'remnant' uncertainty due to inadequacies in the model. Although these typologies are related, they differ to some degree semantically and conceptually.

Methodological approaches for assessing uncertainty mainly address *epistemic uncertainty* relating to limitations of measurement devices, insufficient data, error propagation and stochasticity (Regan *et al.* 2002). Jager and King (2004) reviewed six methods to assess the relationship between spatial uncertainty and model predictions. Crosetto and Tarantola (2001) distinguished between sensitivity analysis for assessing input data quality and uncertainty analysis to assess uncertainties attributed to the model. Grimm *et al.* (2005) introduced 'pattern-oriented modelling' as a validation approach to assess the validity of the model structure through model/reality matching of multiple patterns simultaneously. Harvey and Railsback (2009) focused on data uncertainty and suggested using increasingly abundant fine-resolution remote-sensing data to overcome uncertainty issues due to lacking parameterisation and validation data. Methods to address and quantify *conceptual uncertainties* originating from an incomplete understanding or inadequate representation of the modelled system are rare.

Quantification of uncertainty in complex models is a matter of active research (Larocque *et al*. 2008, Heath *et al.* 2009). However, a comprehensive and generally accepted standard to assess the heterogeneous and intermingled aspects of uncertainty for model validation is still missing, although its need has been expressed repeatedly in the modelling literature (see e.g. Rykiel 1996, Guisan and Thuiller 2005, Parker 2005, Fagiolo *et al.* 2007, Larocque *et al*. 2008). In this article, we contribute towards such a model validation standard and present a framework to systematically investigate and quantify potential sources of uncertainty in a simulation model. As proof-of-concept we apply this framework to the individual-based model (IBM) *TREE LI*ne *M*odel (TREELIM) that simulates the alpine tree line shift (Wallentin *et al*. 2008). We argue that such a concept helps a modeller quantify uncertainty in order to (1) develop a structurally valid model in a systematic way by finding and directly addressing the sources of uncertainty with the highest impact on model results; (2) decide when to stop the modelling cycle, if further refinement of the conceptual model is no longer beneficial for the modelling purpose; and (3) interpret the overall model uncertainty by understanding its sources.

In Section 2, we introduce the conceptual framework for uncertainty assessment and in Section 3, we apply it to the TREELIM case study. By the empirical evidence gained in this case study, we discuss in Section 4 the relevance of the proposed framework of uncertainty assessment to develop and validate simulation models.

2. Framework for uncertainty assessment in model validation

Two approaches to uncertainty assessment can be taken: first, comparison of simulated with empirical data; and second, consideration of uncertainty as a function of all underlying sources of uncertainty. Whereas the first approach jointly assesses the intermingled conceptual and epistemic uncertainty, the second approach addresses epistemic uncertainty only. The framework for uncertainty assessment presented in this article uses both approaches to ultimately determine uncertainty in the conceptual understanding of the modelled system.

Potential sources of uncertainty may be present in each of the five phases of model building (Grimm and Railsback 2005): conceptualisation, formalisation, parameterisation, analysis of results and validation (the *modelling workflow*). The validation process of real-world simulation models measures variation between simulated and empirical data. Therefore, another workflow needs to be considered: the extraction of the objects of interest from the observed reality (*data extraction workflow*). Taking these two workflows as the basis, a structured approach for comprehensive identification and assessment of relevant sources of uncertainty is developed (Figure 1). The range of validation uncertainty in the proposed framework for uncertainty assessment is expressed through minimum and maximum values for each indicator.

2.1. Analysis uncertainty

An analysis turns raw data into useful information. In the case of simulation modelling, raw data refers to both, the outcomes of a model simulation and the empirical data used for its validation. Whether information is useful depends on the model's purpose and the model's context determines the acceptable degree of uncertainty. Analysis uncertainty therefore strongly is related to how well the chosen set of indicators describes the features of interest in the given context.

Thus, an adequate set of indicators is expected to represent all the important aspects of a modelled system, and to equally well describe both, simulated and empirical data. To ensure best possible description of the modelled system at least one indicator for each of the following aspects should be included in the final set of indicators:

- Describe the information that is relevant to the model's purpose, e.g. answer a research question.
- Describe aggregated system level patterns related to the topic of research, e.g. density measures.
- Describe individual level patterns, e.g. attribute distribution.
- Describe processes of interest, e.g. change rates of indicators.

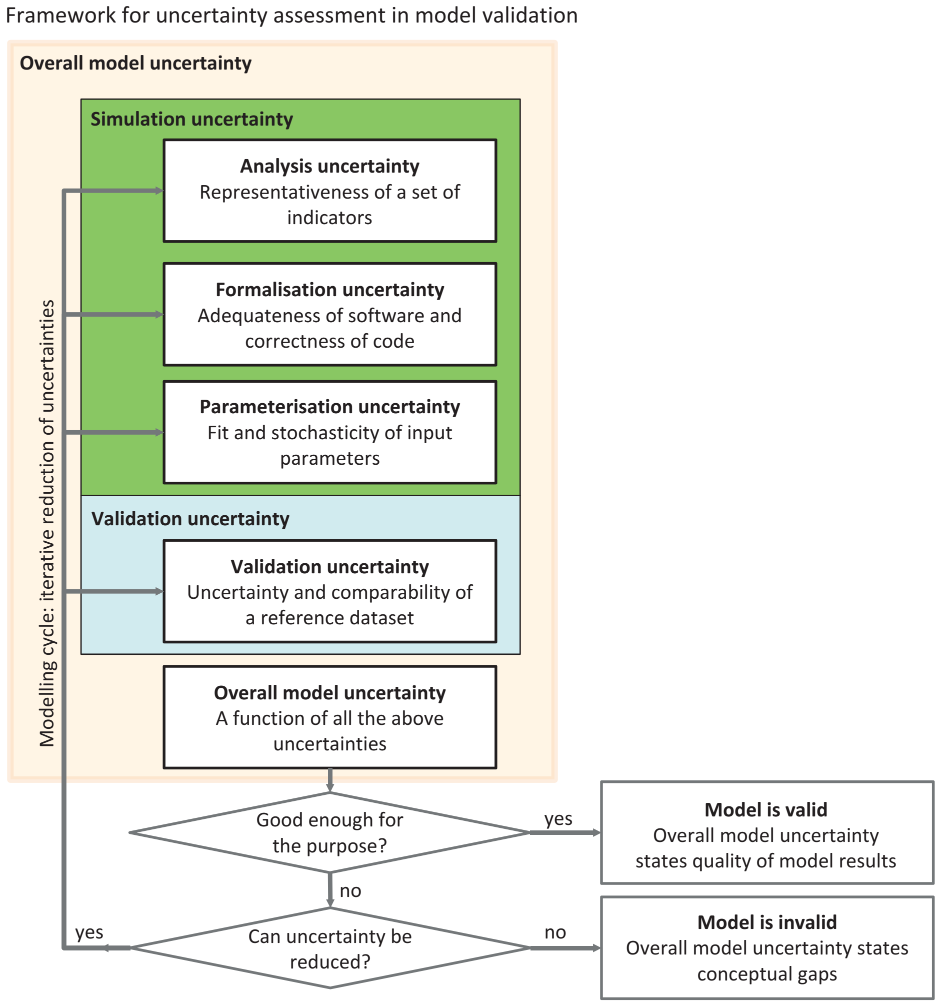

Figure 1. Workflow of uncertainty assessment in a model validation process.

2.2. *Formalisation uncertainty*

Formalisation refers to turning a conceptual model into an executable computer programme (Balci 1997). Whether the model is formalised correctly is assessed in the process of model verification. Formalisation uncertainty can occur due to selection of the software and further in coding within the selected software environment. The magnitude of this uncertainty can be estimated by comparing model results that are based on the same conceptual model but are implemented using different software tools. Further, formalisation uncertainty can be estimated by testing alternative code structures (Turley and Ford 2009).

2.3. *Parameterisation uncertainty*

In this step, the value of each model input parameter is chosen. Uncertainty may arise if these parameters are false, vague or stochastic. Whereas, missing parameters are considered as part of the conceptualisation uncertainty. Model calibration is the process of finding the set of input parameters that make the model output fit best the observed data in order to minimise parameterisation uncertainty (van Ruijven *et al*. 2010). The robustness of a model to alteration of parameter values is analysed through sensitivity analysis, where the input parameters are systematically changed within a range of plausible values. This uncertainty is high if the model is sensitive to small changes in the input parameters. Random or stochastic elements in a model can be addressed through a stochasticity analysis, where repeated model simulation runs show the magnitude of variation in the model output.

2.4. Validation uncertainty

To validate a model, its outcomes are compared to empirical data that represent the features of interest in the real world. However, such real-world representation again is a model and thus uncertain. Therefore, model validation can only be as accurate as the validation data that result from the *data extraction workflow*. Widely agreed spatial data quality standards that report on lineage, positional accuracy, attribute accuracy, logical consistency and completeness (NIST 1994, MacEachren *et al*. 2005, Roth 2009, Skeels *et al*. 2010) can be applied to assess uncertainty of validation data. Respective methods to quantify these uncertainties depend on the acquisition method of the validation data and can include but are not limited to knowledge on data acquisition measurement accuracy or comparison of remotely sensed data with field observations.

2.5. Overall model uncertainty

Overall model (epistemic) uncertainty is composed of all uncertainties that emerge during model development. It is a function of the simulation uncertainty that covers all uncertainties originating in the modelling workflow, and of the validation uncertainty that results from the data extraction workflow. Assuming that the model is successfully verified and well calibrated, the remaining simulation uncertainty is due to stochastic processes.

At this point, the relevance of each source of uncertainty can be understood and also be placed in the context of the overall model uncertainty (see Figure 2). Whether a model needs to be further improved depends on the model's purpose (Figure 1). For example, a weather forecast that predicts a temperature to range between 5°C and 20°C is quite uncertain, but the model would still be good enough if the purpose was to predict days of freezing. In such cases, overall model uncertainty is a statement for the quality of model results. In cases, where uncertainty is too high with respect to the purpose of the model, further reduction of uncertainty is required. The proposed framework allows following an iterative approach to reduce uncertainty, where the sources of uncertainty in the model development workflow are addressed first that contribute most to the overall model uncertainty. If it is not possible to further reduce uncertainty, because of poor validation data or a mismatch between simulated and validation data (Figure 2c and d), the model cannot be successfully validated. Overall model uncertainty in this case describes conceptual gaps and insufficient understanding of the modelled system that are rooted in the conceptualisation phase of model development.

2.6. Conceptualisation uncertainty

Conceptualisation uncertainty refers to the lack of knowledge in terms of the investigated phenomenon itself. Sources of uncertainty during the model conceptualisation can

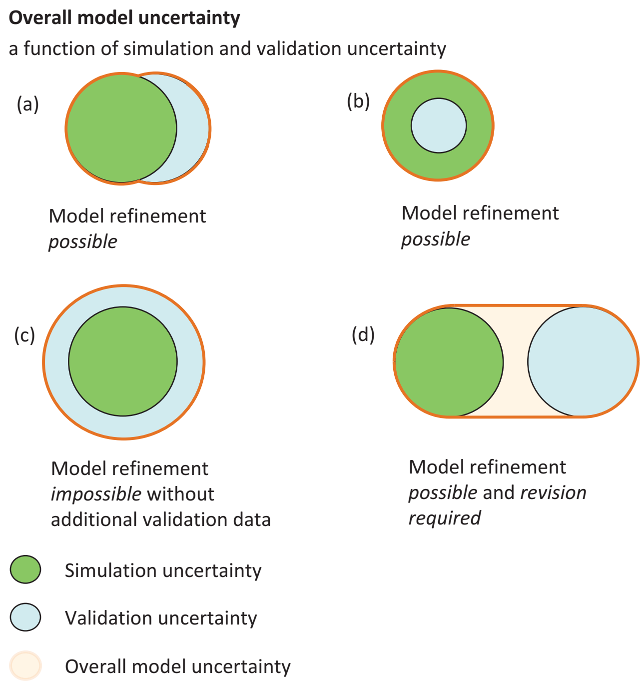

Figure 2. The overall model uncertainty is a function of simulation and validation uncertainty. There are four possible cases of how overall model uncertainty can be determined: (a) simulation and validation uncertainties overlap such that the model either can over- or underestimate reality. (b) The range of validation uncertainty is within simulation uncertainty. (c) Validation uncertainty exceeds simulation uncertainty. Here, the model is more precise than the representation of reality. (d) Simulation and validation uncertainties do not overlap, i.e. the model does not predict reality correctly.

be manifold, originating, for example, in the determination of basic assumptions about objects, processes, attributes, scale, modularisation of model processes and scheduling. Uncertainty at this level can be tackled through comparing scenarios of different conceptual models of the system of interest. By validation of scenarios against empirical data, inappropriate or false assumptions can progressively be excluded. In case of an incomplete specification, uncertainty can be reduced by raising the level of detail in a new modelling cycle.

3. Case study: assessing uncertainty in the TREELIM model

As a proof-of-concept, the conceptual framework for uncertainty assessment introduced in the previous section was applied to the TREELIM. This model is a spatially explicit, IBM that simulates spatio-temporal forest succession patterns at the alpine tree line based on individual tree processes, such as seed dispersal, germination, tree growth and mortality (Wallentin *et al*. 2008). The purpose of TREELIM is to provide an experimental framework to answer the following research question: What are the most relevant processes that drive the upwards shift of the alpine tree line in a spruce-tree dominated study area in Ötztal, Tirol, Austria? Scenarios are formulated to specifically investigate the impact of four driving factors on forest succession: *climate change* that varies

Figure 3. TREELIM scenario for the Ötztal case study: forest patterns in 1954 and 2006.

temperature-induced germination probabilities; *land use change* that varies germination probabilities that are induced through competition with ground vegetation dependent on land use/land cover; *seed abundance* that varies the amount of viable seeds indicating fecundity of forest trees; and *seed dispersal distance* that varies dispersal distances of seeds.

TREELIM was implemented for the Ötztal study area in the time period between 1954 and 2006 (Figure 3). The data used in the model for individual trees (tree location, tree height) and for the environment (land use/land cover, DEM) were derived from remotely sensed imagery: for parameterisation an orthophoto from 1954; for validation an orthophoto from 2006 and a co-referenced LiDAR dataset. Ecological tree process parameters were adopted from the literature.

3.1. Uncertainty in the analysis of model results

Table 1 gives a list of all indicators that were used in an explorative analysis of TREELIM, out of which a set of indicators for further analysis was selected. The first simulation reproduced the patterns in the orthophoto well, although natural reforestation was slightly underestimated. The mean timber line elevation is slightly lower in the model results: 1696 m (simulated) and 1718 m (orthophoto). The huge discrepancy in the number of trees in the orthophoto (2793) and the simulation (7843) relates to a problem in the validation dataset: trees that are either too small to be detected (<4 m height) or hidden under taller trees are invisible in the orthophoto (Figure 4). An adequate set of indicators needed to be selected in order to minimise these uncertainties originating in the *data extraction workflow*. We identified a set of five indicators to be used as assessment criteria for further uncertainty analysis:

(1) Answer the research question: the key indicators that answered the research question were *mean timber line elevation* (mean of upper elevation of forest patches with >50% crown cover) and *mean sparse forest line elevation* (mean of upper elevation of forest patches with >25% crown cover). The distribution of the other values (see Table 1) showed extreme sensitivity to outliers and therefore were considered to be inappropriate as indicators.

Table 1. Explorative model analysis of the first simulation run (sim_v1).

		Analysis uncertainty		
		Orthophoto	Simulation (sim_v1)	Used as indicator?
Information that answers research question				
Timber line elevation	Min	1593	1593	✓
	Max	1853	1753	
	Mean	1718	1696	
Sparse forest line elevation	Min	1590	1593	✓
	Max	1926	1866	
	Mean	1766	1746	
Tree line elevation		2113	2089	
System level patterns				
Number of trees		2793	7843	
Tree density per elevation band			see Figure 5, left	
Total crown cover (m^2)		99,154	70,140	✓
Crown cover per elevation band			see Figure 5, right	
Forest area (dense forest, incl. gaps) (m^2)			20,443	
Ratio sparse/dense forest		1.24	4.05	✓
Crown cover in field plot			–	
Individual level patterns				
Tree height per elevation band			–	
Tree height histogram			–	
Ratio tall (>25 m) *trees/tall trees*$_{real\_06}$		1	0.58	✓
Process descriptor				
Rate of change of crown cover			–	

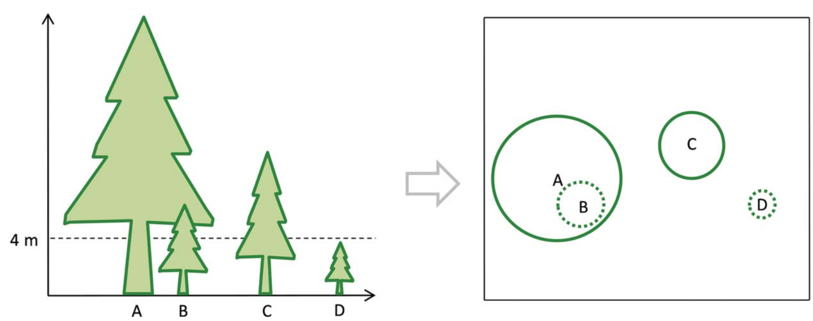

Figure 4. The ‘invisible tree problem’: some trees in a forest stand (left) are invisible in the vertical perspective of an orthophoto (right); either because these trees are hidden below taller trees (tree ‘B’), or because they are too small to be detected, here: <4 m height (tree ‘D’). Only trees ‘A’ and ‘C’ are visible and thus can be extracted from remotely sensed imagery.

(2) System level patterns: crown coverage described well the spatial forest extent. It was preferred over tree density measures that were more prone to the invisible tree problem, which introduced a bias by missing small trees hidden under taller trees (Figure 5). *Total crown cover* and *ratio sparse/dense forest* best described forest extent and forest distribution.

(3) Individual level patterns: only elevation and tree height were direct indicators for trees in both the *data extraction* and the *modelling workflow*. The tree height

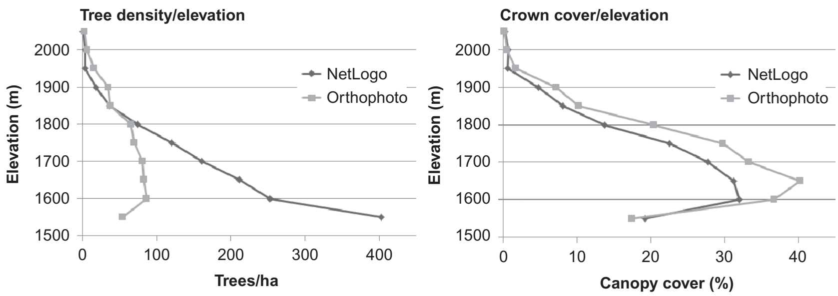

Figure 5. The choice of indicators greatly influences the analysis uncertainty as demonstrated by the two indicators for the same simulation (sim_v1): the tree density per elevation band shows a substantial difference between the real and the simulated system (left), whereas the indicator forest cover per elevation band matches much better between orthophoto and simulation (right).

distribution was an important indicator for the temporal domain, because it helped assess timing of the simulated processes. To minimise bias due to invisible trees, only tall trees were considered. Thus, the ratio between tall trees in a simulated dataset and tall trees as derived from the LiDAR data $tall\ trees/tall\ trees_{real06}$ was chosen as indicator.

(4) Process descriptor: from the above described set of indicators only the calculation of crown cover and the tall trees ratio were computationally simple enough so that it could be used for the temporal analysis in a feasible effort. However, in our study area there was only one orthophoto available for validation so that a temporal indicator could not be validated and was not considered in the final set of indicators.

3.2. Formalisation uncertainty

TREELIM was implemented in two different modelling software solutions to assess formalisation uncertainty: ArcGIS Modelbuilder (ESRI, Redlands, CA, USA) and NetLogo (Wilensky, U., Northwestern University, Evanston, IL, USA). The chosen software imposed restrictions to the implementation of the conceptual model. For example, competition between trees conceptually leads to a higher mortality rate depending on the distance between two trees and the relative tree sizes. In ArcGIS, which is not a true IBM environment, the competition-induced mortality rate was modelled based on a calculation of local tree density with a moving window kernel. In NetLogo the same process was implemented directly as an interaction between individual neighbouring trees. Another restriction related to the number of individuals that could be handled. To overcome this problem the time steps were aggregated into 7-year periods, representing mast-years (Rammig *et al*. 2006). As shown in Table 2, different formalisations produced different results for the same concept and parameters.

3.3. Parameterisation uncertainty

In TREELIM the parameter uncertainty was minimised in a reverse modelling approach by systematically determining parameters that produce the best fitting model results for the available data. The resulting parameterisation with an initialisation phase of 63 years fitted well all indicator values of the validation data (Table 2). Such a systematic analysis

Table 2. Results of the uncertainty assessment in TREELIM for the chosen set of five indicators.

		Timber line elevation (mean) (m a.s.l.)	Sparse forest line elevation (mean) (m a.s.l.)	Total crown cover (m^2)	Ratio sparse/dense forest	Ratio tall (>25 m) trees/tall $trees_{real\_06}$
Formalisation uncertainty	NetLogo	1731	1736	74,967	2.89	0.60
	ArcGIS	1721	1756	73,538	3.85	0.56
Parameterisation uncertainty	stochasticity *range*	1714–1733	1738–1789	112,140–119,406	0.84–1.20	0.88–1.06
Validation uncertainty	ortho-photo	1718	1766	99,154	1.24	1.00
	ortho-photo+	1722	1770	111,490	1.04	1.00
	ortho-photo + +	1732	1828	154,108	0.63	1.01
Overall model uncertainty	simulation uncertainty	1714–1733	1738–1789	112,140–119,406	0.84–1.20	0.88–1.06
	validation uncertainty	1718–1732	1766–1828	99,154–154,108	0.63–1.24	1.00–1.01
	overall model uncertainty	1714–1733	1738–1828	99,154–154,108	0.63–1.24	0.88–1.06
Conceptualisation uncertainty	Scenario *climate change*	1727	1741	129,578	0.80	**1.09**
	Scenario *land use change*	1722	1782	114,136	1.00	0.93
	Scenario *seed abundance*	1731	1747	**63,550**	**3.22**	**0.66**
	Scenario *seed dispersal*	1723	1772	122,162	**0.62**	**1.24**

Note: For the scenarios *climate change, seed abundance* and *seed dispersal* at least one of the indicators exceeds the boundaries of model uncertainty (numbers in bold). A significant impact of these driving factors can therefore be confirmed.

of parameters not only helps finding the best fitting parameters but at the same time acts as sensitivity analysis.

The amount of variability in the TREELIM model was assessed through the range of values that resulted from the stochasticity analysis (Table 2). This stochasticity, inherent to the model itself, is given, for example, by the location a seed would fall from a tree defined by a random direction and a distance along a probabilistic distribution curve. Depending on the amount of stochastic processes in the model, and the runtime for one simulation, this analysis is subject to a trade-off between accurate results based on a high number of repetitions, and feasibility in terms of time spent on computation. In TREELIM the computation time of one simulation run was about 1.5 hours. For a stochasticity analysis with $n = 50$ this analysis took 3 days. Only a case where stochasticity is highly relevant to the overall model uncertainty would justify a higher replication number n.

3.4. Validation uncertainty

In the explorative model analysis, the validation uncertainty in TREELIM was identified to be primarily induced by incompleteness of the reference data through the 'invisible tree problem'. In replacement of the 'invisible' trees, small trees were simulated within the crown radius of visible trees with help of the TREELIM model. To estimate the uncertainty introduced by adding trees, the reference dataset (orthophoto) was compared to the new dataset with additional trees from a 49-year simulation (orthophoto+) and a 98-year simulation (orthophoto++). Beyond 98 years all added trees were tall enough to be visible. Therefore, the 'orthophoto++' dataset represented the upper and the 'orthophoto' dataset the lower limit of the validation uncertainty range (Table 2).

3.5. Overall model uncertainty

The overall model uncertainty of TREELIM is calculated as a function of simulation and validation uncertainty (Figure 2). After successful verification and calibration of the model the remaining uncertainty of a model simulation (simulation uncertainty) is due to stochastic processes and can be represented by the model variability range that resulted from the stochasticity analysis.

In Figure 6, the stochasticity histogram for the indicator *mean timber line elevation* shows the probability with which the model underestimates (14%), overestimates (4%) and correctly represents reality (82%). For the indicator *mean timber line elevation* validation uncertainty is within simulation uncertainty and thus, the overall model uncertainty equals the simulation uncertainty (Table 2). The indicator *mean sparse forest line elevation* has overlapping values for simulation and validation uncertainty. The model underestimates reality with a probability of 77%. The overall model uncertainty ranges over both sources of uncertainty. The indicators *total crown cover* and *ratio sparse/dense forest* show a large range of validation uncertainty, completely covering simulation uncertainty. Here, the overall model uncertainty equals validation uncertainty. For the *ratio tall trees/tall trees$_{real06}$* the validation uncertainty is small with a range of 0.01, 90% of the cases underestimate and 10% overestimate this ratio.

3.6. Conceptualisation uncertainty

We used scenario simulations with TREELIM to investigate the hypothesised driving factors of the alpine tree line shift to improve conceptual understanding of this ecosystem.

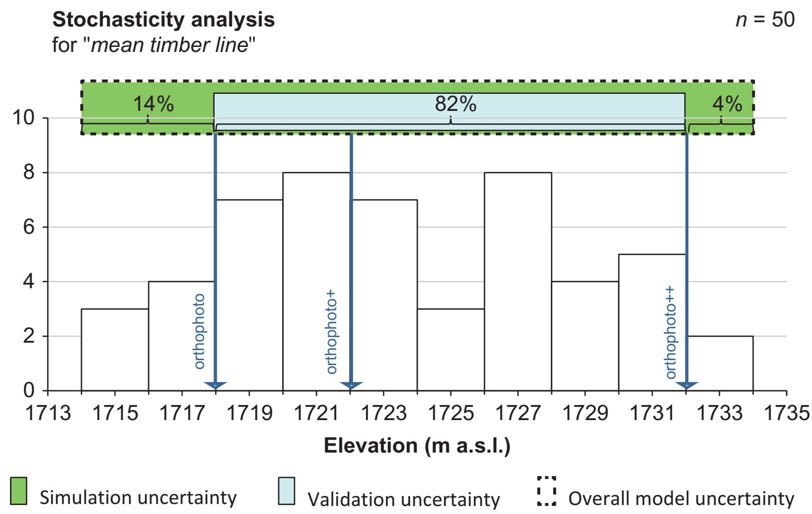

Figure 6. Histogram of the stochasticity analysis for the indicator mean timber line with the corresponding ranges of overall model -, simulation - and validation uncertainty.

Only when the results of these scenarios exceed overall model uncertainty, will the model results confirm significance of a driving factor. Except for *land use change* all scenarios exceed the uncertainty boundaries at least for one of the five indicators, and thus exhibit significantly different patterns (Table 2). Consequently, the TREELIM simulations are proved to be valid for the Ötztal study area in support of the following statements: (1) climate change only marginally accelerated the tree line upwards shift; (2) the tree line shift was not limited by a shortage of viable seeds; (3) spruce seeds were dispersed over far distances, up to 250 m from the seed tree. The model results were too uncertain for the land use change scenario. They neither supported nor falsified the hypothesis that succession processes of the ground vegetation due to land use changes significantly accelerated the tree line shift.

4. Discussion and conclusions

The added value of the proposed framework for uncertainty assessment is given by the structured approach to a comprehensive quantification of uncertainty and to disentangle epistemic from conceptual uncertainties. This way a defensible statement can be given, whether a hypothesis expressed as a scenario can be rejected or not. The framework was successfully tested in the TREELIM case study.

Conceptual gaps of understanding can be termed as ‘unknown unkowns’ in the classification approach of the three levels of uncertainty awareness by Skeels *et al.* (2010): what is actually known (known knowns), what is known that should be known (known unknowns) and unawareness about things that should be known (unknown unknowns). Transferred to the framework of uncertainty assessment, the first level is accomplished in the assessment of sources of uncertainty. The second level of uncertainty awareness could be further reduced in an efficient way with help of the proposed framework by directly addressing these sources of uncertainty that disproportionally contribute to the overall model uncertainty. The list of suggested methods for uncertainty analysis is not comprehensive and exploration of additional methods may be necessary to further reduce the 'known unknowns'. The third level of uncertainty awareness appears as unexplained variation between model outcomes and validation data. Models that simulate real-world data are highly complex in terms of assumptions, abstractions and interacting processes, so that uncertainties most likely outweigh the data available for validation (Crooks *et al.* 2008). To progressively identify these gaps of knowledge in understanding of the system of interest is the basis for development of new hypothesis and simulation scenarios.

Further the proposed framework helps to identify the 'Medawar zone', which is the zone of medium model complexity, for which the greatest pay-off in terms of problem-solving is anticipated (Loehle 1990). After the Occam's Razor principle this optimum is reached by the simplest concept with the fewest assumptions that still answer sufficiently well a research question (Madigan and Raftery 1994, Goodchild 2008). The Medawar zone for simulation models is given, if the model is complex enough to be testable against empirical data and simple enough to explain how the patterns of interest emerge (Grimm and Railsback 2005). Starting from a conceptually simple model, the model is stepwise refined until its uncertainty is sufficiently small to be good enough for the purpose. TREELIM meets both conditions: the model is complex enough to simulate with and test against real world data, which in our case were obtained from remotely sensed imagery; and it is simple enough to explain the emergence of forest succession patterns, driven by the ecological processes of climate change, seed abundance and seed dispersal. We thus are in the position to conclude that TREELIM is in its Medawar zone for three of the four stated research questions. To assess also the impact of land use change, the model would need to be refined with help of further validation data.

Finally, with help of the proposed framework overall model uncertainty could be quantified. It thus serves as a numerical statement for the quality of a model, comparable to the 95% confidence interval for statistical significance. However, stating the validity of a simulation model can probably never be as strikingly simple as the confidence interval (Rykiel 1996). The overall model uncertainty *per se* is insufficient to fully express the multifaceted aspects of uncertainty in a complex model. Quantification of sources of uncertainty helps to adequately interpret simulation results. For example, knowing about the 'invisible tree' problem in the validation dataset prevents the interpreter from drawing premature conclusions about the tree height distribution at the tree line, and knowing about missing time series validation leaves the structural validity of process dynamics an open issue. Aumann (2007) labels this process as 'critique' and introduces it as the third required step of model assessment after verification and validation. Building upon the definition of credibility as the communication of the model's purpose, its performance criteria, its valid context of application and its validation (Rykiel 1996), we argue that a quantitative assessment of the overall model uncertainty as function of its contributing sources is the fifth building block of achieving credibility of a model.

Due to a lack of adequate empirical time-series data uncertainty of spatio-temporal patterns was not analysed in the case study. Absence of adequate time-series data for validation is a common problem in individual-based modelling, as the data are required to be at a resolution of individual agents (Klügl 2008). Although, structural validity of modelled processes can be inferred implicitly if multiple simulated patterns match with empirical data simultaneously (Grimm *et al*. 2005), an explicit validation of spatio-temporal patterns would help to further reduce conceptual uncertainty of underlying process dynamics. To analyse uncertainties in the temporal dimension a process descriptor needs to be included in the set of indicators of the proposed framework of uncertainty assessment. With help of the proposed framework, further research should be directed towards an exploration of spatio-temporal uncertainties in simulation models.

In conclusion, the proposed framework for uncertainty assessment provides modellers with a toolbox to systematically build and validate a model. As successfully demonstrated by this case study, efforts to reduce uncertainty can be efficiently targeted at those sources of uncertainty that contribute most to the overall model uncertainty. Once uncertainty is small enough to fit the purpose, the overall model uncertainty states the quality of model results and the significance of scenarios.

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