Uncertainty propagation in model chains: a case study in nature conservancy

E.P.A.G. Schouwenberg
H. Houweling
M.J.W. Jansen
J. Kros
J.P. Mol-Dijkstra

Alterra-rapport 001

Alterra, Green World Research, Wageningen, 2000

ABSTRACT

Schouwenberg, E.P.A.G., H. Houweling, M.J.W. Jansen, J.Kros and J.P. Mol-Dijkstra, 2000. *Uncertainty propagation in model chains: a case study in nature conservancy.* Wageningen, Alterra, Green World Research. Alterra-rapport 001. 90 p.; 14 fig.; 9 tab.; 36 ref.; 3 annexes

The availability of high-quality models is considered as a critical success factor for Alterra. To answer the complex questions of policy makers it is often necessary to link models that have been developed initially to study more limited questions. When models are linked error propagation may enlarge the uncertainty of the model results. However the quantification of uncertainty propagation may become more complex. This problem of uncertainty propagation in model chains is explored using a chain of the models SMART2/SUMO, P2E and NTM that predicts the potential nature conservation value of natural areas.
Two methods have been explored to study the uncertainty propagation in the model chain, a regression-free method that estimates the uncertainty contributions of groups of sources of uncertainty, and an analysis by means of linear regression approximations of the sub-models of the model chain. The final analysis was done with a regression-free method. The results are presented as the contributions of the various sources of uncertainty to the uncertainty of the potential conservation value. From the results of this study, lessons are learned for the analyses of error propagation in model chains.

Keywords: model chains, NTM, SMART2/SUMO, SMART2, SUMO, uncertainty analysis, uncertainty propagation, WINDINGS

ISSN 1566-7197

This report can be ordered by paying 51,25 Dutch guilders into bank account number 36 70 54 612 in the name of Alterra, Wageningen, the Netherlands, with reference to Alterra-rapport 001. This amount is inclusive of VAT and postage.

Alterra is the amalgamation of the Institute for Forestry and Nature Research (IBN) and the Winand Staring Centre for Integrated Land, Soil and Water Research (SC). The merger took place on 1 January 2000.

Project 636-35374-01 [Alterra-rapport 001/HM/05-2000]

Contents

Annexes

Preface

This project has been carried out within the framework of the program for Strategic Knowledge Development of Alterra, in close co-operation with the Centre for Biometry of Plant Research International. It is one of the projects supervised by VEMI, the Alterra platform that has been established to raise the quality of the models and data used by Alterra.

Summary

The availability of high-quality models is considered as a critical success factor for Alterra. Several models of Alterra are essential tools in the projects for the Dutch Nature Policy Assessment Office (NPB) and the Environmental Policy Assessment Office (MPB). Knowledge of the reliability of the model results is a precondition for the application of these models. To answer the complex questions of policy makers, it is often necessary to link models that have been developed initially to study more limited questions. When models are linked, error propagation may enlarge the uncertainty of the model results and the complexity of the chain with several components and feedback's makes an uncertainty analysis more complicated. To gain insight in this problem of uncertainty propagation we approached the issue from the following research questions:

- how can uncertainty propagation in model chains be analysed?
- how is model input uncertainty translated into model output uncertainty in a real model chain?
- which general recommendations can be made for uncertainty analysis in model chains?

The problem was studied using a model-chain, consisting of the models SMART2, SUMO and NTM. SMART2 and SUMO are fully integrated already. SMART2/SUMO describes nutrient cycling in terrestrial (semi)natural ecosystems and predicts the biomass growth and vegetation succession. Input data for SMART2/SUMO are a deposition scenario and data about soil, hydrology, and vegetation structure and vegetation management. NTM is a model for the prediction of the potential nature conservation value (PCV) of natural areas. SMART2/SUMO is linked to NTM by a module called P2E, that converts mean spring groundwater level and the output of SMART2/SUMO, pH and N availability, into the input for NTM, which means Ellenberg indication values.

To examine the problem of uncertainty propagation in model-chains within a limited period of time, we simplified the problem considerably. Although the model-chain SMART2/SUMO-P2E-NTM is generally used to generate regional or nation-wide images, we only studied a limited number of local spots. Errors in spatial information like soil map and vegetation map were not investigated. Uncertainty in deposition and hydrological scenarios was not considered. The analysis included errors arising from uncertainty about parameter values, given the soil type and the initial vegetation type. Moreover, the analysis included errors in the structure of the sub-models P2E and NTM that showed up during the estimation of the parameters of these sub-models using field measurements. It appeared, not amazingly, that the inputs of these sub-models are not the only factors that influence the output variables in the field: when the inputs are identical, the measurements of the field systems varies more than can be explained by measurement errors. This variation was called ‘unexplained system variation’. For SMART2/SUMO, of which the parameters were estimated previously, only parameter uncertainty was taken into account. In total, 36 individual

sources of error were analysed. Error propagation contributions through the model-chain, was estimated for the following six groups of uncertainty sources having a distinct place in the chain:

- soil related parameters (SMART2/SUMO);
- vegetation-related parameters (SMART2/SUMO);
- P2E parameters;
- NTM parameters;
- unexplained system variation P2E;
- unexplained system variation NTM.

For each group, the contribution to the uncertainty of the potential conservation value (PCV) was estimated.

Two methods have been explored to study the uncertainty propagation in the model chain, a regression-free method that estimates the uncertainty contributions of the above-mentioned six groups of sources of uncertainty, and an analysis by means of linear regression approximations of the three submodels of the model chain.
The final analysis was done with the regression-free method. The analysis was done with and without accounting for unexplained system variation of P2E and NTM. The uncertainty in the model results is most relevant for policy making when two scenarios are compared.

Two policy scenarios and two vegetation management scenarios were considered.
An analysis was done for the policy scenario “business as usual” that supposes unchanged policy concerning deposition, a second analysis was done to compare the scenarios “business as usual” and “European co-ordination” which supposes a decreasing input of potential acid. The analysis was done for uncontrolled succession from bare ground for three soil types and a succession from the current vegetation for one soil type.

The results of the uncertainty analysis of this specific sequence of models are presented as the contributions of the various sources to the uncertainty of the potential conservation value (PCV). When inspecting the difference between the two scenarios, the analysis ends in the following results:

- When the unexplained system variation of P2E and NTM is not taken into account, the SMART2/SUMO vegetation parameters make the largest contribution to the uncertainty of PCV at both succession stages (succession from bare ground and succession of current vegetation). At succession of the current vegetation, the NTM parameters also contribute noticeably to the uncertainty of PCV (*fig. 8, 12*).
- When we take into account the unexplained system variation of P2E and NTM, the USV of P2E also contributes much to the uncertainty of PCV. This contribution decreases in the long run (*fig. 10, 14*).
- There is little influence of the soil type in the case of succession from bare ground. We did not examine the influence of soil type in the case of succession of current vegetation.

When the absolute potential conservation value is examined rather than the difference between to scenarios, the contribution of the unexplained system variation of NTM to the uncertainty of PCV is important (*fig. 9, 13*). When the unexplained system variation is left out of consideration the vegetation-related parameters of SMART2/SUMO, the P2E parameters and NTM parameters contribute most to the uncertainty of PCV. The results also illustrate the more general phenomenon that absolute predictions tend to be less accurate than relative predictions. The variance of the difference between the predicted conservancy values of two scenarios had much smaller values than the variance of the individual predicted conservancy values. Some sources of uncertainty, like unexplained system variation, more or less cancel out when differences are analysed. This is a fortunate circumstance, since differences between scenarios are more relevant for decision making.

We conclude that in this specific case only at managed vegetation development the uncertainty analysis makes sense. At unmanaged vegetation development from bare ground, the vegetation structure and the related nutrient catchment change so radically that the difference due to the two atmospheric deposition scenarios is negligible.

Lessons learned for the analyses of error propagation in model chains are:

- For the analysis of the error propagation in a model-chain like the slightly simplified one studied in this project, the required knowledge and tools are available.
- The main problem is the limited information about the uncertainty of the relevant input data and model parameters. A second problem is the limited possibilities to gain insight in the unexplained system variation in models like SMART2/SUMO.
- In general, the uncertainty analysis asks a substantial effort, even when important aspects like the uncertainty in soil- and vegetation maps are left aside. The most labour-intensive and time-consuming activities are data collection about uncertainty of model inputs and parameters. However, the results of this latter effort can be used in new applications of the model-chain.
- Uncertainty propagation in vegetation and conservation value modelling creates a new need for data. There is a considerable backlog on quantification of uncertainty of model inputs and on documentation of parameterisation.
- With regard to uncertainty analysis, model chains are not different from any kind of complex models arising by combining existing sub-models. However only scientific problems are considered here, there may be serious management problems when sub-models and data come from different organisations.

1 Introduction

The interest of Alterra

Simulation models play an important role in the research at Alterra. The quality of these models is considered as a critical success factor. Several models of Alterra are essential tools in the analyses by the Dutch Nature Policy Assessment Office (NPB) and the Environmental Policy Assessment Office (MPB). To answer complex questions of policy makers models are linked that initially have been developed to study more limited questions. When models are linked some additional problems arise. Error propagation enlarges the uncertainty of the model results and the complexity of the chain with several components and feedback's makes the uncertainty analysis more complicated. Therefore, in the framework of the Alterra programme for Strategic Knowledge Development (Dutch: Strategische Experise Ontwikkeling, SEO), a pilot project has been carried out to gain insight in error propagation and uncertainty aspects of model chains.

The research questions are:

- how can uncertainty propagation in model chains be analysed?
- how is model input uncertainty translated in model output uncertainty in a real model chain?
- Which general recommendations can be made for uncertainty analysis of model chains?

A simple chain of models

In this project uncertainty propagation was studied in a chain of models that is not extremely complicated at first sight. This chain consists of the models SMART2 (Kros et al. 1995), SUMO (Wamelink et al. 2000) and NTM (Wamelink 1997, Schouwenberg in prep.). SMART2 describes nutrient cycling and soil acidification in terrestrial (semi)natural ecosystems. SUMO models biomass growth and vegetation succession and NTM predicts the potential nature conservation value of semi natural ecosystems. SMART2 and SUMO have been fully integrated into one model SMART2/SUMO. SMART2/SUMO is linked to NTM by a conversion module called P2E, that converts mean spring groundwater level and the output of SMART2/SUMO, pH and N availability, into suitable input for NTM, Ellenberg indication values. An interesting aspect of the use of the SMART2/SUMO-P2E-NTM chain in this project is the nature of the models that comprise this chain. SMART2/SUMO is a process model, built up from the mathematical description of physical, chemical and biological processes whereas NTM is a descriptive model that relates measurements of abiotic variables to the conservation value of the spot. They represent two important model types that are developed and used by Alterra. Although the model chain SMART2/SUMO-P2E-NTM will play an important role in the outlooks of NPB and MPB we just use it as an instrument to study the subject of uncertainty propagation in model chains. The results of this project are evaluated and generalised in such a way that they are useful for future analyses of other chains of models.

Uncertainty
Uncertainty analysis translates model input uncertainty into model output uncertainty and pinpoints the inputs that contribute most to output uncertainty. The analysis gives an impression of the accuracy of the predictions of the model study, and suggests ways to improve the accuracy. There is an extensive experience with the sensitivity and uncertainty analysis of more or less complex models. The chains of models studied here has the peculiarity that the need to link the models arose after the components SMART2, SUMO and NTM were developed as separate models with their own limited area of application. The conversion module P2E was needed to link SMART2/SUMO to NTM.

Uncertainty analysis of a model study begins with making up an inventory of the sources of error for the case at hand. In the type of uncertainty analysis discussed here -- the most common one -- uncertainty in a source of error is modelled by considering these sources as random vectors, which are input to the model. The specification of the distributions of the sources of uncertainty is by far the most difficult stage of an uncertainty analysis. The last stage of the analysis translates the uncertainty in these sources into model output uncertainty (randomness) and pinpoints the inputs, or groups of inputs, that contribute most to output uncertainty.

There are several sources of uncertainty; the scenarios that have to be analysed, initial values, parameter values and the mathematical formulation and structure of the model. To explore the problem of uncertainty propagation in model chains within a limited period, we have defined a simplified problem. Firstly errors in exogenous variables like deposition and hydrological scenarios were not considered. Secondly the model chain SMART2/SUMO-P2E-NTM is normally used to generate regional and nation wide images but we did the analysis for a limited number of local spots. Errors in spatial information like soil map and vegetation map were left out of consideration and deposition and hydrological scenarios were taken for sure. The analysis was delimited to uncertainty originating from errors in parameter values and model structure. For SMART2/SUMO only parameter uncertainty was taken into account. The analysis focussed on six groups of model-input data and parameters, covering 36 sources of uncertainty. For each group, the contribution to the uncertainty of the output of NTM (the potential conservation value PCV) was estimated. The models are validated in the project 'Validation Natuurplanner' (Wamelink et al. 2000).

Outline of the report
Chapter 2 describes the components of the chain of models: SMART2/SUMO, NTM and the module P2E that has been developed to convert the output of SUMO to input for NTM. In chapter 3 we present an overview of the sources of uncertainty in the chain of models. In Chapter 4 the methods are discussed that were used in this study. Two methods have been applied; a Monte Carlo type method, the regression free windings stairs analysis and a method where variance contributions are estimated by means of linear approximations of the modules in the chain. In chapter 5 the results are presented. The uncertainty propagation in the model chain is quantified. The uncertainty in the outcome for various scenarios, the uncertainty in the

comparison of scenarios and the relative contributions of the various sources of uncertainty are presented. In the last chapter lessons learned and suggestions for further model development are given.

2 The case study: model chain and experimental design

2.1 The case study

In the case study uncertainty propagation is studied in the chain consisting of the models SMART2/SUMO, P2E and NTM. An advantage of the use of the SMART2/SUMO-P2E-NTM chain in this project is the nature of the models that comprise this chain. SMART2 and SUMO are process orientated models, built up from the mathematical description of physical, chemical and biological processes while NTM and P2E are statistical models that relate the values of observed parameters to a judgement of the potential conservation value of the spot. They represent two important model types that are developed and used by Alterra.

2.2 Description of the model chain

The model chain consists of three models (figure 1). The first model is the soil-vegetationsuccession model SMART2/SUMO that calculates abiotical quantities and succession stages. The last model, NTM calculates the potential conservation value for the considered situation. A conversion model P2E that converts the abiotical output from SMART2/SUMO into Ellenberg indication values for NTM links both models.

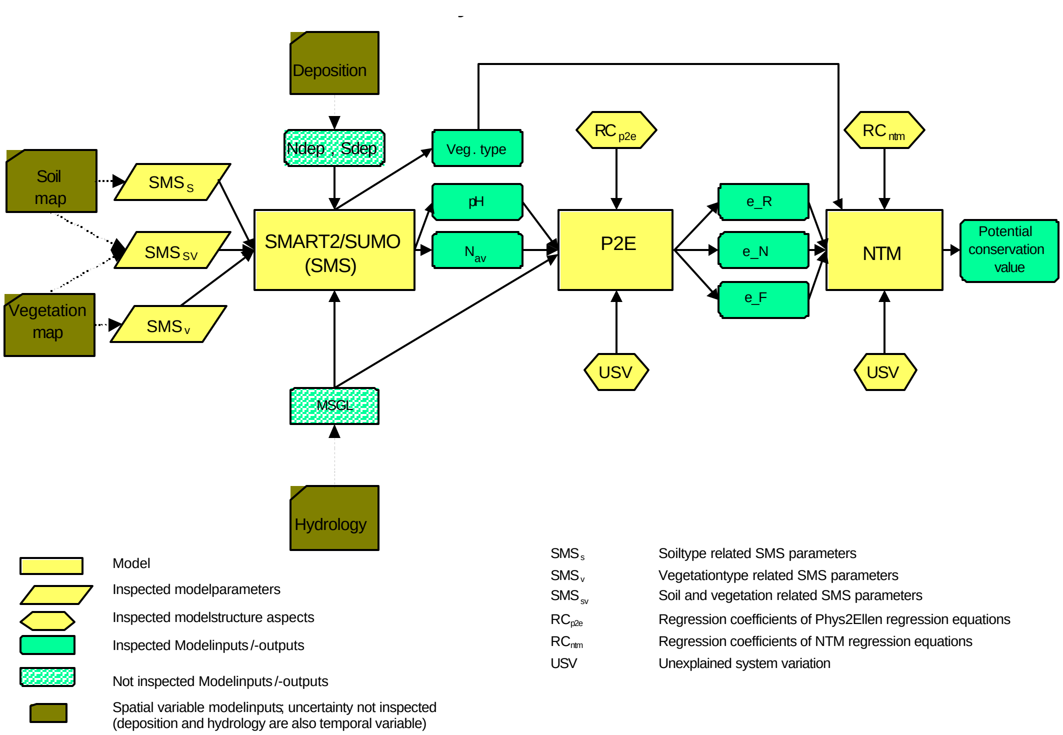


Figure 1: The model chain SMART2/SUMO-P2E-NTM

Input data for the SMART2/SUMO application at a national scale can be divided into system input such as deposition and hydrology and initial values of variables and parameters. Input data refer to: (i) a specific deposition scenario for each gridcell, (ii) model variables and parameters that are either related to a soil type (SMS_s) or to a vegetation type (SMS_v) or a combination of both (SMS_{sv}), and (iii) soil and vegetation maps. The mean spring groundwater level (MSGL) is derived from the groundwater table class from the 1:50,000 soil map and is kept constant. Outputs of the model SMART2/SUMO are the abiotic quantities pH, and N availability and the biotic quality vegetation type or succession stage.

The model P2E converts pH, N availability and MSGL to Ellenberg indication values for respectively acid (e_R), nutrient availability (e_N) and moisture (e_F). At the end, NTM uses these Ellenberg indication values to predict a potential conservation value (PCV) for each gridcell.

Uncertainties in parameters related to soil type (SMS_s), parameters related to vegetation type (SMS_v) and regression coefficients (RC) were considered. Occasionally, however, for instance during the parameterisation of a model, one may identify and quantify model errors of a type that will be called unexplained system variation (USV). This also appeared for P2E and NTM (see section 3.1). The unexplained system variation of SMART2/SUMO was not known and was therefore left out of consideration. Parameters that were related to a combination of soil type and vegetation type (SMS_{sv}) did not occur; hence we did simulations per soil type (see section 2.3).

2.2.1 SMART2/SUMO

SMART2 (Kros et al. 1995) is a simple one-compartment soil acidification and nutrient cycling model that includes the major hydrological and biogeochemical processes in the vegetation, litter and mineral soil. Apart from pH, the model also predicts changes in aluminium (Al^{3+}), base cation (BC), nitrate (NO_3^-) and sulphate (SO_4^{2-}) concentrations in the soil solution and solid phase characteristics depicting the acidification status, i.e. carbonate content, base saturation and readily available Al content. The SMART2 model consists of a set of mass balance equations, describing the soil input-output relationships, and a set of equations describing the rate-limited and equilibrium soil processes. The soil solution chemistry in SMART2 depends solely on the net element input from the atmosphere and groundwater, canopy interactions, geochemical interactions in the soil and a complete nutrient cycle for basic cations and N. The description is based on the assumption that the amount of organic matter (C) is proportional to nitrogen (N). N mineralisation is described in SMART2 by a first order reaction. Litterfall and growth of the vegetation are modelled by the succession model SUMO (Wamelink et al. 2000), that was incorporated in the model SMART2 in 1998 (figure 2). Depending on the amount of available nitrogen (N_{av}) (2 in figure 2), SUMO calculates biomass growth, root uptake and amount of litterfall (3 in figure 2). In the same time step (=year) SMART2 calculates the mineralisation fluxes, using vegetation parameters which are biomass weighted averaged (4 in figure 2) and calculates the amount of available N (N_{av}) and foliar uptake for the next time step (5 in figure 2).

SUMO simulates the growth of five functional vegetation types: herbs, dwarf-shrubs, shrubs, pioneer trees and climax trees. The newly formed biomass is divided into three organs: roots, stems and leaves. The nitrogen-content of the types is varied according to the N-availability that is yearly calculated by SMART2 (2 and 5 in figure 2). Biomass growth is influenced by three main factors: N availability, light availability and management. The total canopy uptake is calculated as a fraction from the deposition and is input for SUMO. The nitrogen availability in the soil is divided between the functional types based on the root biomass per type up to a maximum. Canopy uptake is divided between the types similar to light. Light is available for the different types depending on the length of the type (the tallest first) and the leave biomass according to the extinction formula of Lambert-Beer. Management, for the time being this is only mowing, influences the growth through the removal of biomass. The amount of biomass per type defines in what succession stage the vegetation is (grassland, heath, shrub, forest), so succession from grassland to forest can be simulated.

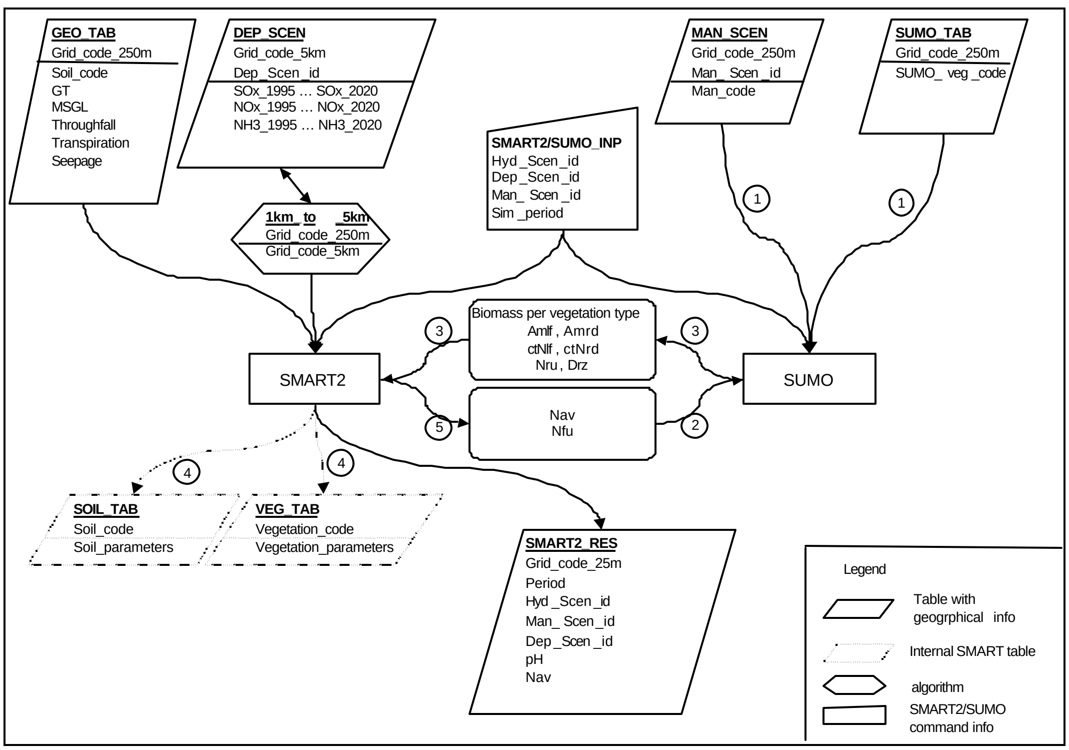


Figure 2: Entity relation diagram SMART2/SUMO

2.2.2 NTM

The statistical model NTM 3.0 is the end of the model chain SMART2/SUMO-P2E-NTM. The model was developed to predict the potential conservation value of natural areas in The Netherlands. Normally conservation values are calculated on the basis of plant species or vegetation types (Clausman et al. 1984, Wheeler 1988, Hertog & Rijken 1992, Witte & Van der Meijden 1992, Bal et al. 1995). This can simply be done for the present situation. For the future however it would be necessary to precisely predict the occurrence of plant species. The uncertainty of this prediction is expected to be high (Van Wirdum 1981). There are several, rather uncertain factors influencing the occurrence of plant species, e.g. distribution of species, presents of a seedbank.

Soil conditions and the development of the vegetation structure can be predicted more precisely. NTM has the possibility to link the vegetation and the site conditions by using ecological indicator values (Ellenberg et al. 1991) of plant species.

The basis of the NTM-model is the so-called NTM-matrix. In the NTM-matrix the habitats of plant species are defined on the basis of moisture, acidity and nutrient availability (figure 3).

The model was calibrated using a calibration set of 160,252 vegetation relevees (Schouwenberg in prep.). A value index per plant species was defined on the basis of rarity, decline and international importance. This index was used to determine a conservation value for each relevée. The value per relevée was then assigned to each species in the relevée and regressed on the Ellenbergs indicator values (Ellenberg et al. 1991) for moisture (e_F), acidity (e_R) and nutrient availability (e_N) using a statistical method (P-splines; Wamelink et al. 1997).

The model has these three Ellenberg indication values as input for the prediction of the potential conservation value. Therefor the abiotic output of SMART2/SUMO has to be translated into Ellenberg indication values, using P2E.

As seen in section 2.1.1 the SMART2/SUMO abiotic output used –after conversion- for NTM are soil acidity and N availability. Another output of SMART2/SUMO used by NTM is the vegetation structure.

A measure for moisture is normally produced by a hydrological model. In this study the MSGL was used and kept constant (3 meters below surface).

After conversion of the mentioned abiotic variables, a potential conservation value is calculated for a combination of the abiotic conditions and vegetation structure (ecotope). Therefore four vegetation types are accounted for, each represented by a submodel of NTM: heathland, grassland, deciduous forest and pine-forest.

Potential conservation value (PCV)
The term potential conservation value is used, because it is the conservation value that potentially can be realised on a certain spot. The occurrence of plant species and the actual realisation of the conservation values depends on several rather uncertain factors other than just abiotic conditions defined by moisture, acidity and nutrient availability. Whether a conservation value finally can be realised depends on factors like distribution of plant species, dispersion, presence of a seedbank and management.

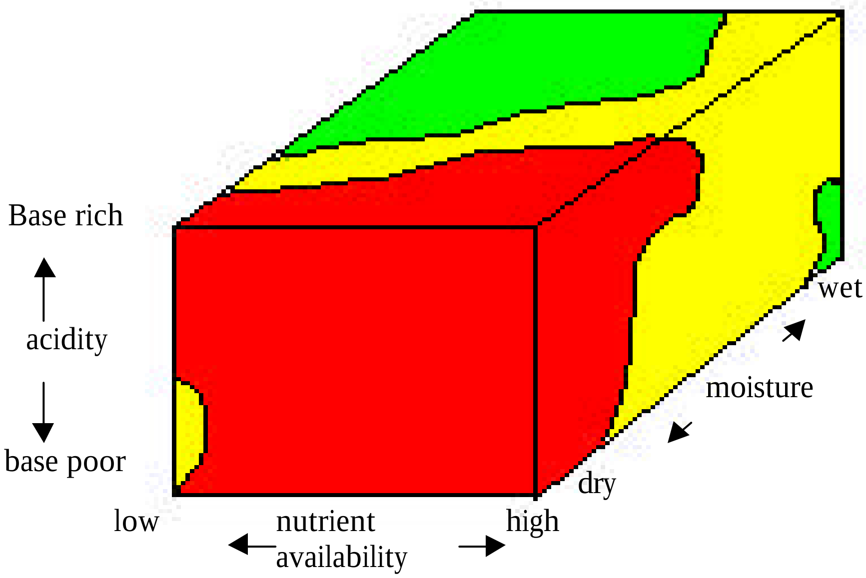


Figure 3: NTM-matrix

2.2.3 Conversion model P2E

As described in section 2.1.1 the abiotic output of SMART2/SUMO and the MSGL can only be used by NTM after a translation into Ellenberg indication values. The conversion model P2E does this translation. The conversion model P2E converts MSGL, pH and N availability to Ellenberg indication values e_F, e_R and e_N. For the conversion simple regression analysis were used.

MSGL and N availability are directly translated into indication values. For the translation of MSGL into e_F and N availability into e_N data from Alkemade et al. (1996) and Liefveld et al. (1998) were used. The following regression equations were used:

$$e\_F = 1.069 + 6.850 * 1.5331^{MSGL} + \varepsilon\_e\_F$$

with : e_F: Ellenberg indication value for moisture
MSGL: Mean Spring Groundwaterlevel (meters below surface)

$$e\_N = ((N_{av} * 14/1000) - 8.125)/16.25 + \varepsilon\_e\_N$$

with: e_N: Ellenberg indication value for nutrient availability
N_{av} = N available (mol N ha^{-1} a^{-1}).

For the conversion of pH an extra step had to be made. The pH resulting from SMART2/SUMO refers tot the pH of the soil solution (pH_{sms}), whereas the pH used for NTM refers to the pH_{H2O} (Schouwenberg, in prep.). In order to convert the pH_{sms} to pH_{H2O} we used linear relationships as derived in Kros (1998; see section 3.3 and 3.4). These relationships are based on soil samples from about 300 forested monitoring locations in The Netherlands. Where the pH_{sms} is measured in the soil solution obtained by centrifugation from a freshly taken composite sample, and the pH_{H2O} according to the standardised soil analysis procedure (i.e. shaking a dried soil sample with demineralised water using a volume based soil/water of 1:5). A different equation was derived from the data for clay and sandy soils.

$$pH_{H2O}=0.7424+0.8708*pH_{sms}+\sigma_{soil}*\varepsilon\_pHpH$$

with: $\sigma^2_{clay}=0.1045$
$\sigma^2_{sand}=0.0052$.

For the translation of pH_{H2O} into e_R, data from Wamelink & Van Dobben (1996) were used (see section 3.3). The regression analysis resulted in the following equation:

$$e\_R = -0.2215 +0.8876*pH_{H2O}+\varepsilon\_e\_R$$

with: e_R: Ellenberg indication value for acidity.

A more precise description of how the equations and uncertainties of parameters and unexplained system variation were derived is given in section 3.4 and appendix 2.
As can be seen in section 3.4 the uncertainties in P2E are very high. Therefore it would be favourable to use SMART2/SUMO output direct as input for NTM, without conversion into Ellenberg indication values. This can't be done at this moment because there are to few data available for a satisfactory calibration.

2.3 Experimental design

Usually, the model SMART2/SUMO is applied at the national scale, which means a simulation for each 250 × 250 m gridcell with nature in The Netherlands. In order to reduce the amount of calculations for the uncertainty analyses, a few assumptions were made. Firstly, uncertainties in the maps as such were not considered. Instead, we analysed the uncertainty propagation for three soil types: Sand Poor (SP) and Sand Rich (SR), which have strong similarities and non-calcareous clay (CN), a different soil type (Table 1). For each soil type the same initial succession stage was chosen, which was a succession starting with bare ground. For the soil type SR, a second succession was simulated, viz. continuous spruce forest. This was done to simulate an existing situation, without a strong increase of N availability due to succession. These four situations were simulated with two levels of deposition. The first scenario had a constant potential acid input of 3193 $mol_c ha^{-1}a^{-1}$ and was called the business as usual scenario (BU). The second deposition scenario was the

European co-ordination scenario (EC) with a decreasing input of potential acid in three steps from 3193 $mol_c ha^{-1}a^{-1}$ in 1995 to 2302 $mol_c ha^{-1}a^{-1}$ in 2020 (Table 2).

Table 1: Overview of simulated situations

Succession	Soil Type	Deposition scenario	
Bare ground --> forest	SP	BU	EC
	SR	BU	EC
	CN	BU	EC
Forest	SR	BU	EC

Table 2: Deposition ($mol_c ha^{-1}a^{-1}$) for the EC-scenario

Year	SO_x	NO_x	NH_3
1995	1074	802	1317
EC			
2000	795	688	1170
2010	620	648	1012
2020	660	700	942

For each situation 6000 Monte Carlo runs were realised. Output was generated after 0, 10, 30 and 100 years of simulation. NTM calculated potential nature values for each realisation at these four points in time.

3 Inventory of sources of uncertainty

3.1 Sources of error

Prediction errors in model studies arise in several ways, in particular by (i) exogenous variables that do not develop as assumed; (ii) by errors in initial values; (iii) by errors in parameter values; and (iv) by errors or simplifications in the model structure. The model structure is the skeleton of the model, in which the quantities just mentioned are unspecified.

i. Exogenous variables

Errors in exogenous variables were not considered in the present study: the deposition and hydrological scenarios were taken for sure.

ii. Errors in initial values

For SMART2/SUMO only errors in initial values were taken into account.

iii. Errors in parameter values

Errors in parameter values of SMART2/SUMO occur because the qualitative soil and vegetation maps contain errors. These will not be considered, because of the complexity of accounting for such errors has been described in Kros et al. (1999). An example of how to account for such errors. But even if the qualitative maps would be perfect, the qualitative features considered do not perfectly determine the quantitative parameters used by SMART2/SUMO.

The parameter values of P2E were estimated by standard regression analyses (Section 3.4.2.). These analyses provide standard errors and correlation's of estimates, which were used in the subsequent analysis.

The mean response of NTM was estimated from a sample of 160,252 vegetation relevées each producing a measurement of the NTM inputs and the conservation value. The response fitted has the form of a penalised regression spline, which has a large number of parameters. For that reason, the uncertainty in the mean NTM response has been assessed by a bootstrap method: the mean response was calculated for a number of bootstrap samples from the original data set, and the uncertainty in the mean response is represented by randomly choosing one of these responses. Nevertheless, this is a form of parametric uncertainty.

iv. Errors or simplifications in the model structure

Most often, in an uncertainty analysis, model structural errors remain out of sight: in absence of counter-evidence, it is assumed that the model structure is correct, and the analysis only studies how input uncertainty propagates through the model as it is. An obvious type of structural error is the omission of a process that has little effect on a small time-scale, but gains importance on larger time-scales. Such a process can easily be overseen when the model is parameterised and tested using data collected over a short period of time, but it may cause sizeable prediction error in a long-term model study. Occasionally, however, for instance during the parameterisation of a sub-model, one may identify and quantify sub-model errors of a type that will be called unexplained system variation. Such errors can be quantified and incorporated in the uncertainty analysis.

The notion of unexplained system variation will be introduced by an example. In Section 2.2.3 we saw that the conversion model P2E translates the soil acidity pH_{SMS} resulting from SMART2/SUMO, into the Ellenberg indication value e_R, which is input to NTM. The conversion takes place in two steps: first pH_{SMS} is translated into the soil acidity pH_{H2O} and next pH_{H2O} is translated into e_R. We will discuss the first step. Analysis of the data set with measurements of both types of soil pH provides evidence that pH_{SMS} does not uniquely determine pH_{H2O}, even if one takes into account that both pH's are measured with some known variance (which we took to be 0.05): if there would be a perfect relation between the two pH's, the scatter plot of the measurements of them would be more slender than it actually is.

The uncertainty that remains when predicting pH_{H2O} given pH_{SMS}, after measurement errors have been allowed for, will be taken into account as 'unexplained system variation'. This uncertainty comes on top of the customary uncertainty about the parameters of the regression formula.

Figure 4a and 4b give new realisations of pH_{H2O}, given a set of 1000 given values of pH_soil. The first for clay with unexplained system variation, the second for clay (or sand) without unexplained system variation. Note the dramatic difference.

In our study of the model-chain, we observed some unexplained system variation in the conversion model P2E, and considerable unexplained system variation in NTM, where it was seen that the three Ellenberg indication values do not uniquely determine the conservation value (which comes as no surprise: other factors than the three considered, e.g. kinds of conservancy measures, have considerable influence on the conservation value).

The concept of unexplained system variation is implicitly present in the well-known calculation of confidence bounds around a regression line, discussed in many statistics textbooks (e.g. Draper & Smith 1998 p80-83; or Oude Voshaar 1994, p69). The point made in these books is that there is a difference between the uncertainty about a new observation, and the expected value of a new observation, but the textbooks do not make a distinction between measurement errors and unexplained system variation.

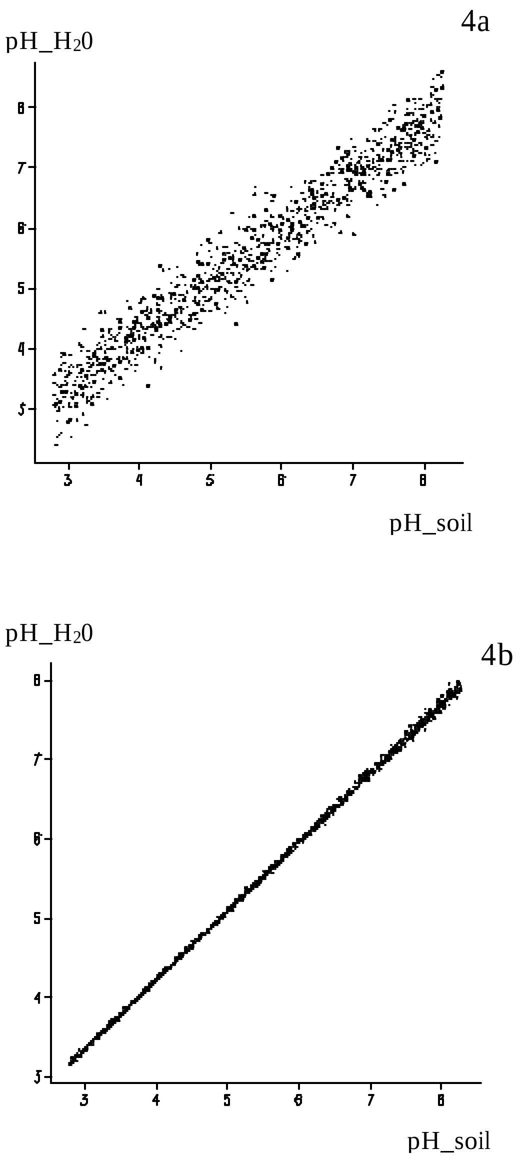


Figure 4 New realisations of pH_{H2O}, for clay with unexplained system variation (4a) and without unexplained system variation (4b)

3.2 Grouping of sources of error reflecting chain character

In the uncertainty analysis of the model-chain, 36 inputs, pooled in six stochastically independent groups of inputs, are discerned, connected to different components of the model-chain. The groups will be named ‘vegpar’ (13 SMART2/SUMO vegetation parameters); ‘soilpar’ (11 SMART2/SUMO soil parameters); ‘p2epar’ (7 conversion-model parameters); ‘p2eusv’ (3 numbers expressing unexplained system variation in the conversion model); ‘ntmusv’ (1 number expressing unexplained system variation in NTM); and ‘ntmpar’ (NTM’s response uncertainty: 1 random number pointing to the collection of bootstrap responses).

3.3 Overview of inspected parameters and unexplained system variation

In order to restrict the number of Monte Carlo simulations we have tried to limit the number of inspected input data. In the used sequel the term input data for all type of considered uncertainty sources, i.e., initial values of variables, parameters and unexplained system variation. The limitation was based on a sensitivity analysis and expert judgement on the uncertainty of the parameters. All rather certain and rather insensitive parameters were left out.

For SMART2/SUMO this resulted in thirteen vegetation-related parameters and eleven soil related parameters. For P2E seven parameters and three terms for the USV where selected. For NTM one parameter and one term for the USV where selected (Table 3).

3.4 Specification of errors in parameter values

3.4.1 SMART2/SUMO

An overview of the specified distributions is given in table 4. Vegetation parameters are either related to a vegetation type or a compartment (i.e., stem, branch, leave, and root) or both. The non-zero correlation coefficients are given in table 5.

3.4.2 P2E

A conversion is required to translate the hydrology scenario and the outputs pH_{SMS} and N_{av} of SMART2/SUMO into the Ellenberg indication values, which are input to NTM. This conversion, which entailed additional uncertainty, was parameterised by regression on several data sets. One data set contained hydrology data and e_F values. Another contained nitrogen availability N_{av} and e_N values. There were no data directly linking pH_{SMS} and e_R; instead there was a set of data linking pH_{SMS} and pH_{H2O}, which was mentioned earlier in this paper, and another data set linking pH_{H2O} and e_R

To supplement the currently used conversion parameters (Wamelink et al. 1997) with information about their accuracy was more difficult than expected on forehand. The originally used regression equations used by NTM could not always be reconstructed. For e_F the parameterisation was improved. An overview of the specified distributions is given in table 6. The non-zero correlation coefficients are given in table 7. In Appendix 2 a more precise description of the construction of the parameterisation is given.

Table 3: Overview of inspected parameters in SMART2/SUMO, P2E and NTM

Codes	Description	Uncertainty
SMART2/SUMO: Vegetation-related parameters		
SMART2		
ffSO2	Forest filtering SO2	Literature[1]
ffNH3	Forest filtering NH3	Literature
ffNOx	Forest filtering Nox	Literature
fdd	Dry deposition factor	Literature
Tr[2]	Transpiration	Literature/calibration
kmimx	Mineralisation rate constant	Literature
SUMO		
Gmx	Maximum growth rate	Literature
BMdist	Biomass distribution	Literature
ctN_imn	Minimum N content in	Literature
ctN_imx	Maximum N content in	Literature
flf_i	Litterfall fraction of compartment	Literature
fre_i	Reallocation fraction of	Literature
Ext_l	Extinction fraction of layer l	Literature +measurements
SMART2/SUMO: Soil related parameters		
CNom	C/N ratio of organic matter	Derived from 250 monitoring sites in The Netherlands[5]
frnimx	Nitrification fraction	Calibration
frdemx	Denitrification fraction	Calibration
KAlox	Dissolution constant Alox	Derived from 250 monitoring sites in The Netherlands
ctAlox	Secondary Al compounds	Derived from 250 monitoring sites in The Netherlands
Nawe[3]	Na weathering rate	Literature/EFSDF[4]
BC2we	BC2 weathering rate	Literature/EFSDF
CEC	CEC	Derived from 250 monitoring sites in The Netherlands
frBC2ac	Fraction BC2 at CEC	Derived from 250 monitoring sites in The Netherlands
KAlex	Al-BC2 exchange constant	Derived from 250 monitoring sites in The Netherlands
KHex	H-BC2 exchange constant	Derived from 250 monitoring sites in The Netherlands
P2E		
	Transformation pH_{sms} to pH_{H2O}	Data Alterra (Kros 1998)
a_pHpH	Regression coef.	
b_pHpH	Regression coef.	
ε_pHpH	USV	
	MSGL to e_F	Data RIVM[6] (Alkemade et al 1996)
r_e_F	Regression coef.	
b_e_F	Regression coef.	
a_e_F	Regression coef.	
ε_e_F	USV	
	PH_{H2O} to e_R	Data Alterra (Wamelink et al 1996)
a_e_R	Regression coef.	
b_e_R	Regression coef.	
ε_e_R	USV	
	N_{av} to e_N	-
	-	
NTM		
PCV	Potential Conservation value	160,252 relevées
u_NTM	Regr. Coef.	
ε_NTM	USV	

1. "literature" refers to Kros et al. (1993), Kros et al. (1995) (SMART2), Wamelink et al. (2000.)(SUMO), and references therein.
2. Kwe was set equal to Nawe.
3. Transpiration rate basically depends on both vegetation and soil, but we have only included the dependence on vegetation
4. European Forest Soil Data Base (Reinds 1994)
5. See Leeters et al. (1993) and Klap et al. (1998)
6. RIVM: National institute of public health and the environment

Table 4: Distributions of the vegetation-related model parameters

Parameter	Unit	Vegetation- or soiltype[1]	Distribution	Mean[2]	St	Min	Max
Vegetation-related parameters							
SMART2							
a_ffSO2[4]	[-]	ALL	G	1.0	0.1	0	
a_ffNH3	[-]	ALL	G	1.0	0.1	0	
a_ffNOx	[-]	ALL	G	1.0	0.1	0	
a_fdd	[-]	ALL	G	1.0	0.2	0	
a_Tr[3]	[-]	ALL	G	1.0	0.15	0	
a_kmimx	[-]	ALL	G	1.0	0.3	0	
SUMO							
a_Gmx	[-]	ALL	G	1.0	0.2	0	
a_Bmdist	[-]	ALL	G	1.0	0.1	0	
a_CtNimn	[-]	ALL	G	1.0	0.1	0	
a_CtNimx	[-]	ALL	G	1.0	0.1	0	
a_Flfi	[-]	ALL	G	1.0	0.15	0	
a_Frei	[-]	ALL	G	1.0	0.2	0	
a_Exti	[-]	ALL	G	1.0	0.25	0	
Soil related parameters							
logCNom	[log(g g^{-1})]	SP	G	1.4(25)	0.17	0.8(6)	
		SR	G	1.3(20)	0.14	0.8(6)	
		CN	G	1.2((16)	0.26	0.8(6)	
frnimx	[-]	SP	B	0.9	0.05	0.8	1.0
		SR	B	0.9	0.05	0.8	1.0
		CN	B	0.8	0.1	0.6	1.0
frdemx	[-]	SP	B	0.5	0.25	0.0	1.0
		SR	B	0.5	0.25	0.0	1.0
		CN	B	0.75	0.13	0.5	1.0
KAlox	[log(mol l^{-1})]	SP	N	8.1	0.32		
		SR	N	7.3	0.62		
		CN	N	9.4	0.69		
ctAlox	[log($mol_c kg^{-1}$)]	SP	B	2.1(139)	0.42	0.77(6)	
		SR	B	2.1(139)	0.29	1.2(6)	
		CN	B	2.3(200)	0.31	1.6(40)	
Nawe	[mol_c m^{-3} a^{-1}]	SP	N	0.009	0.004		
		SR	N	0.025	0.008		
		CN	N	0.030	0.010		
BC2we	[mol_c m^{-3} a^{-1}]	SP	N	0.013	0.004		
		SR	N	0.020	0.005		
		CN	N	0.040	0.010		
logCEC	[log($mmol_c kg^{-1}$)]	SP	G	1.7(50)	0.28	0.83(7)	
		SR	G	1.6(40)	0.25	1.1(13)	
		CN	G	1.8(63)	0.42	0.50(3)	
frBC2ac	[-]	SP	B	0.14	0.16	0.01	0.99
		SR	B	0.14	0.21	0.02	0.95
		CN	B	0.31	0.27	0.01	1.0
KAlex	[log(mol l^{-1})]	SP	N	0.68	0.65		
		SR	N	0.48	0.45		
		CN	N	-3.5	0.62		
Khex	[log(mol l^{-1})]	SP	N	4.0	0.29		
		SR	N	4.0	0.31		
		CN	N	6.6	1.4		

1 Refers to applicable vegetationstructure type (SMART2 uses five types; SUMO uses twelve types) . ALL means that all vegetation type were treated together, i.e., the average (Pveg) of the value per vegetation type may be different, but the assigned uncertainties (fmn,fmx) were set equal. The Monte Carlo realisation for a specific vegetation-related parameter (P(veg mc)) was calculated as:
P(veg mc)= fmc × Pveg
with fmc drawn form the distribution B(fmn,fmx)
It is obvious that in these cases the unit, mean, min and max does not refer to the mentioned parameter as such but to factor by which the parameter must be multiplied in order to get the appropriate value; soiltypes: SP=poor sandy soil; SR=rich sandy soil; CN=clay soil.

2 for lognormal distributions, value in brackets denotes the nominal values; the other value denotes the log-transformed value.

3 in fact transpiration is a function of both vegetation and soil. For sake of simplicity we only include a vegetation type dependency.

4 a_… refers to fmc, see footnote 1

Table 5: Non-zero Correlation coefficients

Parameter1	Parameter2	Corr. Coeff[1]
ffNH3	ffSO2	0.61
ffNOx	ffSO2	0.61
ffNOx	FfNH3	0.06
ffdd	ffSO2	0.61
ffdd	ffNH3	0.06
ffdd	ffNOx	0.06
frBC	CEC	0.50
frBC	CNom	-0.50
CEC	CNom	0.50

[1] Because assigned correlation coefficients where based on expert judgement, which does not necessarily lead to a valid correlation structure, assigned values were transferred into compatible correlation coefficients. These latter values are shown.

Conversion from MSGL to e_F

The original parameterisation, using regression of MSGL on Ellenberg's e_F, could be flawlessly reconstructed. Nevertheless, we constructed a new parameterisation. Firstly, in order to avoid predicted values of e_F outside the allowed range from 1 to 12, the original regression used a trick which gives rise to some problems when one wishes to assess the covariance matrix of the parameters. The data set was obtained from RIVM (Alkemade et al. 1996).

The estimates of the regression coefficients, their variances and correlation's describe the parametric uncertainty (PUNC) of the conversion.

The residual mean square 0.6009 is caused by measurement errors and system variability unexplained by the regression (USV). Assuming that the measurement error is by far the smaller of the two, 0.6009 was used as variance of the unexplained system variation.

The most obvious way to draw a new realisation of e_F, would seem to be

new_e_F = a_e_F + b_e_F * r_e_F^MSGL + ε_e_F

in which ε_e_F has mean 0 and variance vsys (see table 6). But this way a value may fall outside the range from 1 to 12; if this occurs, the value is set to the nearest value in the range, i.e. 1 or 12.

Table 6: Distribution of the P2E parameters

Name	Distribution	Mean	Unit	s.d	min	max
r_e_F	N	1.5331	[-]	0.0455	-	-
b_e_F	N	6.850	[-]	0.191	-	-
a_e_F	N	1.069	[-]	0.177	-	-
ε_e_F	N	0	[-]	0.775	-	-
a_pHpH	N	0.7424	[-]	0.0525	-	-
b_pHpH	N	0.8708	[-]	0.0124	-	-
ε_pHpH	N	0	[-]	0.999	-	-
a_e_R	N	-0.2215	[-]	1.1498	-	-
b_e_R	G	0.8876	[-]	0.0375	-	-
ε_e_R	N	0	[-]	2.633	-	-

Table 7: Non-zero correlation coefficients

Parameter1	Parameter2	Corr. Coeff.
r_e_F	b_e_F	-0.26
r_e_F	a_e_F	0.47
a_e_F	b_e_F	-0.92
a_pHpH	b_e_pHpH	-0.97
a_e_R	b_e_R	-0.98

Conversion from pH_{sms} to e_R

As mentioned in section 2.1.3 the pH resulting from SMART2/SUMO refers to the pH in the soil solution (pH_{sms}), whereas the pH used in P2E refers to the pH_{H2O} (Schouwenberg in prep). Therefore the conversion takes place in two steps: first conversion of pH_{sms} into pH_{H2O} and secondly conversion of pH_{H2O} into e_R.

Conversion from pH_{sms} of SMART2Sumo to pH_{H2O}

Here we reconsidered the datasets as described in Kros (1998) in order to determine the uncertainty in both pH_{sms} and pH_{H2O}. The data were restricted to soils sand and clay.

The analyses for sand and clay were combined because the regression coefficients were much the same. The differences between the residual mean squares, however, 0.09314 and 0.1924 respectively, were a bit too large to be ignored. In the combined analysis for sand and the inverses of these residual mean squares were used as weight. As was to be expected, the residual mean square of the combined analysis was close to 1, namely 0.9984. The ensuing residual mean squares, 0.9984*0.09314 for sand and 0.9984*0.1924 for clay, are caused by measurement errors and system variability unexplained by the regression. Assuming that the measurement error variance was approximately 0.05 for both x_ph and y_ph, and assuming independence of measurement errors, the error variance in y_ph given x_ph was equal to $(1+0.8708^2)$ * 0.05 = 0.08791. It is obvious that the residual variances were much larger than can be accounted for by mere measurement errors. Thus, we used σ^2_{sand} = 0.09314-0.08791 = 0.0052, and σ^2_{clay} = 0.1924-0.08791 = 0.1045 as unexplained system variation.

New values of pH_water, given pH_soil, were drawn as:

$$new\_pH\_water = a\_pHpH + b\_pHpH*pH\_soil + \sigma_{soil} * \varepsilon\_pHpH$$

in which σ^2_{sand} =0.0052 and σ^2_{clay} = 0.1045.

Conversion from pH_{H2O} to e_R

The original parameterisation, using regression of pH on Ellenberg’s e_R, could not sufficiently be reconstructed. Thus, a new parameterisation was constructed. Regression of the Ellenberg indication values on the pH was done, rather than the converse used originally, because the purpose is to derive Ellenberg indication values from pH.

The data set for this new parameterisation was obtained from Alterra (Wamelink & Van Dobben 1996).

New cases of e_R, given pH were simulated by

$$e\_R = a\_e\_R + b\_e\_R*pH + \varepsilon\_e\_R$$

The estimates of the regression coefficients, their variances and correlation's describe the parametric uncertainty of the conversion. Normal distributions for both parameters were assumed, but also a gamma distribution with minimum 0 for the slope coefficient can be used in order to rule completely out the possibility of negative slopes (but the probability was already very small under a normal distribution).

The residual mean square 2.716 is partly caused by the fact that the Ellenberg indication values in the dataset are integers. The variance of the homogeneous distribution on an interval of length 1 is equal to 1/12. When this variance is subtracted from 2.716 there remains a variance 2.633 caused by measurement errors and system variability unexplained by the regression. Assuming that the measurement error is by far the smaller of the two, 2.633 was used as variance of the unexplained system variation.

Conversion from N available to e_N

The original conversion of e_N based on expert judgement could not satisfactory be reconstructed. Therefore for this conversion the uncertainty could not be accounted for.

3.4.3 NTM

The uncertainty in several regression relations in the SMART2/SUMO-P2E-NTM model chain has been defined by the means and covariance-matrix of the regression estimates. In the case of NTM, however, the situation is somewhat different because NTM has not been calibrated via ordinary regression, but via penalised spline regression. In this form of regression, quite a large number of parameters are adapted, and the ensuing risk of overfitting is avoided by means of a penalty for roughness of the response. Thus, the method strikes a balance between the two evils roughness of the response and infidelity to the data. But the result is that the response uncertainty cannot be characterised in the standard way for a small number of parameters. Instead, the uncertainty in the NTM response, given the Ellenberg numbers e_F, e_N and e_R, has been characterised in the form of a bootstrap sample of 100 response functions. Thus, a response is defined by a random integer between 1 and 100, which will be calculated as 100*uniform(0.1), rounded to the nearest higher integer (see table 8).

But, given the Ellenberg numbers e_F, e_N and e_R, and given the NTM response, the potential nature value is not unique. There is quite some variation that cannot be accounted for by the regression. The potential nature value has a distribution (for simplicity assumed to be normal unless this lead to physically impossible response) with the NTM-response as mean, and a variance σ^2_NTM.

The potential conservation value (PCV) was calculated as:

$$new\_PCV = f_n(e\_F, e\_N , e\_R) + sd\_ntm * \varepsilon\_NTM$$

in which n = roundup(100*u_NTM), and in which f_1 … f_{100} are 100 bootstrap realisations of the NTM response.

sd_ntm = sqrt(10.1277) = 3.18 (heathland); sqrt(5.0025) = 2.24 (deciduous forest); sqrt(2.268)= 1.51 (pine-forest); sqrt(8.955)=2.99 (other)

Table 8: The specified uncertainty distributions of NTM

Name	Distribution	Mean	s.d.	min	max
u_NTM	uniform	-	-	0	1
ε_NTM	normal	0	1	-	-

4 Methods

In the type of uncertainty analysis applied in this report, uncertainty in a source of error is modelled by considering this source as a random vector, which is input to the model. The analysis applied is of the Monte Carlo type, which means that the analysis is based on a random sample from the inputs. The model outputs chosen for analysis are calculated by running the model for each set of values in the sample. Already for a long time, most analyses work like this, but they differ with respect to the way in which the sample is constructed, the measures used to express uncertainty and uncertainty contributions, and the actual estimation of these measures. In the last decade, these differences tend to become smaller.

Firstly, consensus seems to grow between uncertainty analysts that variances and variance components are very suitable to characterise output uncertainty and uncertainty contributions.

Secondly, most uncertainty analysts would agree that estimation of uncertainty contributions of a small number of meaningful groups of inputs is more sensible than estimation of uncertainty contributions of a large number of individual (scalar) inputs (in this case: 6 groups instead of 36 individual inputs, see section 3.2).

Thirdly, it is often found embarrassing that many types of uncertainty analyses are based upon a regression approximation of the model studied. Often, however, these regression approximations are not entirely successful, and this seriously limits the possibilities of regression-based uncertainty analysis (see example on p. 39). The method of Sobol' (1990) and the winding stairs method (Jansen et al. 1994) can be used to estimate uncertainty contributions without recourse to regression approximations: they are regression-free. The two methods are based on the same principles. Both can be applied in the case of independent groups of inputs; and both require a special type of input sample. In general, regression-free uncertainty analysis requires larger samples than regression-based analysis. In this report we use the winding stairs method.

Section 4.1 treats variance-based uncertainty contributions of groups of inputs. Section 4.2 describes the winding stairs method. Section 4.3 discusses the possibilities of an alternative method, namely to estimate variance contributions by means of linear approximations of the sub-models of the chain. An attractive property of this approach is that one may perform such an analysis on basis of analyses of the individual components of the chain: one may study the chain before it exists. A disadvantage of this approach is that the linear approximations used may be unsatisfactory, implying that the whole method is unsatisfactory.

4.1 Variance-based uncertainty contributions of groups of inputs

In the past, uncertainty, and uncertainty contributions have been expressed in very diverse measures. In the last decade, however, many uncertainty analysts seem to have turned to variances and variance components as an uncertainty measure (Sobol' 1990; Krzykacz 1990; Jansen et al. 1994; McKay 1996; Jansen 1999; Saltelli et al. 1999). This has the great advantage that there is a rich statistical literature on the subject (e.g. Searle et al. 1992). Moreover, many of the earlier measures can be re-interpreted as variances.

We now define two types of variance-based uncertainty contributions for an arbitrary group of inputs (Jansen et al. 1994; Jansen 1999). Let S denote a, possibly pooled, source of uncertainty, and let T denote the group of all other sources of uncertainty. The groups S and T are allowed to be dependent. The model output studied is assumed to depend deterministically on S and T and may thus be written as f(S,T). The total variance, say VTOT, is equal to VTOT = Var[f(S,T)]. The *top marginal variance* of S is defined as the expected reduction in output variance if one would obtain perfectly certain information about S. No direct information about T will come in, but if S and T are dependent, some information about T may be conveyed through S. Thus, the top-marginal variance of S might be called the part of variance accounted for by S. Formally, the top marginal variance of S, TMV_S, is defined in terms of conditional means and variances:

$$TMV_S = VTOT - E[Var[f(S,T)] \mid S] = Var[E[f(S,T) \mid S] .$$

The *bottom marginal variance* of S is defined as the output variance that would remain if one has obtained perfect information about all sources, except S, i.e. perfect information about the complementary sources T. The bottom marginal variance might be called the part of the variance that is not accounted for without S. The formal definition of the bottom marginal variance of S, BMV_S, is as follows:

$$BMV_S = E[Var[f(S,T) \mid T] .$$

Note that it follows directly from the above definitions that BMV_S and TMV_T are complementary:

$$BMV_S + TMV_T = VTOT.$$

Figure 5 gives an illustration of TMV and BMV. Usually, TMV and BMV are expressed as percentage of VTOT.

In the case that S and T are *independent* something more can be said. Then, f(S,T) has the following *analysis of variance* decomposition (e.g. Efron & Stein 1981)

$$f(S,T) = \mu + f_S(S) + f_T(T) + f_{ST}(S,T) ,$$

in which μ is the expectation of f(), whereas $\mu + f_S(S)$ and $\mu + f_T(T)$ are conditional expectations given S and T respectively, these terms are called the *main effects* of S and T. The remainder term $f_{ST}(S,T)$ is called the *interaction* of S and T. More formally:

$\mu = E[f(S,T)]$,
$\mu + f_S(S) = E[f(S,T) | S]$,
$\mu + f_T(T) = E[f(S,T) | T]$.

The top and bottom marginal variances of S may now be expressed as

$TMV_S = Var[f_S(S)]$,
$BMV_S = Var[f_S(S)] + Var[f_{ST}(S,T)]$.

Similar expressions may be given for T. Thus, in the case of independent sources, TMV_S may be called the *main effect variance* of S, whereas BMV_S may be called the *all effects variance* of S. Several other names have been proposed for TMV and BMV, most often in the context of independent sources of uncertainty: importance measures, sensitivity estimates, global sensitivity indices. The classical correlation ratio is the top marginal variance as fraction of the total variance (Sobol' 1990; Krzykacz 1990; McKay 1996; Saltelli et al. 1999).

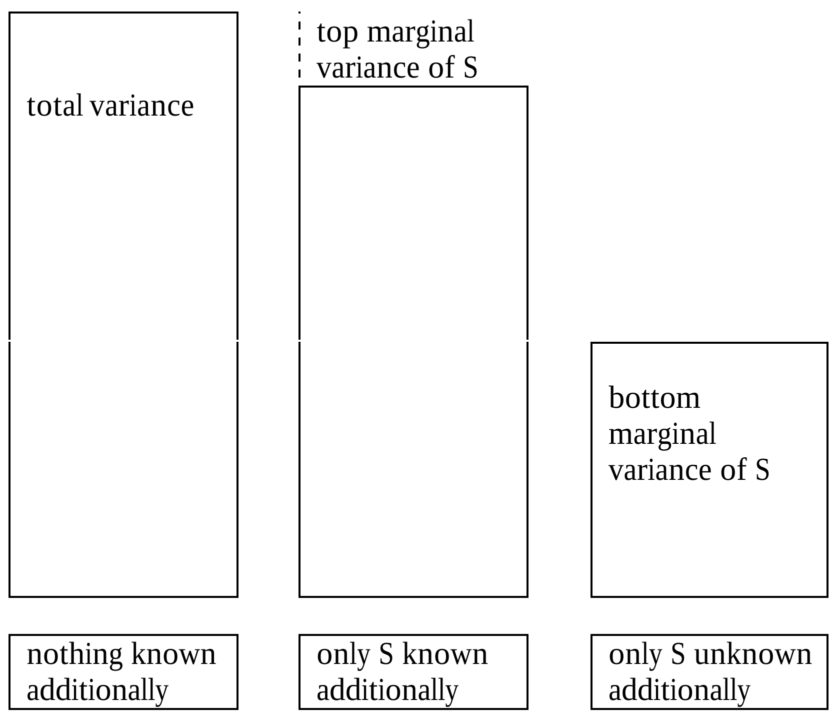


Figure 5: Graphical representation of total variance $VTOT$, top-marginal variance of S, TMV_S, and bottom-marginal variance of S, BMV_S

4.2 Estimation of uncertainty contributions of independent pooled sources

For the definition of uncertainty contributions, it sufficed to discern only a group S and the complementary group T. For the actual estimation we now consider a scalar model output Y = f(A, B, C ...) that depends deterministically on a number of vector and/or scalar-valued random inputs. We consider the case that the uncertainty sources A, B, C ..., have *independent* probability distributions. The vectors A, B, C... may have different lengths. Elements of the same vector may be dependent.

The uncertainty contributions of the sources A, B, C... can be estimated by means of a so-called *winding stairs sample*. In the box below, a winding stairs sample of f() is sketched (figure 6).

Column	1	2	3	...
Row				
1	$f(a_1, b_1, c_1,...)$	$f(a_1, b_2, c_1,...)$	$f(a_1, b_2, c_2,...)$	...
2	$f(a_2, b_2, c_2,...)$	$f(a_2, b_3, c_2,...)$	$f(a_2, b_3, c_3,...)$	...
3	$f(a_3, b_3, c_3,...)$	$f(a_3, b_4, c_3,...)$	$f(a_3, b_4, c_4,...)$	...
4	$f(a_4, b_4, c_4,...)$	$f(a_3, b_5, c_4,...)$	$f(a_4, b_5, c_5,...)$	...
5	$f(a_5, b_5, c_5,...)$	$f(a_5, b_6, c_5,...)$	$f(a_5, b_6, c_6,...)$	...
6	$f(a_6, b_6, c_6,...)$	$f(a_6, b_7, c_6,...)$	$f(a_6, b_7, c_7,...)$	...
7	$f(a_7, b_7, c_7,...)$	$f(a_7, b_8, c_7,...)$	$f(a_7, b_8, c_8,...)$	...
8	$f(a_8, b_8, c_8,...)$	$f(a_8, b_9, c_8,...)$	$f(a_8, b_9, c_9,...)$	...
...	...			

Figure 6: Sketch of a winding stairs sample of model output f, for independent sources A, B, C.... Independent random draws from these sources are indicated by a_1, a_2..., b_1, b_2..., c_1, c_2...

When going through the sample in reading order, one sees that A, B, C... get new values in cyclic order. Consecutive elements of the first column contains values of f() for independent draws of all inputs. This column contains information about the total variance of f(). The other columns are required to estimate the contributions of A, B, C... to the total variance.

From a winding stairs sample, the top and bottom marginal variances of A, B, C… may be estimated. For instance, the covariance between columns 1 and 2 of Fig.6 is an estimate of the top marginal variance of B, whereas half the squared difference between these columns is an estimate of the bottom marginal variance of B. Other variances are estimated similarly. The estimates have asymptotic normal distributions. The accuracy of estimates can be assessed through time-series methods. One may also estimate the variance of some pools of sources, for instance half the variance of column 1 minus column 3 is an estimate of the bottom marginal variance of B and C pooled. Note that the values taken by A,B,C... play no role in the analysis. For more details, see Jansen et al. (1994) and Jansen (1999). Sobol' (1990) proposes a similar way to estimate uncertainty contributions, with the only difference that he uses a slightly different type of sample, in which only one source of uncertainty can be analysed per sample. The advantage of the winding stairs method is that many sources and pooled sources can be estimated from one sample.

The analysis of this report studies the uncertainty contributions of the 6 groups of inputs mentioned in Section 3.2. After the quantification of the input uncertainty described in Chapter 2, an ordinary random sample of size 1000 has been drawn from the input distribution. This sample was constructed with the Genstat procedure library USAGE (Jansen & Withagen 1999). Subsequently, this ordinary random sample was post-processed with Genstat (Genstat 5 Committee 1993) into a winding stairs input sample for 6 groups of inputs: a sample of 6000 sets of inputs. Next, the model-chain was run for the input sample. This produced a winding stairs sample with 1000 rows and 6 columns for each of the outputs studied. Finally, these samples were analysed with the program WINDINGS (Jansen 1996). The results of the analysis will be presented in Chapter 5.

4.3 Chain analysis via linear approximations of i/o relations of sub-models

The theory of the previous subsection allows studying the model as a chain by the pooling of the inputs into different groups pertaining to different sub-models in the chain. We now consider an altogether different approach that can be applied if the model is a chain of *known* sub-models. Then one can study the chain, before it even exists, by combining knowledge about the sub-models.

In this section, a vector x of dimension 36 will denote the inputs. The first 24 elements of x pertain to SMART2/SUMO; the next 10 are input to P2E, and the last 2 to NTM. For a sample of x's, one may calculate the corresponding SMART2/SUMO outputs pH_{SMS} and N_{av}. Using these data, one may construct a linear approximation of the outputs by means of two linear least squares regressions. The result can be summarised in matrix form

$$\begin{pmatrix} pH_{SMS} \\ N_{av} \end{pmatrix} \approx A_{SMS} + C_{SMS}x \ ,$$

in which A_{SMS} is a 2x1 matrix and C_{SMS} is a 2x36 matrix. These matrices contain the regression coefficients; the rows 25...36 of C_{SMS} contain nothing but zeros, because SMART2/SUMO is insensitive to the inputs of the other models in the chain, i.e. to x_{25}...x_{36}.

Similarly, one can construct an approximation of the 3 outputs of P2E, given a sample of x's and of values of pH_{SMS} and N_{av}, for which the P2E outputs e_F, e_R and e_N have been calculated. Regressions of these 3 outputs on the inputs lead to the approximation

$$\begin{pmatrix} e\_F \\ e\_R \\ e\_N \end{pmatrix} \approx A_{P2E} + B_{P2E}\begin{pmatrix} pH_{SMS} \\ N_{av} \end{pmatrix} + C_{P2E}x$$

in which A_{P2E} is a 3x1 matrix and C_{P2E} is a 3x36 matrix. The rows 1...24, 35 and 36 of C_{P2E} contain only zeros.

The same method applied to NTM output PCV, leads to an approximation of the form

$$PCV \approx A_{NTM} + B_{NTM} \begin{pmatrix} e\_F \\ e\_R \\ e\_N \end{pmatrix} + C_{NTM}\, x$$

where A_{NTM} is a 1x1 matrix and C_{NTM} is a 1x36 matrix. The rows 1...34 of C_{SMS} contain purely zeros.

The combined linear approximation, obtained by substitution of the second and first formula in the last, has the form

$$PCV \approx A + Bx \,,$$

in which A is a scalar,

$$A = A_{NTM} + B_{NTM} A_{P2e} + B_{NTM} B_{P2E} A_{SMS} \,,$$

whereas *B* is a 1x36 matrix representing the sensitivity of the approximation of PCV with respect to the input vector *x*:

$$B = C_{NTM} + B_{NTM} C_{P2E} + B_{NTM} B_{P2E} C_{SMS} \,.$$

Note that the coefficients of the linear approximation $PCV \approx A + Bx$ depend on time and on all model inputs that are absent in *x*, in particular the hydrological and deposition scenarios. The linear is far from universal. In theory, one may also incorporate the inputs that are absent now, but it is to be expected that this would deteriorate the quality of the approximation.

Example. For the case of a rich-sand plot starting with spruce trees in 1995, we calculated the expected conservation value PCV in 2025, under the business as usual scenario. Since expected conservation value was calculated, there was no unexplained system variation in the NTM inputs: i.e. x_{35}=0. The modelled PCV for the sample of *x*'s had mean 9.64 and variance 0.604. The linear approximation calculated as described above also had mean 9.64 but the variance was only 0.340. Thus, 44% of the variance of PCV got lost in the linear approximation. This is a bad omen for an uncertainty analysis based on this approximation, since it is the variance that has to be analysed and ascribed to the different sources of uncertainty: if the object of analysis has shrunken so much, there is little ground to assume that the relative uncertainty contributions are not much altered. Nevertheless, in the current example, uncertainty analysis of the true model and of the linearised version both point to unexplained system variation in P2E as the major source of uncertainty in PCV.

5 Results of the case study

5.1 Overview of the performed analysis

The uncertainty analysis was done by using the program WINDINGS (Jansen 1996). With this program the uncertainty contributions of the different sources (6 groups of input data, see section 3.2) can be estimated by means of a so-called winding stairs sample (see section 4.2). The analysis was done for the scenario BU to analyse the results of the model output throughout time. Also an analysis was done to compare the two scenarios BU and EC. Therefore the differences of the predictions of both scenarios were used. No separate analysis for the absolute predictions of EC was done since differences between scenarios are more relevant for decision making then the absolute predictions. The analysis was done for uncontrolled succession from bare ground (succession 1; section 5.2) for the three soil types and a succession from the current vegetation (succession 2; section 5.3) for the soil type SR. The analysis was done without and with accounting for USV of P2E and NTM to get a better view on the role of USV in the predictions.

The uncertainty contributions of the different sources for the prediction of the PCV are presented in the sections 5.2 and 5.3. An overview of the total analysis, the analysis of the output of SMART2/SUMO and P2E included, is given in Appendix 3. In section 5.4 a summary of the results is presented.

5.2 Uncontrolled succession from bare ground

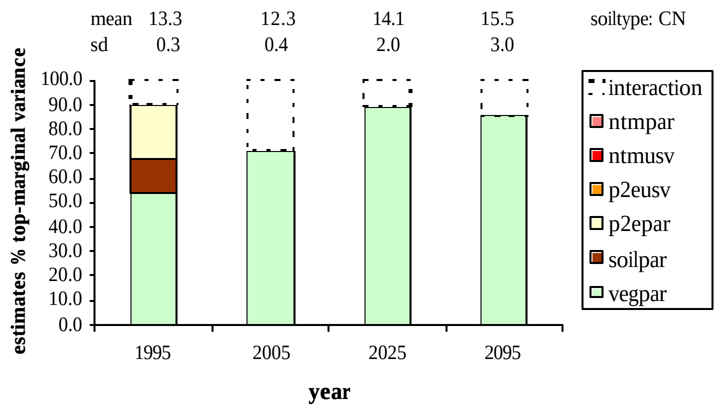
5.2.1 Analysis without USV

Scenario BU

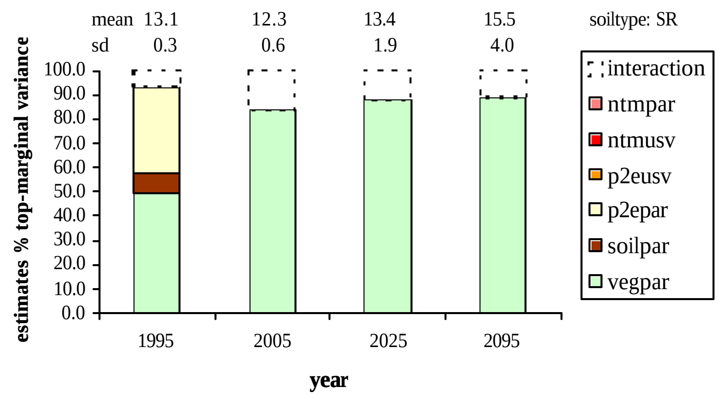
In figure 7 the results of the analysis of the predictions for the three soiltypes are given. In 1995 vegpar, soilpar and p2epar are the main sources of uncertainty, whereas from 2005 onwards, the main source of uncertainty are the vegetation-related parameters. This is mainly caused by the fact that succession takes place from bare ground to forest. There is a huge increase in biomass, resulting in a huge increase of N availability (see Appendix 3) and the associated uncertainty in e_N, whereas there is hardly increase in the uncertainty of e_R. Because N availability in SMART2/SUMO is mainly affected by vegpar, it is obvious that the uncertainty contribution of vegpar increased during the simulation period. In 1995, however, the uncertainty in e_R is relatively high compared to e_N. Consequently parameters that affecting the soil pH, i.e., soilpar and p2epar, contributed substantially to the uncertainty of the PCV. The uncertainty contribution of soilpar in 1995 increased in the direction SP > SR > CN (Figure 7a-c).

There is also a clear change in pH during 100 years of succession, although less extreme than the change in N availability. Which is not surprising, because the pH is a rather stable parameter. More surprisingly, however, is that the pH is increasing under maintaining the actual deposition, i.e. the BU scenario. This pH increase was caused by the uncontrolled vegetation succession from bare ground. The increase in biomass during the succession resulted in an accumulation of N in the vegetation, which in turn yield an additional buffering of acid deposition. Normally, it is found that during such simulations the pH decreases in time. This is confirmed by the simulation of the succession of the current vegetation under the BU scenario. (not shown)

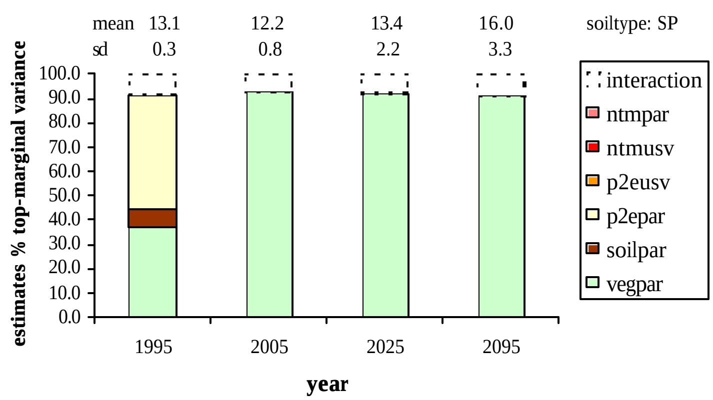
After a decrease of the PCV in the first 10 years of succession, the PCV increases in the next 90 years. This increase however is not significant (high variances in 2025 and 2095). This is caused by the succession from bare ground to forest. In time there is an increase in the uncertainty of the PCV. The prediction of the PCV becomes less reliable in time. In this case it is mainly caused by the fact that N availability increases in time and so e_N is in a range of the NTM-matrix in which strong extrapolation takes place from the range on which the model was calibrated.. The most reliable PCV can be found in the centre of the NTM-matrix. Another factor is the higher uncertainty in the forest submodels compared to the other submodels. This is caused by the fact that less input-data were available for the calibration of these submodels.



7a



7b



7c

Figure 7 a-c: Estimates of the % top-marginal variances for PCV, the BU-scenario, Succession 1 (succession from bare ground), without USV for the soil types non-calcareous clay (7a), Sand Rich (7b) and Sand Poor (7c); above the bars the values of the estimates of mean and standard deviation (sd) are given

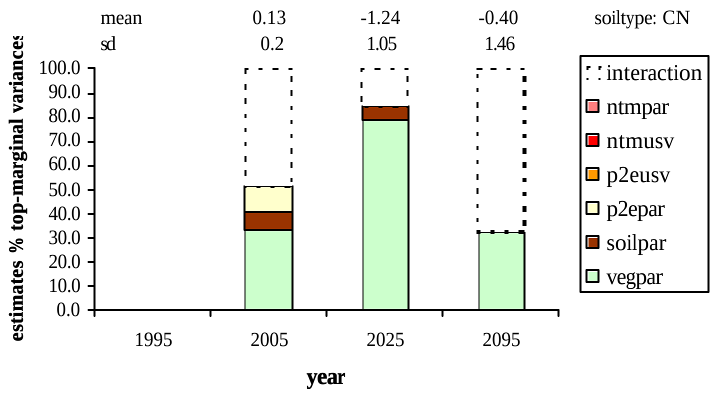
Difference between the two scenarios

For decision making the relative differences between the predictions of different scenarios is more important then the absolute predictions. Therefore an analysis was done for the difference of the two scenarios (MV-BU). Both scenarios have the same input variables at t=0 (1995). So the differences between the predicted values of the two scenarios are zero at that time.

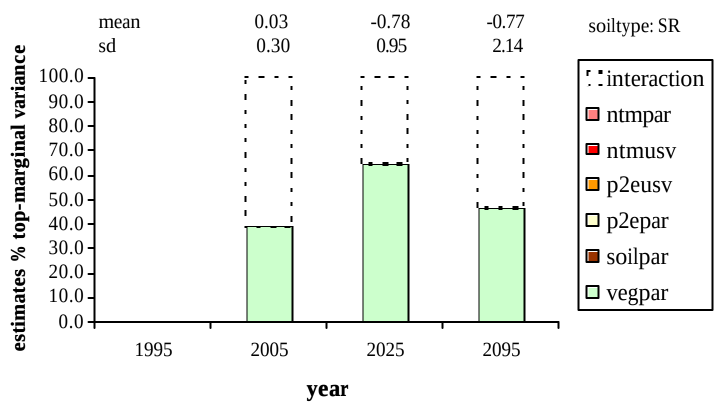
The results of the analysis are presented in figure 8. There are no significant differences between the two scenarios. It was expected on forehand that the PCV 's in the EC scenarios would be higher than in the BU scenarios because of the lower N deposition. The N deposition however is negligible to the increase of biomass during the succession from bare ground to forest.

As seen in the analysis of the BU scenario the vegetation-related parameters are also the main sources of uncertainty for the differences between the two scenarios.

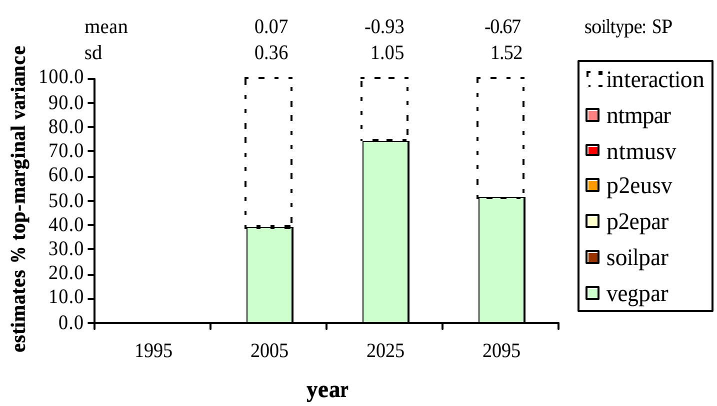
The variance of the differences between the PCV's of the two scenarios have smaller values than the individual predicted PCV's.



8a



8b



8c

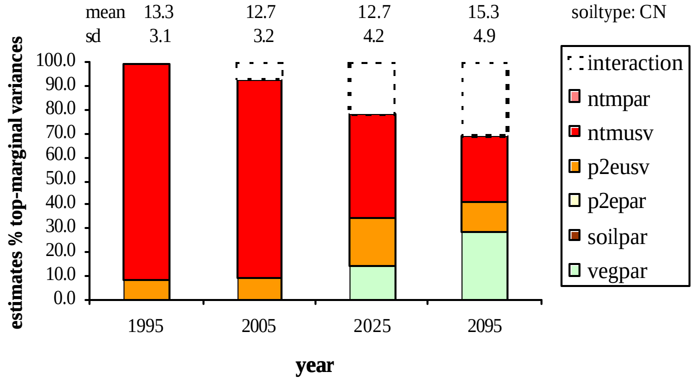
Figure 8: Estimates of the % top-marginal variances for the difference in PCV between the two scenarios (EC-BU), Succession 1, without USV for the soil types non-calcareous clay (8a), Sand Rich (8b) and Sand Poor (8c); above the bars the values of the estimates of mean and standard deviation (sd) are given

5.2.2 Analysis with USV

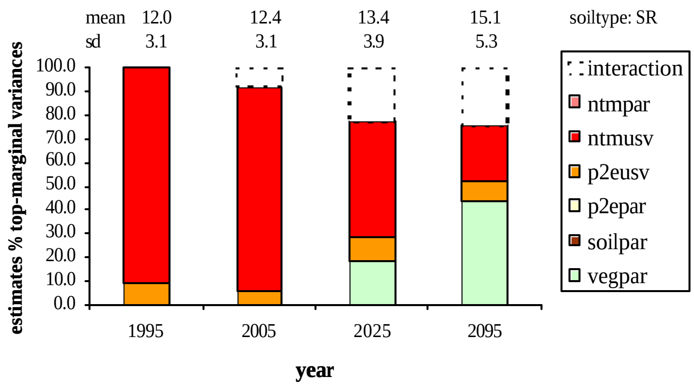
Scenario BU

Because the data used for parameterisation of P2E and NTM were still available it was possible to estimate the USV of both the models. As can be seen in Appendix 2 predictions with or without USV can give a dramatic difference. Therefore the WINDINGS analysis was also done with USV.

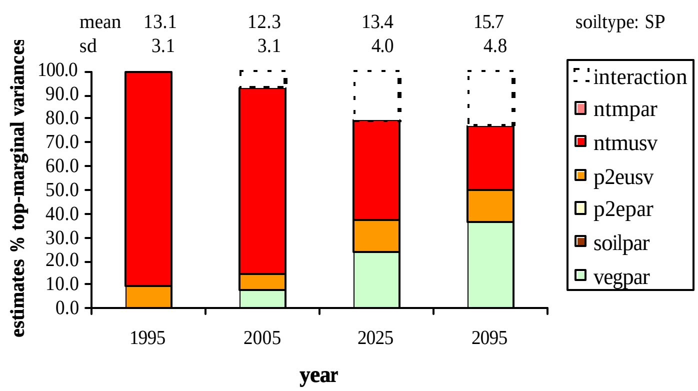
The results of the analysis are presented in figure 9. The variance is much higher than the predictions without USV. The main source of uncertainty is unexplained system variation of NTM. Other sources are the unexplained system variation in P2E and the vegetation-related parameters.



9a



9b



9c

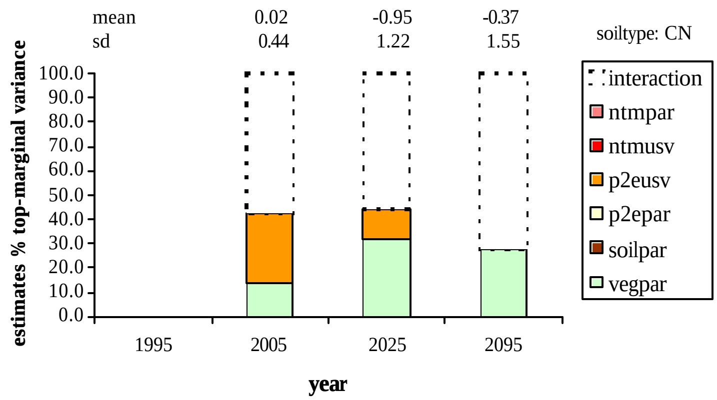
Figure 9: Estimates of the % top-marginal variances for PCV, the BU-scenario, Succession 1 (succession from bare ground), with USV for the soil types non-calcareous clay (9a), Sand Rich (9b) and Sand Poor (9c); above the bars the values of the estimates of mean and standard deviation (sd) are given

Difference between the two scenarios

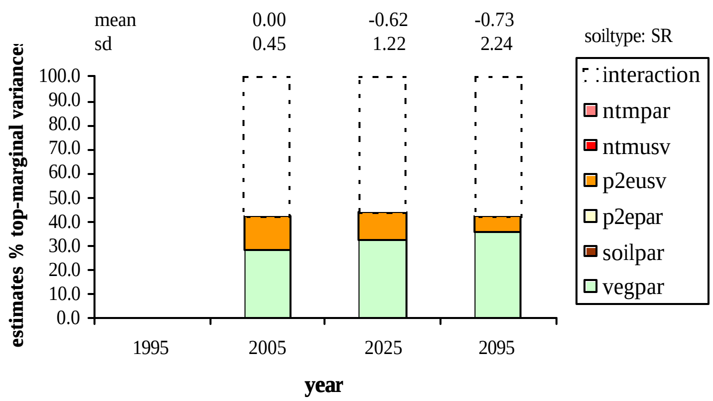
The results of the analysis of the differences of the predictions of the different scenarios are presented in figure 10.

The analysis of the differences illustrates the phenomenon that absolute predictions tend to be less accurate than the relative predictions. The differences between predicted PCV's of two scenarios have smaller values and variances than individual predicted PCV's. The several sources of uncertainty more or less cancel out when differences are analysed. It can be concluded that USV is not relevant in comparing scenarios.

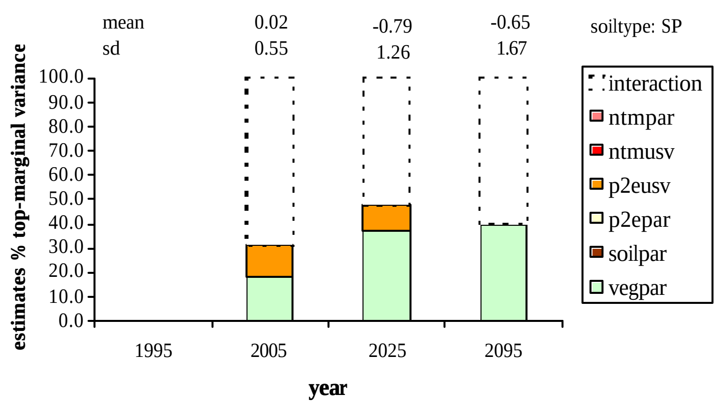
The USV of P2E however still has to be accounted for. Again the vegetation-related parameters are another source of uncertainty.



10a



10b



10c

Figure 10: Estimates of the % top-marginal variances for the difference in PCV between the two scenarios (EC-BU), Succession 1, with USV for the soil types non-calcareous clay (10a), Sand Rich (10b) and Sand Poor (10c); above the bars the values of the estimates of mean and standard deviation (sd) are given

5.3 Succession of current vegetation

For the prediction of the PCV of the succession of the current vegetation, spruce-forest, the NTM submodel for pine-forest was used.

5.3.1 Analysis without USV

Scenario BU

Regarding the predictions for the scenarios for the succession of the current vegetation, there is a small decrease in pH and N availability. The PCV decreases slightly in 100 years (see figure 11).

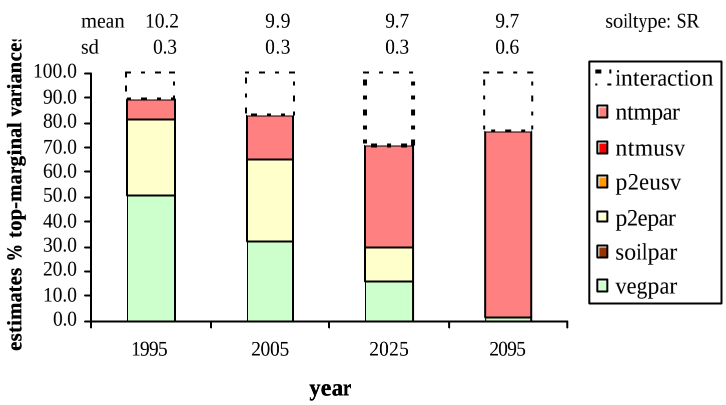


Figure 11: Estimates of the % top-marginal variances for PCV, the BU-scenario, Succession 2 (succession of the current vegetation), without USV. Soiltype: Sand Rich; above the bars the values of the estimates of mean and standard deviation (sd) are given

In the 1995 and 2005 the vegetation-related parameters are the main sources of uncertainty. During time there is a huge increase in the uncertainty caused by the parameter uncertainty of NTM. This increase is due to the fact that the abiotic conditions are in a range of the NTM-matrix in which strong extrapolation took place during the calibration of the pine-forest submodel. For this calibration just a small number of relevées (n=2505) were available, all more or less located in the middle of the NTM-matrix.

The influence of the uncertainty of the vegetation-related parameters are much smaller than during succession from bare ground because the increase of N availability (increase in biomass) due to succession is much smaller.

Difference between the two scenarios

The main sources of uncertainty of the differences in the predictions of PCV's are the vegetation-related parameters and the NTM parameters (figure 12).

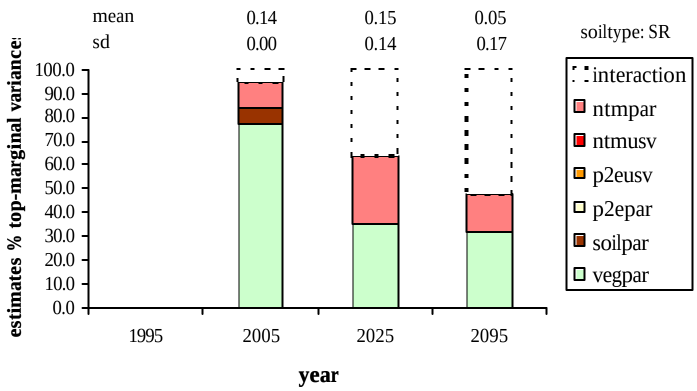


Figure 12: Estimates of the % top-marginal variances for the difference in PCV between the two scenarios (EC-BU), Succession 2, without USV. Soiltype: Sand Rich; above the bars the values of the estimates of mean and standard deviation (sd) are given

5.3.2 Analysis with USV

The results of the WINDINGS analysis for the succession from the current vegetation (spruce-forest) with USV are given in figure 13. It is obvious that uncertainty contribution of NTMUSV is also in this case the main source of uncertainty.

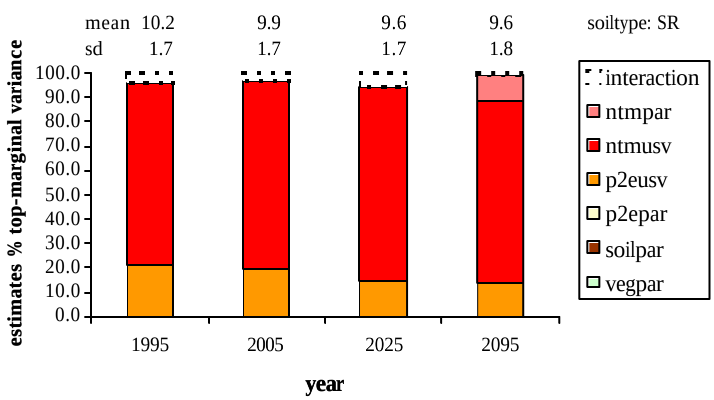


Figure 13: Estimates of the % top-marginal variances for PCV, the BU-scenario, Succession 2 (succession of the current vegetation), with USV. Soiltype: Sand Rich; above the bars the values of the estimates of mean and standard deviation (sd) are given

In the analysis of the differences between the scenarios the USV of NTM disappears as a source for uncertainty (just like the analysis of succession 1; figure 14).

The USV of P2E and the parameter uncertainty of NTM are still an important source of uncertainty.

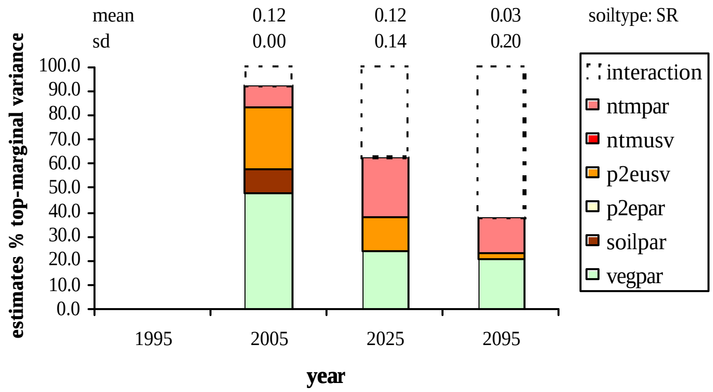


Figure 14: Estimates of the % top-marginal variances for the difference in PCV between the two scenarios (EC-BU), Succession 2, with USV. Soiltype: Sand Rich; above the bars the values of the estimates of mean and standard deviation (sd) are given

5.4 Summary

Table 9 presents a (qualitative) summary of the results of the WINDINGS analysis. Looking at the absolute values of the estimations of the PCV, USV of NTM is an important source of uncertainty. A different set-up of NTM with more and/or different input variables could possibly lead to better predictions.

Otherwise it may be questioned whether or not one should account for unexplained system variation in NTM. It depends on whether one wishes to predict conservation value or potential conservation value. On the other hand, there seems to be little ground for neglecting USV in the conversion model P2E.

The different analyses illustrate that absolute predictions tend to be less accurate than relative predictions. In the example, differences between predicted conservation values of two scenarios had smaller values than individual predicted conservation values. Several sources of uncertainty more or less cancel out when differences are analysed. This is a fortunate circumstance, since differences between scenarios are more relevant for decision making.

Table 9: Summary of the results of the WINDINGS analysis for absolute predictions and differences between scenarios; Source of uncertainty: +++: very important; ++: important; + sometimes important; blank: not important

	pH_{sms}	N_{av}	e_F	e_R	e_N	PCV
Absolute values						
Vegpar	+	+++			++	+
Soilpar	+++					
P2Epar						
P2EUSV			+++	+++		++
NTMUSV						+++
NTMPAR						+
Differences						
Vegpar	++	+++		++	+++	+++
Soilpar	++			++		
P2Epar				++		++
P2EUSV				++		
NTMUSV						
NTMPAR						+

6 Conclusions

6.1 Uncertainty propagation in the model chain SMART / SUMO-P2E-NTM

Two methods have been explored to study the uncertainty propagation in the model chain, at first a Monte Carlo type method, the regression free winding stairs analysis and at second a method were variance contributions are estimated by means of linear approximations of the components in the model chain. The analysis was done by the first method.

The results of the uncertainty analysis of this specific chain of models are presented as the contributions of the various sources to the uncertainty of the potential conservation value (PCV). The uncertainty in the model results is most relevant for policy making when two scenarios are compared. In this case the analysis ends in the following results:

- When the unexplained system variation of P2E and NTM (USV) is not taken into account, the SMART2 / SUMO vegetation parameters make the largest contribution to the uncertainty of PCV at both succession stages (succession from bare ground and succession of current vegetation). At succession of the current vegetation, the NTM parameters also contribute to the uncertainty of PCV; (fig 8, 12)
- When we take into account the unexplained system variation of P2E and NTM, the USV of P2E also contributes to the uncertainty of PCV. This contribution decreases in the long run; (fig 10, 14)
- There is little influence of the soil type in the case of succession from bare ground. We did not examine the influence of soil type in the case of succession of current vegetation.

For vegetation development from bare ground to forest the vegetation structure and the related nutrient catchment change so radically that the difference in nutrient deposition related to different scenarios is negligible.

The uncertainty analysis asks a substantial effort, even when important aspects like the uncertainty in soil- and vegetation maps are left aside. The most labour-intensive and time-consuming activities are data collection about uncertainty of model inputs and parameters.

In general, regression-free uncertainty analyses require more model runs than regression-based analyses, but in the example of this paper, a regression based-analysis would have produced seriously biased estimates of uncertainty contributions, since a well-fitting regression approximation could not be obtained because the model is strongly non-linear. On the other hand, it was no problem to execute the 6,000 model runs required for the regression-free analysis performed. Of course, in other situations, the computer time required for a large number of model runs might become prohibitive, and for efficiency reasons, one might then be forced to accept the bias associated with a regression-based uncertainty analysis.

6.2 Lessons learned for analyses of error propagation in model chains

The main problem with linking models is a data problem

For the analysis of the error propagation in a model-chain like the slightly simplified one studied in this project, the required knowledge and tools are available. The main problem is the limited availability of information about the uncertainty of the relevant input data and model parameters and the limited knowledge about the model structural error of process models

Relative predictions tend to be more accurate then absolute predictions

The case study illustrates the more general phenomenon that absolute predictions tend to be less accurate than relative predictions. In the example, differences between predicted potential conservancy values of two scenarios had smaller variances than individual predicted potential conservancy values. Several sources of uncertainty more or less cancel out when differences are analysed. This is a fortunate circumstance, since differences between scenarios are more relevant for decision making

Unintentional results are valuable

Not only the intended results of the analysis are valuable, but also the troubles experienced when performing the steps of the analysis: the ease with which one makes up an inventory of the sources of uncertainty and quantifies them, forms a check of the management of model quality. The analysis also constitutes a test if the model runs without problems under a wide range of circumstances.

Uncertainty analysis creates a new need for data

Uncertainty propagation in vegetation and conservation value modelling creates a new need for data. So there is a considerable backlog on quantification of uncertainty of model inputs and on documentation of parameterisation.

Model chains are not essentially different from complex models

Model chains are not essentially different from any kind of complex models. Only scientific problems are discussed here. There may be serious management problems however when sub-models and data come from different organisations.

As well accumulation of errors as cancelling out may occur

An accumulation of errors may occur when the model chain grows. An analogy between a sequence of models and a river basin with various branches comes up. The beginning is rather well ordered but when the chain is extended with various modules, state variables, parameters and input data, little by little more uncertainty is added. The uncertainty may partially cancels out however.

6.3 Recommendations for development and uncertainty analysis of model chains

Direction of continuation

Since some important sources of uncertainty were neglected up to now, the project must have a continuation to include these sources in the analysis. The model sequence SMART2/SUMO-P2E-NTM is not meant to predict conservation value in a limited number of points but to generate regional or nation wide images of conservation value. The uncertainties in the input data concerning soil properties and vegetation and the uncertainty in the spatial images that are the output of the model chain, have to be included in the analysis.

Implementation of the used method

Since the development of a high quality modelling systems is an interest of Alterra and because uncertainty analysis contributes considerable to insight in the reliability of model results, a decisive implementation of methods for uncertainty analysis of model sequences is recommended. The method used in this study works well, provided that model runs take little time. Therefore the procedure has to be streamlined and implemented.

Application of information technology

Since there may be serious management problems when sub-models and data from different organisations are combined, information technology and management tools have to be applied to manage reliable information exchange.

Data acquisition and model development

To solve the problems related to the lack of information about the quality of input data and the accuracy of model parameters, the issue of accuracy of model prediction should get more attention in the data acquisition and model development projects. A well-documented inventory of sources of uncertainty in the full sequence should be part of the quality system of the model chain.

Careful definition of model improvement projects

Since absolute predictions tend to be less accurate than relative predictions and because increasing the reliability of model results ask for serious effort, the application of the model chain has to be considered carefully when projects are defined to increase reliability of model predictions.

References

Alkemade, J.R.M., J. Wiertz & J.B. Latour 1996 Kalibratie van Ellenberg's milieu-indicatieschalen aan werkelijk gemeten bodemfactoren. Rapport nr. 711901016, RIVM, Bilthoven

Bal, D., H.M. Beije, Y.R. Hoogeveen, S.R.J. Jansen & P.J. van der Reest 1995. Handboek Natuurdoeltypen in Nederland. Informatie- en Kenniscentrum Natuurbeheer, Ministerie van Landbouw, Natuurbeheer en Visserij. Wageningen.

Clausman, P.H.M.A., W. van Wijngaarden & A.J. den Held 1984. Verspreiding en ecologie van wilde planten in Zuid-Holland. Deel A, waarderingsparameters. Provinciale Planologische Dienst Zuid-Holland.

Draper, N.R. & H. Smith 1998. Applied regression analysis (third edition), New York: Wiley.

Efron, B. & C. Stein 1981. The jackknife estimate of variance. Ann. Stat. 9 (1981) 586-596.

Eilers, P.H.C. & B.D. Marx 1996. Flexible smoothing with B-splines amd penalties. Statistical Science 11: 89-121.

Ellenberg, H., H.E. Weber & R. Duell 1991. Zeigerwerte von Pflanzen in Mitteleuropa. Scripta Geobotanica XVIII. Goltze Verlag, Göttingen, Duitsland.

Genstat 5 Committee 1993, Genstat 5 Reference Manual, Oxford : Clarendon Press.

Hertog, A.J. & M. Rijken 1992. Geautomatiseerde bepaling van natuurbehoudswaarde in vegetatieopnamen. Provincie Gelderland, Dienst Ruimte, Wonen en Groen. Intern document.

Jansen, M.J.W., W.A.H. Rossing. & R.A. Daamen 1994. Monte Carlo estimation of uncertainty contributions from several independent multivariate sources, In: Grasman, J. & G. van Straten (eds.), Predictability and Nonlinear Modelling in Natural Sciences and Economics, p334-343, Kluwer, Dordrecht 1994.

Jansen, M.J.W. 1996. Winding stairs sample analysis program WINDINGS 2.0, Wageningen: DLO-GLW-note MJA-96-2 1996.

Jansen, M.J.W. & J.C.M. Withagen 1999. Usage: uncertainty and sensitivity analysis in a Genstat environment. Manual and Genstat procedures. Version 1.0 , http://www.cpro.wageningen-ur.nl/cbw/genstat/.

Jansen, M.J.W. 1999. Analysis of variance designs for model output, Computer Physics Communications 117, 1999, 35-43.

Klap, J.M., W. de Vries, & E.E.J.M. Leeters. 1998. Effects of acid atmospheric deposition on the chemical composition of loess, clay and peat soils under forest in The Netherlands. SC-DLO, Report 97.1, Wageningen, The Netherlands.

Kros, J. 1998. De modellering van de effecten van verzuring, vermesting en verdroging voor bossen en natuurterreinen ten behoeve van de milieubalans, milieuverkenning en natuurverkenning. Verbetering, verfijning en toepassing van het model SMART2 (in Dutch). Wageningen, DLO-Staring Centrum, Reeks Milieuplanbureau 3.

Kros, J., W. de Vries, P.H.M. Janssen, & C.I. Bak. 1993. The uncertainty in forecasting regional trends of forest soil acidification. Water, Air and Soil Pollut. 66:29-58.

Kros, J., G.J. Reinds, W. De Vries, J.B. Latour, & M. Bollen. 1995. Modelling of soil acidity and nitrogen availability in natural ecosystems in response to changes in acid deposition and hydrology. Report 95. DLO Winand Staring Centre, Wageningen, The Netherlands.

Kros, J., E.J. Pebesma, G. J. Reinds & P.A. Finke 1999. Uncertainty in Modelling Soil Acidification at the European Scale, A case study, Journal of Environmental Quality 28/2: 366-377

Krzykacz, B. 1990. SAMOS: a computer program for the derivation of empirical sensitivity measures of results from large computer models, Gesellschaft für Reaktorsicherheit, GRS-A-1700, 1990.

Leeters, E.E.J.M., H. Hartholt, W. de Vries, & L.J.M. Boumans 1993. Effects of acid deposition on 150 forest stands in The Netherlands. Relationships between deposition level, stand and site characteristics and the chemical composition of needles, mineral soil, soil solution and groundwater. Report 69.4, DLO Winand Staring Centre, Wageningen, The Netherlands.

Liefveld, W.M., A.H. Prins & G. van Wirdum 1998. Geïntegreerd Ruimtelijk Evaluatie-Instrument voor Natuurontwikkelings Scenarios (GREINS). NatuurTechnisch Model (NTM-2) B. Kwantificeren van de indicatieschalen van het NTM-2 en analyse van de modeloutput van SMART2 en SIMGRO. NBP-Onderzoeksrapport 15. DLO-Instituut voor Bos- en Natuuronderzoek. Wageningen.

McKay, M.D. 1996. Variance-based methods for assessing uncertainty importance in NUREG-1150 analyses, Los Alamos National Laboratory, LA-UR-96-2695.

Oude Voshaar, J.H. 1994. Statistics for researches, with examples from agriculture and environmental sciences [in Dutch], Wageningen Press.

Reinds, G.H. 1994. A data base for European forest soils. Technical DocumentDLO Winand Staring Centre, Wageningen, The Netherlands.

Saltelli A., S. Tarantola & K. Chan 1999. A quantitative, model independent method for global sensitivity analysis of model output, Technometrics, 41(1), 39-56.

Schouwenberg, E.P.A.G. in prep. Geïntegreerd Ruimtelijk Evaluatie-Instrument voor Natuurontwikkelings Scenario's - Beerze-Reusel(GREINS2). Natuurtechnisch Model (NTM 3.0). Alterra-rapport. Alterra, Green World Research, Wageningen.

Searle, S.R., G. Casella & C.E. McCulloch 1992. Variance components, New York: Wiley.

Sobol' I.M. 1990. Sensitivity Estimates for Nonlinear Mathematical Models. Matematicheskoe Modelirovanie 2 (1990) 112-118 [in Russian]; translated in Mathematical Modelling and Computational Experiments, 1 (1993) 407-414

Van der Sluis, T. 1996. Vegetatiekundige natuurwaardebepaling. NBP-onderzoekrapport 7. DLO-Instituut voor Bos- en Natuuronderzoek. Wageningen, 117 p.

Van Wirdum, G. 1981. Design for a land ecological survey of nature protection. In: S.P. Tjallingii & A.A. De Veer (ed.). Perspectives in land ecology. Pudoc, Wageningen; 245-251.

Wamelink, G.W.W. & H.F. van Dobben 1996. Schatting van responsies van soorten op de milieufactoren vocht, pH en macronutriënten: een aanzet tot calibratie van Ellenberg's indicatiegetallen. DLO-instituut voor Bos- en natuuronderzoek. Rapport 233, Wageningen.

Wamelink, G.W.W., C.J.F. ter Braak & H.F. van Dobben 1997. De Nederlandse natuur in 2020: schatting van de potentiële natuurwaarde in drie scenario's. IBN-rapport 312. DLO-Instituut voor Bos- en Natuuronderzoek. Wageningen. 79 p.

Wamelink, G.W.W., J.P. Mol-Dijkstra, H.F. van Dobben, J. Kros & F. Berendse 2000. Eerste fase van de ontwikkeling van Successie Model SUMO 1.0. Verbetering van de vegetatiemodellering in de Natuurplanner. Alterra-rapport 045. Alterra, Green World Research, Wageningen.

Wamelink, G.W.W., H. van Oene, J.P. Mol-Dijkstra, J. Kros, H.F. van Dobben
F. Berendse, 2000 Validatie van de modellen SMART2, SMART2-SUMO1.0, NUCOM en MOVE op site, regionaal en nationaal niveau. Alterra-rapport 65, Alterra, Green World Research, Wageningen.

Wheeler B.D. 1988. Species richness , species rarity and conservation evaluation of rich-fen vegetation in lowland England and Wales. Journal of Applied Ecology 25: 331-353.

Witte, J.P.M. & R. van der Meijden 1992. Verspreiding en natuurwaarden van ecotoopgroepen in Nederland. Onderzoek effecten grondwaterwinning. Rijksinstituut voor Volksgezondheid en Milieuhygiëne, Bilthoven

Annex 1 List of symbols

Symbol	*Explanation*
Amlf	Amount of litterfall
Amrd	Amount of dead roots
BU	Business as usual scenario
BMV_S	see p.36
CN	Soiltype: non-calcareous clay
ctNlf	Content of Nitrogen in litterfall
ctNrd	Content of Nitrogen in dead roots
Dep_Scen	Deposition scenario
Drz	Thickness of root zone
EC	European co-ordination scenario
e_F	Ellenberg indication value for moisture
e_N	Ellenberg indication value for nutrient availability
e_R	Ellenberg indication value for acidity.
GT	Groundwater table class
Hyd_Scen	Hydrology scenario
Man_Scen	Management scenario
MSGL	Mean spring groundwater level
N_{av}	N available (mol N ha^{-1} a^{-1}).
Nfu	foliar uptake of N
Nru	Nitrogen root uptake
NTM	Model for the prediction of potential conservation value
ntmpar	NTM's response uncertainty
ntmusv	unexplained system variation in NTM
P2E	Model for the conversion of physical entities into Ellenberg indication values
p2epar	Group of P2E parameters
p2eusv	Group of numbers expressing unexplained system variation in the conversion model P2E
PCV	Potential conservation value
pH_{H2O}	pH measured in the soil solution obtained by centrifugation from a freshly taken composite sample
pH_{sms}	pH according to a standardised soil analysis procedure (i.e. shaking a dried soil sample with demineralised water using a volume based soil/water of 1:5).
RC	Regression coefficient
Sim_period	Simulation period
SMART2	Soil acidification and nutrient cycling model
SMS_s	SMART2/SUMO-model variables and parameters related to a soil type
SMS_{sv}	SMART2/SUMO-model variables and parameters related to a soil type and vegetation type

SMS_v	SMART2/SUMO-model variables and parameters related to a soil type
soilpar	group of SMART2/SUMO soil parameters
SP	Soiltype: Sand poor
SR	Soiltype: Sand rich
SUMO	Succession model
SUMO_veg_code	SUMO vegetation code
TMV_S	see p. 36
USV	Unexplained system variation
vegpar	Group of SMART2/SUMO vegetation parameters
VTOT	see p. 36

Annex 2 Estimation of uncertainties in P2E and NTM

P2E

To supplement the currently used conversion parameters (Wamelink et. al. 1997) with information about their accuracy was more difficult than expected.

The original parameterisation, using regression of MSGL on Ellenberg's e_F, could be flawlessly reconstructed. Nevertheless, we constructed a new parameterisation. Firstly, in order to avoid predicted values of e_F outside the allowed range from 1 to 12, the original regression used a trick which gives rise to some problems when one wishes to assess the covariance matrix of the parameters. Moreover, we preferred regression of the Ellenbergs indication values on MSGL, rather than the converse used originally, because the purpose is to derive Ellenberg scores from pH. An exponential regression of e_F on MSGL was performed, and doing so the objections mentioned were circumvented.

The data set was obtained from RIVM (Alkemade et al. 1996).

To every 10 observations, a fake observation with MSGL=-25 and e_F=1 was added, in order to ensure that the fitted curve would be very close to that point when one extrapolates from the original MSGL range, which has minimum –2.12 for MSGL. Thus, 19 fake observations were added to the original 193 measurements.

The estimates of the regression coefficients, their variances and correlation's describe the *parametric uncertainty* of the conversion.

The residual mean square 0.6009 is caused by measurement errors and *system variability unexplained by the regression*. Assuming that the measurement error is by far the smaller of the two, vsys=0.6009 ws used as variance of the unexplained system variation.

The most obvious way to draw a new realisation of e_R, would seem to be

new_e_F = a_e_F + b_e_F * r_e_F^MSGL + ε_e_F

in which eps_e_R has mean 0 and variance vsys. But this way a value may fall outside the range from 1 to 12; if this occurs, the value is set to the nearest value in the range, i.e. 1 or 12.

Summary

The uncertainty in e_F, given MSGL, is described by the following table

Name	distribution	mean	s.d.	min	max
r_e_F	normal	1.5331	0.0455	-	-
b_e_F	normal	6.850	0.191	-	-
a_e_F	normal	1.069	0.177	-	-
ε_e_F	normal	0	0.775	-	-

Percentage correlation's between r_e_F, b_e_F, a_e_F

R	100.00		
B	-25.73	100.00	
A	46.71	-92.38	100.00
	R	B	A

Other correlation's are 0.

New values are drawn as

new_e_F = a_e_F + b_e_F * r_e_F^MSGL + ε_e_F
(truncated to range 1-12).

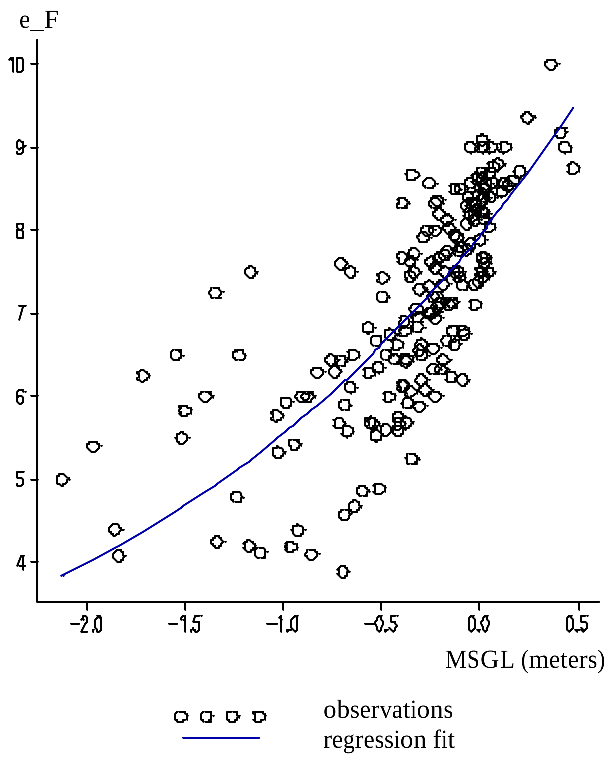


Figure 15: Graph of observations and regression fit on true data range.

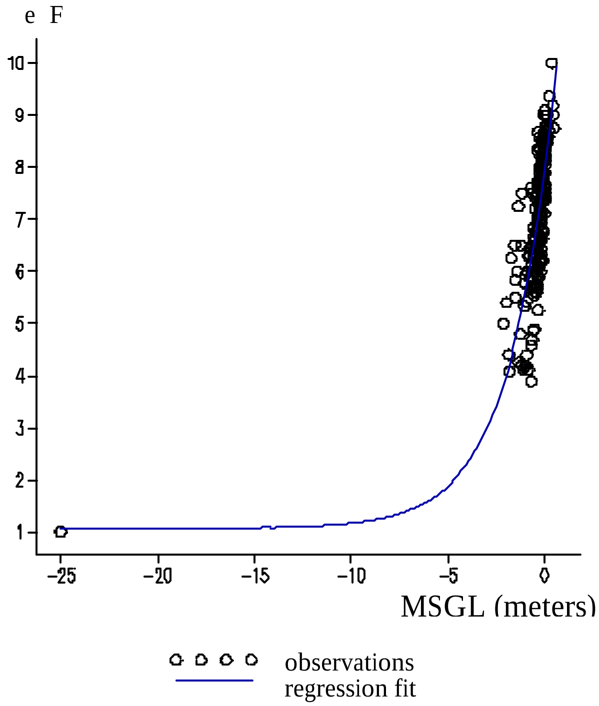


Figure 16: Graph of observations and regression fit on fake data range.

Conversion from pH_{sms} to e_R

As mentioned in section 2.1.3 the pH resulting from SMART2/SUMO refers to the pH in the soil solution (pH_{sms}), whereas the pH used in P2E refers to the pH_{H2O} (Schouwenberg in prep). Therefore the conversion takes place in two steps: first conversion of pH_{sms} into pH_{H2O} and secondly conversion of pH_{H2O} into e_R.

Conversion from pH_{sms} of SMART2Sumo to pH_{H2O}

Here we reconsidered the datasets as described in Kros (1998) in order to determine the uncertainty in both pH_{sms} and pH_{H2O}. The data were restricted to soils sand and clay.

The analyses for sand and clay were combined because the regression coefficients were much the same. The differences between the residual mean squares, however, 0.09314 and 0.1924 respectively, were a bit too large to be ignored. In the combined analysis for sand and the inverses of these residual mean squares were used as weight. As was to be expected the residual mean square of the combined analysis was very nearly equal to 1, namely 0.9984. The ensuing residual mean squares, 0.9984*0.09314 for sand and 0.9984*0.1924 for clay, are caused by measurement errors and *system variability unexplained by the regression*. Assuming that the measurement error variance was approximately 0.05 for both x_pH and y_pH, and assuming independence of measurement errors, the error variance in y_pH given x_pH was equal to $(1+0.8708^2) * 0.05 = 0.08791$. It is obvious that the residual variances were much larger than can be accounted for by mere measurement errors. Thus, we used σ^2_{sand} = 0.09314-0.08791 = 0.0052, and σ^2_{clay} = 0.1924-0.08791 = 0.1045 as unexplained system variation.

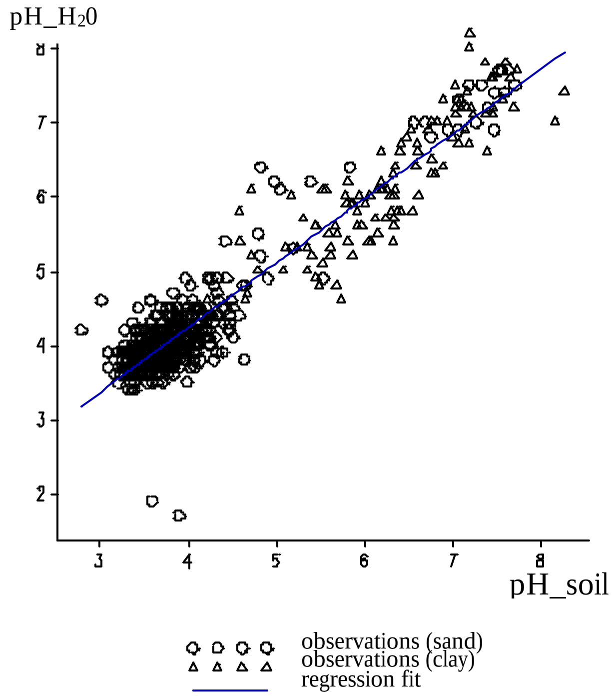


Figure 17: Graph of observations and regression fit

Summary

The following table describes the uncertainty in pH_{H2O}, given pHsms

Name	Distribution	mean	s.d.	min	max
a_pHpH	Normal	0.7424	0.0525	-	-
b_pHpH	normal	0.8708	0.0124	-	-
ε_pHpH	normal	0	0.999	-	-
ρ(a_pHpH, b_pHpH) = -0.972; the other correlation's are 0.					

New values of pH_water, given pH_soil, were drawn as

$$\text{new\_pH\_water} = \text{a\_pHpH} + \text{b\_pHpH}*\text{pH\_soil} + \sigma_{soil} * \varepsilon\text{\_pHpH}$$

in which $\sigma^2_{sand} = 0.0052$ and $\sigma^2_{clay} = 0.1045$.

Graphs

In the next graph, of observations and regression fit, 'o' indicates sand and 'Δ' indicates clay.

As seen in figure 4a-b there was a dramatic difference in new realisations of pH_{H2O}, given a set of 1000 given values of pH_soil between the graph with unexplained system variation the graph without unexplained system variation.

Conversion from pH_{H2O} of SMART2Sumo to e_R

To supplement the currently used conversion parameters (Wamelink & Van Dobben 1996) with information about their accuracy was more difficult than expected. The original parameterisation, using regression of pH on Ellenberg's e_R, could not sufficiently be reconstructed. Thus, a new parameterisation was constructed. Regression of the Ellenberg indication values on the pH was done, rather than the converse used originally, because the purpose is to derive Ellenberg scores from pH.

The data set for this new parameterisation was prepared as follows.

Summary

New cases of e_R, given pH were simulated by

$$e\_R = a\_e\_R + b\_e\_R*pH + \varepsilon\_e\_R$$

The estimates of the regression coefficients, their variances and correlation's describe the parametric uncertainty of the conversion. Normal distributions for both parameters were assumed, but also a gamma distribution with minimum 0 for the slope coefficient can be used in order to rule completely out the possibility of negative slopes (but the probability was already very small under a normal distribution).

The residual mean square 2.716 is partly caused by the fact that the Ellenberg indication values in the dataset are integers. The variance of the homogeneous distribution on an interval of length 1 is equal to 1/12. When this variance is subtracted from 2.716 there remains a variance 2.633 caused by measurement errors and system variability unexplained by the regression. Assuming that the measurement error is by far the smaller of the two, 2.633 was used as variance of the unexplained system variation.

The following table describes the distribution.

Name	distribution	mean	Variance	Min	max
A_e_R	normal	-0.2215	1.1498	-	-
B_e_R	gamma	0.8876	0.0375	0	-
ε_e_R	normal	0	2.633	-	-
ρ(a_e_R, b_e_R) = -0.9835; other correlation's are 0					

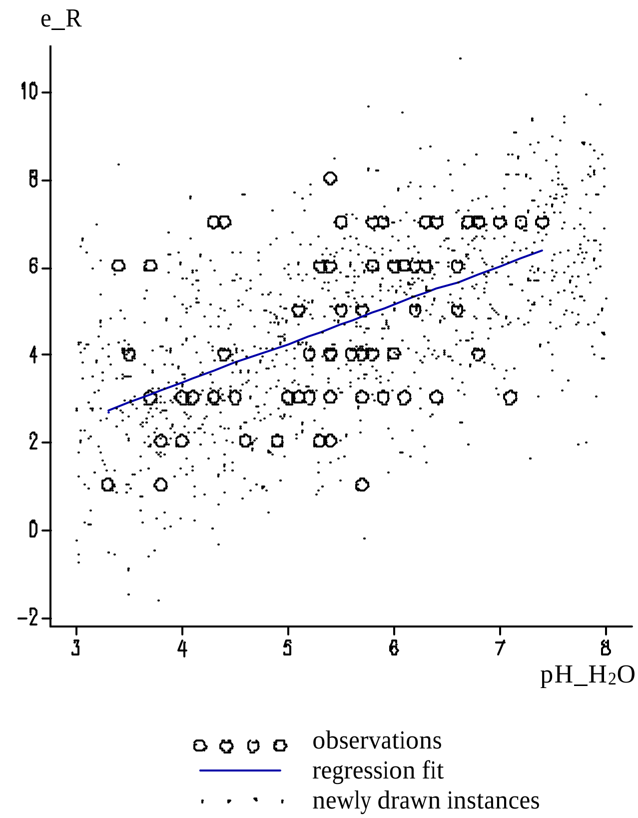


Figure 18: Graph of observations, regression fit and 1000 newly drawn instances, with given pH homogeneous on 3-8.

NTM

Uncertainty in prediction of potential nature value, given the Ellenberg numbers

The uncertainty in several regression relations in the SMART2/SUMO-P2E-NTM model chain has been defined by the means and covariance-matrix of the regression estimates. In the case of NTM, however, the situation is somewhat different because NTM has not been calibrated via ordinary regression, but via penalised spline regression. In this form of regression, quite a large number of parameters are adapted, and the ensuing risk of overfitting is avoided by means of a penalty for roughness of the response. Thus, the method strikes a balance between the two evils roughness of the response and infidelity to the data. But the result is that the response uncertainty cannot be characterised in the standard way for a small number of parameters. Instead, the uncertainty in the NTM response, given the Ellenberg numbers e_F, e_N and e_R, has been characterised in the form of a bootstrap sample of 100 response functions. Thus, a response is defined by a random integer between 1 and 100, which will be calculated as 100*uniform(0.1), rounded to the nearest higher integer.

Given the Ellenberg numbers e_F, e_N and e_R, and given the NTM response, the potential conservation value is not unique. There is quite some variation that cannot be accounted for by the regression. The potential nature value has a distribution (for simplicity assumed to be normal unless this lead to physically impossible response) with the NTM-response as mean, and a variance σ^2_NTM.

Summary

$$new\_PCV = f_n(e\_F, e\_N, e\_R) + sd\_ntm * \varepsilon\_NTM$$

in which n = roundup(100*u_NTM), and in which f_1 ... f_{100} are 100 bootstrap realisations of the NTM response.

sd_ntm = sqrt(10.1277) = 3.18 (heather); sqrt(5.0025) = 2.24 (deciduous forest); sqrt(2.268)= 1.51 (pine-forest); sqrt(8.955)=2.99 (other)

Name	distribution	mean	s.d.	min	max
u_NTM	uniform	-	-	0	1
ε_NTM	normal	0	1	-	-
Correlation's are 0					

Annex 3 Results of the WINDINGS analysis

Table I: Estimates of mean and standard deviation (s.d.) for the BU-scenario and succession 1 (bare ground to forest); with and without USV

BU		**without USV P2E and without USV NTM**													
		msgl		pH		N_{av}l		e_F		e_R		e_N		PCV	
				-		mol ha-1 a-1		-		-		-		-	
		mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
CN	1995	3	0	5.16	0.20	2270	229	2.99	0.15	4.43	0.41	1.46	0.20	13.3	0.3
	2005	3	0	5.13	0.15	4530	660	2.99	0.15	4.40	0.36	3.40	0.57	12.3	0.5
	2025	3	0	5.27	0.16	8740	1822	2.99	0.15	4.51	0.37	6.94	1.40	14.1	2.0
	2095	3	0	5.48	0.23	17200	4858	2.99	0.15	4.68	0.43	8.79	0.80	15.5	3.0
SP	1995	3	0	4.26	0.22	2180	212	2.99	0.15	3.73	0.32	1.38	0.18	13.1	0.2
	2005	3	0	4.28	0.22	4040	602	2.99	0.15	3.75	0.32	2.98	0.52	12.2	0.9
	2025	3	0	4.33	0.22	7530	1603	2.99	0.15	3.79	0.31	5.98	1.34	13.4	2.2
	2095	3	0	4.52	0.43	16600	4940	2.99	0.15	3.93	0.42	8.72	0.91	16.0	3.3
SR	1995	3	0	4.03	0.29	2160	208	2.99	0.15	3.65	0.37	1.36	0.18	13.1	0.3
	2005	3	0	4.09	0.29	3890	606	2.99	0.15	3.60	0.36	2.85	0.52	12.3	0.6
	2025	3	0	4.20	0.29	7290	1609	2.99	0.15	3.69	0.35	5.77	1.35	13.4	2.0
	2095	3	0	4.49	0.57	15800	1628	2.99	0.15	3.91	0.51	8.56	1.14	15.5	4.0

BU		**with USV P2E and with USV NTM**													
		msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
				-		mol ha-1 a-1		-		-		-		-	
		mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
CN	1995	3	0	5.16	0.45	2270	229	2.99	0.78	4.44	1.66	1.46	0.20	13.3	3.1
	2005	3	0	5.13	0.39	4530	660	2.99	0.78	4.41	1.65	3.40	0.57	12.7	3.2
	2025	3	0	5.27	0.39	8740	1822	2.99	0.78	4.52	1.65	6.94	1.40	12.7	4.2
	2095	3	0	5.48	0.48	17200	4858	2.99	0.78	4.68	1.72	8.79	0.80	15.3	4.9
SP	1995	3	0	4.26	0.22	2180	212	2.99	0.78	3.76	1.58	1.38	0.18	13.1	3.1
	2005	3	0	4.28	0.22	4040	602	2.99	0.78	3.78	1.58	2.98	0.52	12.3	3.1
	2025	3	0	4.33	0.22	7530	1603	2.99	0.78	3.82	1.58	5.98	1.34	12.3	4.0
	2095	3	0	4.52	0.43	16600	4940	2.99	0.78	3.96	1.61	8.72	0.91	15.7	4.8
SR	1995	3	0	4.03	0.29	2160	208	2.99	0.78	3.60	1.57	1.36	0.18	12.0	3.1
	2005	3	0	4.09	0.29	3890	606	2.99	0.78	3.64	1.57	2.85	0.52	12.4	3.1
	2025	3	0	4.20	0.29	7290	1609	2.99	0.78	3.72	1.58	5.77	1.35	12.4	3.9
	2095	3	0	4.49	0.57	15800	1628	2.99	0.78	3.94	1.63	8.56	1.14	15.1	5.3

Table II: Estimates of the % top-marginal variances of the predictions from Table I; Scenario with and without USV

BU **with USV P2E and with USV NTM**

CN 1995

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**-2.5**	3.1	**97.2**	4.3	**-0.6**	3.2	**-2.8**	3.1	**97.1**	4.3	**2.1**	3.0
soilpar	-	-	**99.4**	4.7	**-2.0**	3.3	**-0.6**	3.2	**0.9**	3.2	**-2.0**	3.3	**1.7**	3.0
p2epar	-	-	**-2.6**	3.1	**-3.4**	3.3	**3.5**	3.1	**-1.0**	3.1	**-3.5**	3.3	**1.6**	3.1
p2eusv	-	-	**-2.6**	3.1	**-3.4**	3.3	**96.3**	4.2	**93.3**	3.7	**-3.5**	3.3	**8.1**	3.1
ntmusv	-	-	**-2.6**	3.1	**-3.4**	3.3	**-0.7**	3.2	**-2.8**	3.1	**-3.5**	3.3	**91.6**	4.5
ntmpar	-	-	**-2.6**	3.1	**-3.4**	3.3	**-0.7**	3.2	**-2.8**	3.1	**-3.5**	3.3	**0.8**	3.1

BU **with USV P2E and with USV NTM**

CN 2005

	msgl		pH		N_{av}l		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**-0.5**	3.1	**93.1**	4.5	**-0.6**	3.2	**-0.6**	3.2	**93.1**	4.5	**2.1**	3.2
soilpar	-	-	**93.5**	4.9	**1.7**	3.3	**-0.6**	3.2	**-0.6**	3.2	**1.7**	3.3	**-0.5**	3.1
p2epar	-	-	**-1.9**	2.9	**-4.9**	3.2	**3.5**	3.1	**3.5**	3.1	**-4.9**	3.2	**0.4**	3.0
p2eusv	-	-	**-1.9**	2.9	**-4.9**	3.2	**96.3**	4.2	**96.3**	4.2	**-4.9**	3.2	**8.8**	3.1
ntmusv	-	-	**-1.9**	2.9	**-4.9**	3.2	**-0.7**	3.2	**-1.7**	2.4	**-4.9**	3.2	**84.0**	4.4
ntmpar	-	-	**-1.9**	2.9	**-4.9**	3.2	**-0.7**	3.2	**-1.7**	2.4	**-4.9**	3.2	**-2.4**	3.3

BU **with USV P2E and with USV NTM**

CN 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**9.5**	3.2	**94.2**	4.8	**-0.6**	3.2	**-2.1**	3.1	**93.7**	4.1	**14.4**	3.2
soilpar	-	-	**72.9**	4.2	**1.6**	3.5	**-0.6**	3.2	**-0.2**	3.2	**1.7**	3.4	**-1.1**	3.1
p2epar	-	-	**-6.5**	2.9	**-4.0**	3.5	**3.5**	3.1	**-0.7**	3.1	**-3.4**	3.5	**-0.9**	3.0
p2eusv	-	-	**-6.5**	2.9	**-0.8**	2.4	**96.3**	4.2	**94.4**	3.8	**-3.4**	3.5	**19.8**	3.1
ntmusv	-	-	**-6.5**	2.9	**-0.8**	2.4	**-0.7**	3.2	**-2.5**	3.1	**-3.4**	3.5	**43.9**	3.3
ntmpar	-	-	**-6.5**	2.9	**-0.8**	2.4	**-0.7**	3.2	**-2.5**	3.1	**-3.4**	3.5	**-10.0**	3.6

BU **with USV P2E and with USV NTM**

CN 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**19.2**	3.5	**92.0**	4.3	**-0.6**	3.2	**-0.4**	3.1	**92.1**	14.3	**28.3**	3.5
soilpar	-	-	**60.5**	3.6	**-3.9**	3.2	**-0.6**	3.2	**0.9**	3.1	**-6.5**	1.5	**-2.4**	3.0
p2epar	-	-	**-9.1**	3.1	**-4.3**	3.3	**3.5**	3.1	**-0.7**	3.1	**-6.1**	1.5	**-4.6**	3.1
p2eusv	-	-	**-9.1**	3.1	**-4.3**	3.3	**96.3**	4.2	**92.7**	3.8	**-6.1**	1.5	**12.9**	3.3
ntmusv	-	-	**-9.1**	3.1	**-4.3**	3.3	**-0.7**	3.2	**-2.8**	3.1	**-6.1**	1.5	**27.8**	3.2
ntmpar	-	-	**-9.1**	3.1	**-4.3**	3.3	**-0.7**	3.2	**-2.8**	3.1	**-6.1**	1.5	**-10.7**	3.5

BU **with USV P2E and with USV NTM**

PS 1995

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**3.2**	3.0	**98.1**	4.5	**-0.6**	3.2	**-2.8**	3.1	**98.1**	4.4	**2.4**	3.0
soilpar	**-**	**-**	**96.0**	4.6	**-1.4**	3.4	**-0.6**	3.2	**-2.0**	3.2	**-1.6**	3.4	**2.1**	3.1
p2epar	**-**	**-**	**-1.7**	3.1	**-3.1**	3.4	**3.5**	3.1	**-1.0**	0.2	**-3.3**	3.4	**2.1**	3.1
p2eusv	**-**	**-**	**-1.7**	3.1	**-3.1**	3.4	**96.3**	4.2	**96.1**	3.9	**-3.3**	3.4	**9.3**	3.1
ntmusv	**-**	**-**	**-1.7**	3.1	**-3.1**	3.4	**-0.7**	3.2	**-2.8**	3.2	**-3.3**	3.4	**90.6**	4.4
ntmpar	**-**	**-**	**-1.7**	3.1	**-3.1**	3.4	**-0.7**	3.2	**-2.8**	3.2	**-3.3**	3.4	**2.0**	3.0

BU **with USV P2E and with USV NTM**

PS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**3.1**	3.0	**93.1**	4.5	**-0.6**	3.2	**-2.7**	3.2	**93.0**	4.5	**8.1**	3.1
soilpar	**-**	**-**	**95.5**	4.7	**0.2**	3.3	**-0.6**	3.2	**-2.1**	3.2	**0.2**	3.3	**0.2**	3.0
p2epar	**-**	**-**	**-2.6**	3.1	**-7.0**	3.3	**3.5**	3.1	**0.1**	3.2	**-7.0**	3.3	**-0.2**	3.0
p2eusv	**-**	**-**	**-2.6**	3.1	**-7.0**	3.3	**96.3**	4.2	**96.2**	3.9	**-7.0**	3.3	**6.4**	3.1
ntmusv	**-**	**-**	**-2.6**	3.1	**-7.0**	3.3	**-0.7**	3.2	**-2.8**	3.2	**-7.0**	3.3	**78.5**	4.4
ntmpar	**-**	**-**	**-2.6**	3.1	**-7.0**	3.3	**-0.7**	3.2	**-2.8**	3.2	**-7.0**	3.3	**-1.9**	3.2

BU **with USV P2E and with USV NTM**

PS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**6.5**	3.1	**94.2**	4.9	**-0.6**	3.2	**-2.6**	3.2	**94.4**	4.4	**23.6**	3.2
soilpar	**-**	**-**	**91.1**	4.7	**3.5**	3.6	**-0.6**	3.2	**-2.2**	3.2	**3.5**	3.6	**0.2**	3.1
p2epar	**-**	**-**	**-3.5**	3.2	**-2.1**	3.6	**3.5**	3.1	**-0.1**	3.2	**-1.8**	3.6	**0.4**	3.1
p2eusv	**-**	**-**	**-3.5**	3.2	**-2.1**	3.6	**96.3**	4.2	**96.3**	3.9	**-1.8**	3.6	**13.5**	3.2
ntmusv	**-**	**-**	**-3.5**	3.2	**-2.1**	3.6	**-0.7**	3.2	**-2.7**	3.2	**-1.8**	3.6	**41.9**	3.6
ntmpar	**-**	**-**	**-3.5**	3.2	**-2.1**	3.6	**-0.7**	3.2	**-2.7**	3.2	**-1.8**	3.6	**-9.8**	3.6

BU **with USV P2E and with USV NTM**

PS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**19.7**	3.6	**91.8**	4.0	**-0.6**	3.2	**-1.5**	3.2	**88.1**	11.7	**36.2**	3.2
soilpar	**-**	**-**	**52.6**	3.6	**0.9**	3.2	**-0.6**	3.2	**-0.6**	3.2	**-1.0**	3.5	**-1.6**	3.0
p2epar	**-**	**-**	**-6.5**	3.3	**0.3**	3.1	**3.5**	3.1	**-0.4**	3.1	**-3.5**	2.3	**-0.9**	3.1
p2eusv	**-**	**-**	**-6.5**	3.3	**0.3**	3.1	**96.3**	4.2	**93.0**	3.7	**-3.5**	2.3	**13.5**	3.2
ntmusv	**-**	**-**	**-6.5**	3.3	**0.3**	3.1	**-0.7**	3.2	**-2.7**	3.3	**-3.5**	2.3	**27.5**	3.3
ntmpar	**-**	**-**	**-6.5**	3.3	**0.3**	3.1	**-0.7**	3.2	**-2.7**	3.3	**-3.5**	2.3	**-7.2**	3.4

BU **with USV P2E and with USV NTM**

RS 1995

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**2.9**	3.0	**96.8**	4.4	**-0.6**	3.2	**-2.8**	3.2	**96.8**	4.4	**2.4**	3.0
soilpar	**-**	**-**	**95.9**	5.2	**-0.2**	3.4	**-0.6**	3.2	**-1.5**	3.3	**-0.4**	3.5	**2.0**	3.0
p2epar	**-**	**-**	**-2.0**	3.0	**-2.9**	3.4	**3.5**	3.1	**0.5**	3.2	**-3.1**	3.5	**2.1**	3.0
p2eusv	**-**	**-**	**-2.0**	3.0	**-2.9**	3.4	**96.3**	4.2	**94.8**	3.8	**-3.1**	3.5	**9.3**	3.1
ntmusv	**-**	**-**	**-2.0**	3.0	**-2.9**	3.4	**-0.7**	3.2	**-3.0**	3.2	**-3.1**	3.5	**90.7**	4.4
ntmpar	**-**	**-**	**-2.0**	3.0	**-2.9**	3.4	**-0.7**	3.2	**-3.0**	3.2	**-3.1**	3.5	**1.4**	3.0

BU **with USV P2E and with USV NTM**

RS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**3.3**	3.0	**88.2**	4.5	**-0.6**	3.2	**-2.8**	3.2	**88.2**	4.5	**3.9**	3.0
soilpar	**-**	**-**	**94.6**	5.3	**4.6**	3.3	**-0.6**	3.2	**-1.6**	3.2	**4.6**	3.3	**0.0**	3.0
p2epar	**-**	**-**	**-2.9**	3.0	**-6.8**	3.2	**3.5**	3.1	**0.4**	3.2	**-6.8**	3.2	**0.0**	3.0
p2eusv	**-**	**-**	**-2.9**	3.0	**-6.8**	3.2	**96.3**	4.2	**95.1**	3.8	**-6.8**	3.2	**5.7**	3.1
ntmusv	**-**	**-**	**-2.9**	3.0	**-6.8**	3.2	**-0.7**	3.2	**-2.9**	3.2	**-6.8**	3.2	**86.3**	4.4
ntmpar	**-**	**-**	**-2.9**	3.0	**-6.8**	3.2	**-0.7**	3.2	**-2.9**	3.2	**-6.8**	3.2	**-0.3**	3.1

BU **with USV P2E and with USV NTM**

RS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**8.2**	3.2	**90.9**	4.7	**-0.6**	3.2	**-2.4**	3.2	**91.4**	4.4	**18.5**	3.2
soilpar	**-**	**-**	**85.9**	4.9	**5.1**	3.5	**-0.6**	3.2	**-1.8**	3.2	**5.1**	3.5	**1.0**	3.2
p2epar	**-**	**-**	**-4.0**	3.0	**-2.6**	3.5	**3.5**	3.1	**0.1**	3.1	**-2.3**	3.5	**0.7**	3.1
p2eusv	**-**	**-**	**-4.0**	3.0	**-2.6**	3.5	**96.3**	4.2	**95.3**	3.8	**-2.3**	3.5	**9.9**	3.3
ntmusv	**-**	**-**	**-4.0**	3.0	**-2.6**	3.5	**-0.7**	3.2	**-2.7**	3.2	**-2.3**	3.5	**48.8**	3.5
ntmpar	**-**	**-**	**-4.0**	3.0	**-2.6**	3.5	**-0.7**	3.2	**-2.7**	3.2	**-2.3**	3.5	**-9.0**	3.4

BU **with USV P2E and with USV NTM**

RS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**20.9**	3.8	**86.1**	4.0	**-0.6**	3.2	**-0.6**	3.2	**83.6**	9.1	**44.0**	3.6
soilpar	**-**	**-**	**51.9**	3.5	**-1.8**	3.3	**-0.6**	3.2	**0.8**	3.2	**-0.7**	2.9	**0.0**	3.1
p2epar	**-**	**-**	**-2.4**	3.5	**-3.3**	3.3	**3.5**	3.1	**0.3**	3.1	**-1.5**	3.2	**0.2**	2.9
p2eusv	**-**	**-**	**-2.4**	3.5	**-3.3**	3.3	**96.3**	4.2	**90.1**	3.7	**-1.5**	3.2	**7.8**	3.2
ntmusv	**-**	**-**	**-2.4**	3.5	**-3.3**	3.3	**-0.7**	3.2	**-2.7**	3.3	**-1.5**	3.2	**23.8**	3.1
ntmpar	**-**	**-**	**-2.4**	3.5	**-3.3**	3.3	**-0.7**	3.2	**-2.7**	3.3	**-1.5**	3.2	**-6.9**	3.4

BU **without USV P2E and without USV NTM**

CN 1995

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**-2.5**	3.1	**97.2**	4.3	**4.4**	3.2	**-4.6**	3.3	**97.1**	4.3	**53.6**	10.8
soilpar	**-**	**-**	**99.4**	4.7	**-2.0**	3.3	**4.4**	3.2	**69.0**	3.8	**-2.0**	3.3	**14.3**	2.9
p2epar	**-**	**-**	**-2.6**	3.1	**-3.4**	3.3	**100**	4.6	**19.1**	3.3	**-3.5**	3.3	**22.3**	3.1
p2eusv	**-**	**-**	**-2.6**	3.1	**-3.4**	3.3	**4.6**	3.2	**-4.7**	3.2	**-3.5**	3.3	**-5.6**	2.7
ntmusv	**-**	**-**	**-2.6**	3.1	**-3.4**	3.3	**4.6**	3.2	**-4.7**	3.2	**-3.5**	3.3	**-5.6**	2.7
ntmpar	**-**	**-**	**-2.6**	3.1	**-3.4**	3.3	**4.6**	3.2	**-4.7**	3.2	**-3.5**	3.3	**-3.7**	2.8

BU **without USV P2E and without USV NTM**

CN 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**-0.5**	3.1	**93.1**	4.5	**4.4**	3.2	**-4.4**	3.2	**93.1**	4.5	**71.4**	4.3
soilpar	**-**	**-**	**93.5**	4.9	**1.7**	3.3	**4.4**	3.2	**58.8**	3.9	**1.7**	3.3	**-0.6**	3.2
p2epar	**-**	**-**	**-1.9**	2.9	**-4.9**	3.2	**100**	4.6	**24.5**	3.2	**-4.9**	3.2	**3.1**	3.4
p2eusv	**-**	**-**	**-1.9**	2.9	**-4.9**	3.2	**4.6**	3.2	**-5.0**	3.1	**-4.9**	3.2	**-5.1**	3.1
ntmusv	**-**	**-**	**-1.9**	2.9	**-4.9**	3.2	**4.6**	3.2	**-5.0**	3.1	**-4.9**	3.2	**-5.1**	3.2
ntmpar	**-**	**-**	**-1.9**	2.9	**-4.9**	3.2	**4.6**	3.2	**-5.0**	3.1	**-4.9**	3.2	**-5.0**	3.2

BU **without USV P2E and without USV NTM**

CN 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**9.5**	3.2	**94.2**	4.8	**4.4**	3.2	**4.3**	3.2	**93.7**	4.1	**89.3**	3.3
soilpar	**-**	**-**	**72.9**	4.2	**1.6**	3.5	**4.4**	3.2	**48.3**	3.7	**1.7**	3.4	**0.1**	3.0
p2epar	**-**	**-**	**-6.5**	2.9	**-4.0**	3.5	**100**	4.6	**22.9**	3.4	**-3.4**	3.5	**1.2**	3.1
p2eusv	**-**	**-**	**-6.5**	2.9	**-0.8**	2.4	**4.6**	3.2	**-4.7**	3.0	**-3.4**	3.5	**-3.3**	3.1
ntmusv	**-**	**-**	**-6.5**	2.9	**-0.8**	2.4	**4.6**	3.2	**-4.7**	3.0	**-3.4**	3.5	**-3.3**	3.1
ntmpar	**-**	**-**	**-6.5**	2.9	**-0.8**	2.4	**4.6**	3.2	**-4.7**	3.0	**-3.4**	3.5	**-3.2**	3.1

BU **without USV P2E and without USV NTM**

CN 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**19.2**	3.5	**92.0**	4.3	**4.4**	3.2	**15.2**	3.4	**92.1**	14.3	**85.4**	5.8
soilpar	**-**	**-**	**60.5**	3.6	**-3.9**	3.2	**4.4**	3.2	**45.0**	3.6	**-6.5**	1.5	**-0.8**	2.9
p2epar	**-**	**-**	**-9.1**	3.1	**-4.3**	3.3	**100**	4.6	**15.7**	3.7	**-6.1**	1.5	**-4.2**	2.7
p2eusv	**-**	**-**	**-9.1**	3.1	**-4.3**	3.3	**4.6**	3.2	**-4.2**	3.1	**-6.1**	1.5	**-5.3**	2.6
ntmusv	**-**	**-**	**-9.1**	3.1	**-4.3**	3.3	**4.6**	3.2	**-4.2**	3.1	**-6.1**	1.5	**-5.3**	2.6
ntmpar	**-**	**-**	**-9.1**	3.1	**-4.3**	3.3	**4.6**	3.2	**-4.2**	3.1	**-6.1**	1.5	**-5.1**	2.6

BU **without USV P2E and without USV NTM**

PS 1995

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**3.2**	3.0	**98.1**	4.5	**4.4**	3.2	**-2.3**	2.8	**98.1**	4.4	**37.4**	6.2
soilpar	**-**	**-**	**96.0**	4.6	**-1.4**	3.4	**4.4**	3.2	**24.6**	2.8	**-1.6**	3.4	**6.9**	3.5
p2epar	**-**	**-**	**-1.7**	3.1	**-3.1**	3.4	**100**	4.6	**67.0**	3.8	**-3.3**	3.4	**47.4**	3.8
p2eusv	**-**	**-**	**-1.7**	3.1	**-3.1**	3.4	**4.6**	3.2	**-3.8**	2.8	**-3.3**	3.4	**-5.2**	3.0
ntmusv	**-**	**-**	**-1.7**	3.1	**-3.1**	3.4	**4.6**	3.2	**-3.8**	2.8	**-3.3**	3.4	**-5.2**	3.0
ntmpar	**-**	**-**	**-1.7**	3.1	**-3.1**	3.4	**4.6**	3.2	**-3.8**	2.8	**-3.3**	3.4	**-3.1**	3.0

BU **without USV P2E and without USV NTM**

PS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**3.1**	3.0	**93.1**	4.5	**4.4**	3.2	**-2.6**	2.8	**93.0**	4.5	**92.6**	5.7
soilpar	**-**	**-**	**95.5**	4.7	**0.2**	3.3	**4.4**	3.2	**24.8**	2.8	**0.2**	3.3	**-1.0**	3.0
p2epar	**-**	**-**	**-2.6**	3.1	**-7.0**	3.3	**100**	4.6	**66.2**	3.8	**-7.0**	3.3	**-1.7**	2.9
p2eusv	**-**	**-**	**-2.6**	3.1	**-7.0**	3.3	**4.6**	3.2	**-4.3**	2.8	**-7.0**	3.3	**-2.0**	2.8
ntmusv	**-**	**-**	**-2.6**	3.1	**-7.0**	3.3	**4.6**	3.2	**-4.3**	2.8	**-7.0**	3.3	**-2.0**	2.8
ntmpar	**-**	**-**	**-2.6**	3.1	**-7.0**	3.3	**4.6**	3.2	**-4.3**	2.8	**-7.0**	3.3	**-2.4**	2.8

BU **without USV P2E and without USV NTM**

PS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**6.5**	3.1	**94.2**	4.9	**4.4**	3.2	**-1.2**	2.9	**94.4**	4.4	**92.1**	4.0
soilpar	**-**	**-**	**91.1**	4.7	**3.5**	3.6	**4.4**	3.2	**24.3**	2.8	**3.5**	3.6	**0.0**	3.2
p2epar	**-**	**-**	**-3.5**	3.2	**-2.1**	3.6	**100**	4.6	**64.9**	3.8	**-1.8**	3.6	**0.6**	3.2
p2eusv	**-**	**-**	**-3.5**	3.2	**-2.1**	3.6	**4.6**	3.2	**-4.1**	2.8	**-1.8**	3.6	**-2.3**	3.3
ntmusv	**-**	**-**	**-3.5**	3.2	**-2.1**	3.6	**4.6**	3.2	**-4.1**	2.8	**-1.8**	3.6	**-2.3**	3.3
ntmpar	**-**	**-**	**-3.5**	3.2	**-2.1**	3.6	**4.6**	3.2	**-4.1**	2.8	**-1.8**	3.6	**-2.3**	3.3

BU **without USV P2E and without USV NTM**

PS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**19.7**	3.6	**91.8**	4.0	**4.4**	3.2	**10.6**	3.0	**88.1**	11.7	**91.2**	4.1
soilpar	**-**	**-**	**52.6**	3.6	**0.9**	3.2	**4.4**	3.2	**34.4**	3.4	**-1.0**	3.5	**0.7**	3.2
p2epar	**-**	**-**	**-6.5**	3.3	**0.3**	3.1	**100**	4.6	**29.3**	3.6	**-3.5**	2.3	**1.3**	3.3
p2eusv	**-**	**-**	**-6.5**	3.3	**0.3**	3.1	**4.6**	3.2	**-5.9**	3.3	**-3.5**	2.3	**-0.3**	3.2
ntmusv	**-**	**-**	**-6.5**	3.3	**0.3**	3.1	**4.6**	3.2	**-5.9**	3.3	**-3.5**	2.3	**-0.3**	3.2
ntmpar	**-**	**-**	**-6.5**	3.3	**0.3**	3.1	**4.6**	3.2	**-5.9**	3.3	**-3.5**	2.3	**0.4**	3.2

BU **without USV P2E and without USV NTM**

RS 1995

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**2.9**	3.0	**96.8**	4.4	**4.4**	3.2	**-1.4**	2.9	**96.8**	4.4	**49.4**	9.5
soilpar	-	-	**95.9**	5.2	**-0.2**	3.4	**4.4**	3.2	**31.9**	2.9	**-0.4**	3.5	**7.9**	3.1
p2epar	-	-	**-2.0**	3.0	**-2.9**	3.4	**100**	4.6	**58.5**	3.6	**-3.1**	3.5	**35.9**	3.2
p2eusv	-	-	**-2.0**	3.0	**-2.9**	3.4	**4.6**	3.2	**-3.2**	2.8	**-3.1**	3.5	**-4.8**	2.6
ntmusv	-	-	**-2.0**	3.0	**-2.9**	3.4	**4.6**	3.2	**-3.2**	2.8	**-3.1**	3.5	**-4.8**	2.6
ntmpar	-	-	**-2.0**	3.0	**-2.9**	3.4	**4.6**	3.2	**-3.2**	2.8	**-3.1**	3.5	**-3.3**	2.7

BU **without USV P2E and without USV NTM**

RS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**3.3**	3.0	**88.2**	4.5	**4.4**	3.2	**-1.4**	2.9	**88.2**	4.5	**83.9**	4.8
soilpar	-	-	**94.6**	5.3	**4.6**	3.3	**4.4**	3.2	**31.5**	2.9	**4.6**	3.3	**-0.2**	3.2
p2epar	-	-	**-2.9**	3.0	**-6.8**	3.2	**100**	4.6	**58.1**	3.6	**-6.8**	3.2	**3.0**	3.3
p2eusv	-	-	**-2.9**	3.0	**-6.8**	3.2	**4.6**	3.2	**-3.7**	2.8	**-6.8**	3.2	**2.1**	3.3
ntmusv	-	-	**-2.9**	3.0	**-6.8**	3.2	**4.6**	3.2	**-3.7**	2.8	**-6.8**	3.2	**2.1**	3.3
ntmpar	-	-	**-2.9**	3.0	**-6.8**	3.2	**4.6**	3.2	**-3.7**	2.8	**-6.8**	3.2	**2.0**	3.3

BU **without USV P2E and without USV NTM**

RS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**8.2**	3.2	**90.9**	4.7	**4.4**	3.2	**0.8**	2.9	**91.4**	4.4	**88.0**	4.3
soilpar	-	-	**85.9**	4.9	**5.1**	3.5	**4.4**	3.2	**30.5**	2.9	**5.1**	3.5	**0.6**	3.2
p2epar	-	-	**-4.0**	3.0	**-2.6**	3.5	**100**	4.6	**54.6**	3.6	**-2.3**	3.5	**0.5**	3.3
p2eusv	-	-	**-4.0**	3.0	**-2.6**	3.5	**4.6**	3.2	**-3.9**	2.8	**-2.3**	3.5	**-2.5**	3.3
ntmusv	-	-	**-4.0**	3.0	**-2.6**	3.5	**4.6**	3.2	**-3.9**	2.8	**-2.3**	3.5	**-2.5**	3.3
ntmpar	-	-	**-4.0**	3.0	**-2.6**	3.5	**4.6**	3.2	**-3.9**	2.8	**-2.3**	3.5	**-2.5**	3.3

BU **without USV P2E and without USV NTM**

RS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**20.9**	3.8	**86.1**	4.0	**4.4**	3.2	**14.5**	3.4	**83.6**	9.1	**89.0**	4.3
soilpar	-	-	**51.9**	3.5	**-1.8**	3.3	**4.4**	3.2	**39.7**	3.5	**-0.7**	2.9	**0.0**	3.3
p2epar	-	-	**-2.4**	3.5	**-3.3**	3.3	**100**	4.6	**21.5**	3.7	**-1.5**	3.2	**0.1**	3.3
p2eusv	-	-	**-2.4**	3.5	**-3.3**	3.3	**4.6**	3.2	**-3.6**	3.5	**-1.5**	3.2	**-0.4**	3.3
ntmusv	-	-	**-2.4**	3.5	**-3.3**	3.3	**4.6**	3.2	**-3.6**	3.5	**-1.5**	3.2	**-0.4**	3.3
ntmpar	-	-	**-2.4**	3.5	**-3.3**	3.3	**4.6**	3.2	**-3.6**	3.5	**-1.5**	3.2	**-0.4**	3.3

Table III: Estimates of mean and standard deviation (s.d.) for the difference between the two scenarios (EC-BU) and succession 1 (bare ground to forest); with and without USV

EC-BU without USV P2E and without USV NTM

		msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
				-		mol ha-1 a-1		-		-		-		-	
		mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
CN	1995	0	0	0.00	0.00	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00
	2005	0	0	0.02	0.03	-415	84	0	0	0.02	0.02	-0.36	0.07	0.13	0.19
	2025	0	0	0.11	0.16	-1370	506	0	0	0.09	0.12	-1.09	0.42	-1.24	1.05
	2095	0	0	0.14	0.24	-1240	2516	0	0	0.11	0.19	-0.18	0.71	-0.40	1.46
SP	1995	0	0	0.00	0.00	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00
	2005	0	0	0.06	0.01	-374	73	0	0	0.04	0.01	-0.32	0.06	0.07	0.36
	2025	0	0	0.15	0.06	-1090	348	0	0	0.12	0.05	-0.93	0.29	-0.93	1.04
	2095	0	0	0.35	0.26	-1520	8216	0	0	0.27	0.21	-0.26	0.77	-0.67	1.51
SR	1995	0	0	0.00	0.00	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00
	2005	0	0	0.08	0.02	-356	74	0	0	0.06	0.02	-0.31	0.06	0.03	0.31
	2025	0	0	0.32	0.22	-838	409	0	0	0.24	0.18	-0.71	0.34	-0.78	0.97
	2095	0	0	0.44	0.39	-1390	2891	0	0	0.34	0.31	-0.34	0.86	-0.77	2.14

EC-BU with USV P2E and with USV NTM

		msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
				-		mol ha-1 a-1		-		-		-		-	
		mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
CN	1995	0	0	0.00	0.00	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00
	2005	0	0	0.02	0.03	-415	84	0	0	0.02	0.02	-0.36	0.07	0.02	0.45
	2025	0	0	0.11	0.16	-1370	506	0	0	0.08	0.12	-1.09	0.42	-0.95	1.22
	2095	0	0	0.14	0.24	-1240	2516	0	0	0.10	0.19	-0.18	0.71	-0.37	1.53
SP	1995	0	0	0.00	0.00	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00
	2005	0	0	0.06	0.01	-374	73	0	0	0.04	0.01	-0.32	0.06	0.02	0.53
	2025	0	0	0.15	0.06	-1090	348	0	0	0.11	0.05	-0.93	0.29	-0.79	1.25
	2095	0	0	0.35	0.26	-1520	8216	0	0	0.26	0.07	-0.26	0.77	-0.65	1.66
SR	1995	0	0	0.00	0.00	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00
	2005	0	0	0.08	0.02	-356	74	0	0	0.06	0.02	-0.31	0.06	0.00	0.46
	2025	0	0	0.32	0.22	-838	409	0	0	0.23	0.18	-0.71	0.34	-0.62	1.21
	2095	0	0	0.44	0.39	-1390	2891	0	0	0.33	0.31	-0.34	0.86	-0.73	2.24

Table IV: Estimates of the % top-marginal variances of the predictions from table III; Scenario with and without USV

EC-BU **without USV P2E and without USV NTM**

CN 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**27.7**	5.5	**61.5**	6.1	**-**	**-**	**25.8**	5.0	**61.5**	6.1	**33.3**	11.0
soilpar	**-**	**-**	**38.3**	6.7	**1.1**	3.4	**-**	**-**	**35.8**	7.2	**1.1**	3.4	**7.6**	6.0
p2epar	**-**	**-**	**2.5**	3.0	**-5.3**	3.5	**-**	**-**	**1.9**	2.7	**-5.3**	3.5	**10.3**	2.1
p2eusv	**-**	**-**	**2.5**	3.0	**-5.3**	3.5	**-**	**-**	**0.7**	2.6	**-5.3**	3.5	**1.1**	2.4
ntmusv	**-**	**-**	**2.5**	3.0	**-5.3**	3.5	**-**	**-**	**0.7**	2.6	**-5.3**	3.5	**1.1**	2.4
ntmpar	**-**	**-**	**2.5**	3.0	**-5.3**	3.5	**-**	**-**	**0.7**	2.6	**-5.3**	3.5	**1.7**	2.4

EC-BU **without USV P2E and without USV NTM**

CN 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**40.9**	7.4	**69.6**	7.9	**-**	**-**	**37.4**	6.2	**66.8**	8.5	**79.0**	4.5
soilpar	**-**	**-**	**24.8**	4.1	**8.9**	3.1	**-**	**-**	**20.7**	4.3	**10.9**	3.1	**5.3**	2.8
p2epar	**-**	**-**	**-2.4**	2.3	**-1.9**	3.0	**-**	**-**	**-1.1**	2.6	**3.8**	2.9	**2.3**	2.9
p2eusv	**-**	**-**	**-2.4**	2.3	**-1.9**	3.0	**-**	**-**	**-1.7**	2.4	**3.8**	2.9	**2.0**	3.0
ntmusv	**-**	**-**	**-2.4**	2.3	**-1.9**	3.0	**-**	**-**	**-1.7**	2.4	**3.8**	2.9	**2.0**	3.0
ntmpar	**-**	**-**	**-2.4**	2.3	**-1.9**	3.0	**-**	**-**	**-1.7**	2.4	**3.8**	2.9	**2.1**	3.0

EC-BU **without USV P2E and without USV NTM**

CN 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**37.6**	9.1	**55.3**	8.3	**-**	**-**	**34.5**	9.0	**71.8**	15.3	**32.5**	9.1
soilpar	**-**	**-**	**17.5**	3.4	**3.7**	4.1	**-**	**-**	**15.8**	3.5	**1.6**	2.9	**-0.9**	1.6
p2epar	**-**	**-**	**-0.9**	2.1	**-0.8**	2.4	**-**	**-**	**-0.1**	2.4	**-0.4**	2.9	**-7.7**	2.4
p2eusv	**-**	**-**	**-0.9**	2.1	**-0.8**	2.4	**-**	**-**	**-1.0**	2.2	**-0.4**	2.9	**-7.4**	2.3
ntmusv	**-**	**-**	**-0.9**	2.1	**-0.8**	2.4	**-**	**-**	**-1.0**	2.2	**-0.4**	2.9	**-7.4**	2.3
ntmpar	**-**	**-**	**-0.9**	2.1	**-0.8**	2.4	**-**	**-**	**-1.0**	2.2	**-0.4**	2.9	**-7.5**	2.4

EC-BU **without USV P2E and without USV NTM**

PS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**31.4**	4.0	**73.7**	7.3	**-**	**-**	**11.3**	3.4	**73.7**	7.3	**39.1**	11.4
soilpar	**-**	**-**	**45.8**	3.9	**3.3**	3.2	**-**	**-**	**14.1**	3.3	**3.3**	3.2	**-2.4**	1.6
p2epar	**-**	**-**	**1.8**	3.3	**-1.7**	2.9	**-**	**-**	**69.3**	3.8	**-1.7**	2.9	**-2.1**	1.9
p2eusv	**-**	**-**	**1.8**	3.3	**-1.7**	2.9	**-**	**-**	**4.3**	3.5	**-1.7**	2.9	**-4.5**	1.9
ntmusv	**-**	**-**	**1.8**	3.3	**-1.7**	2.9	**-**	**-**	**4.3**	3.5	**-1.7**	2.9	**-4.5**	1.9
ntmpar	**-**	**-**	**1.8**	3.3	**-1.7**	2.9	**-**	**-**	**4.3**	3.5	**-1.7**	2.9	**-4.5**	1.9

EC-BU **without USV P2E and without USV NTM**

PS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**34.2**	5.5	**80.4**	5.1	-	-	**27.7**	4.7	**75.8**	4.9	**74.6**	6.9
soilpar	-	-	**34.9**	5.2	**6.4**	3.4	-	-	**25.9**	5.1	**7.9**	3.1	**-0.7**	3.1
p2epar	-	-	**-2.3**	3.1	**1.3**	3.3	-	-	**23.5**	3.3	**3.3**	3.0	**-1.4**	3.1
p2eusv	-	-	**-2.3**	3.1	**1.3**	3.3	-	-	**0.5**	3.4	**3.3**	3.0	**-0.5**	3.2
ntmusv	-	-	**-2.3**	3.1	**1.3**	3.3	-	-	**0.5**	3.4	**3.3**	3.0	**-0.5**	3.2
ntmpar	-	-	**-2.3**	3.1	**1.3**	3.3	-	-	**0.5**	3.4	**3.3**	3.0	**-0.4**	3.2

EC-BU **without USV P2E and without USV NTM**

PS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**28.3**	3.7	**55.0**	7.8	-	-	**26.7**	3.7	**60.3**	10.4	**51.4**	9.5
soilpar	-	-	**13.7**	3.5	**-0.4**	3.0	-	-	**12.5**	3.3	**-4.7**	2.4	**-3.7**	2.2
p2epar	-	-	**1.7**	2.9	**-1.2**	2.4	-	-	**9.6**	3.2	**-4.2**	3.0	**-3.2**	2.2
p2eusv	-	-	**1.7**	2.9	**-1.2**	2.4	-	-	**3.1**	3.2	**-4.2**	3.0	**-3.7**	1.9
ntmusv	-	-	**1.7**	2.9	**-1.2**	2.4	-	-	**3.1**	3.2	**-4.2**	3.0	**-3.7**	1.9
ntmpar	-	-	**1.7**	2.9	**-1.2**	2.4	-	-	**3.1**	3.2	**-4.2**	3.0	**-3.9**	1.8

EC-BU **without USV P2E and without USV NTM**

RS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**30.4**	4.5	**64.7**	8.0	-	-	**18.2**	3.7	**64.7**	8.0	**38.9**	9.2
soilpar	-	-	**46.4**	4.2	**6.4**	3.3	-	-	**21.7**	3.4	**6.4**	3.3	**-3.0**	1.3
p2epar	-	-	**-3.7**	3.1	**4.3**	3.0	-	-	**44.9**	3.3	**4.3**	3.0	**0.1**	1.3
p2eusv	-	-	**-3.7**	3.1	**4.3**	3.0	-	-	**-1.1**	3.4	**4.3**	3.0	**-2.4**	1.4
ntmusv	-	-	**-3.7**	3.1	**4.3**	3.0	-	-	**-1.1**	3.4	**4.3**	3.0	**-2.4**	1.4
ntmpar	-	-	**-3.7**	3.1	**4.3**	3.0	-	-	**-1.1**	3.4	**4.3**	3.0	**-2.4**	1.4

EC-BU **without USV P2E and without USV NTM**

RS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**22.4**	4.2	**41.2**	4.6	-	-	**20.5**	4.1	**38.2**	4.2	**64.5**	5.1
soilpar	-	-	**42.9**	5.4	**20.9**	3.5	-	-	**38.7**	5.7	**21.2**	3.4	**-1.1**	3.1
p2epar	-	-	**-0.7**	3.6	**3.7**	3.3	-	-	**10.7**	3.9	**5.0**	2.9	**0.1**	3.2
p2eusv	-	-	**-0.7**	3.6	**3.7**	3.3	-	-	**2.3**	3.7	**5.0**	2.9	**1.6**	3.3
ntmusv	-	-	**-0.7**	3.6	**3.7**	3.3	-	-	**2.3**	3.7	**5.0**	2.9	**1.6**	3.3
ntmpar	-	-	**-0.7**	3.6	**3.7**	3.3	-	-	**2.3**	3.7	**5.0**	2.9	**1.4**	3.3

EC-BU **without USV P2E and without USV NTM**

RS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**22.2**	4.3	**42.1**	7.1	-	-	**20.1**	4.1	**58.6**	8.8	**46.6**	8.0
soilpar	-	-	**10.3**	3.4	**-0.9**	3.0	-	-	**6.8**	3.4	**-0.2**	2.3	**2.2**	3.8
p2epar	-	-	**5.2**	3.0	**4.1**	2.9	-	-	**11.0**	3.1	**2.6**	2.7	**4.3**	3.4
p2eusv	-	-	**5.2**	3.0	**4.1**	2.9	-	-	**5.4**	3.0	**2.6**	2.7	**4.6**	3.4
ntmusv	-	-	**5.2**	3.0	**4.1**	2.9	-	-	**5.4**	3.0	**2.6**	2.7	**4.6**	3.4
ntmpar	-	-	**5.2**	3.0	**4.1**	2.9	-	-	**5.4**	3.0	**2.6**	2.7	**4.5**	3.6

EC-BU **with USV P2E and with USV NTM**

CN 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**27.7**	5.5	**61.5**	6.1	-	-	**24.5**	5.1	**61.5**	6.1	**13.7**	9.1
soilpar	-	-	**38.3**	6.7	**1.1**	3.4	-	-	**35.6**	7.2	**1.1**	3.4	**0.8**	2.4
p2epar	-	-	**2.5**	3.0	**-5.3**	3.5	-	-	**1.7**	2.8	**-5.3**	3.5	**3.3**	2.8
p2eusv	-	-	**2.5**	3.0	**-5.3**	3.5	-	-	**1.7**	2.7	**-5.3**	3.5	**28.6**	3.6
ntmusv	-	-	**2.5**	3.0	**-5.3**	3.5	-	-	**0.0**	2.5	**-5.3**	3.5	**0.3**	2.3
ntmpar	-	-	**2.5**	3.0	**-5.3**	3.5	-	-	**0.0**	2.5	**-5.3**	3.5	**-0.4**	2.0

EC-BU **with USV P2E and with USV NTM**

CN 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**40.9**	7.4	**69.6**	7.9	-	-	**37.3**	6.2	**66.8**	8.5	**31.7**	3.4
soilpar	-	-	**24.8**	4.1	**8.9**	3.1	-	-	**20.4**	4.3	**10.9**	3.1	**-0.1**	2.8
p2epar	-	-	**-2.4**	2.3	**-1.9**	3.0	-	-	**-0.7**	2.7	**3.8**	2.9	**-1.5**	3.1
p2eusv	-	-	**-2.4**	2.3	**-1.9**	3.0	-	-	**-0.8**	2.4	**3.8**	2.9	**12.5**	3.0
ntmusv	-	-	**-2.4**	2.3	**-1.9**	3.0	-	-	**-1.5**	2.4	**3.8**	2.9	**-1.2**	2.5
ntmpar	-	-	**-2.4**	2.3	**-1.9**	3.0	-	-	**-1.5**	2.4	**3.8**	2.9	**-1.5**	2.4

EC-BU **with USV P2E and with USV NTM**

CN 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**37.6**	9.1	**55.3**	8.3	-	-	**33.1**	9.3	**71.8**	15.3	**27.3**	8.5
soilpar	-	-	**17.5**	3.4	**3.7**	4.1	-	-	**16.9**	3.6	**1.6**	2.9	**1.1**	1.8
p2epar	-	-	**-0.9**	2.1	**-0.8**	2.4	-	-	**0.6**	2.5	**-0.4**	2.9	**-6.7**	2.4
p2eusv	-	-	**-0.9**	2.1	**-0.8**	2.4	-	-	**-0.1**	2.3	**-0.4**	2.9	**-6.8**	2.4
ntmusv	-	-	**-0.9**	2.1	**-0.8**	2.4	-	-	**-1.1**	2.2	**-0.4**	2.9	**-5.7**	2.0
ntmpar	-	-	**-0.9**	2.1	**-0.8**	2.4	-	-	**-1.1**	2.2	**-0.4**	2.9	**-6.0**	2.1

EC-BU **with USV P2E and with USV NTM**

PS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**31.4**	4.0	**73.7**	7.3	**-**	**-**	**10.6**	3.0	**73.7**	7.3	**18.1**	7.8
soilpar	**-**	**-**	**45.8**	3.9	**3.3**	3.2	**-**	**-**	**10.5**	2.9	**3.3**	3.2	**0.6**	1.9
p2epar	**-**	**-**	**1.8**	3.3	**-1.7**	2.9	**-**	**-**	**37.3**	3.8	**-1.7**	2.9	**0.0**	2.1
p2eusv	**-**	**-**	**1.8**	3.3	**-1.7**	2.9	**-**	**-**	**33.9**	5.2	**-1.7**	2.9	**13.0**	2.0
ntmusv	**-**	**-**	**1.8**	3.3	**-1.7**	2.9	**-**	**-**	**4.5**	3.1	**-1.7**	2.9	**-2.0**	1.7
ntmpar	**-**	**-**	**1.8**	3.3	**-1.7**	2.9	**-**	**-**	**4.5**	3.1	**-1.7**	2.9	**-0.8**	1.9

EC-BU **with USV P2E and with USV NTM**

PS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**34.2**	5.5	**80.4**	5.1	**-**	**-**	**22.8**	4.7	**75.8**	4.9	**37.0**	6.3
soilpar	**-**	**-**	**34.9**	5.2	**6.4**	3.4	**-**	**-**	**21.8**	4.8	**7.9**	3.1	**-0.8**	2.5
p2epar	**-**	**-**	**-2.3**	3.1	**1.3**	3.3	**-**	**-**	**16.6**	3.5	**3.3**	3.0	**-1.2**	2.8
p2eusv	**-**	**-**	**-2.3**	3.1	**1.3**	3.3	**-**	**-**	**13.4**	3.6	**3.3**	3.0	**10.6**	2.7
ntmusv	**-**	**-**	**-2.3**	3.1	**1.3**	3.3	**-**	**-**	**0.0**	3.4	**3.3**	3.0	**-4.0**	2.5
ntmpar	**-**	**-**	**-2.3**	3.1	**1.3**	3.3	**-**	**-**	**0.0**	3.4	**3.3**	3.0	**-3.4**	2.6

EC-BU **with USV P2E and with USV NTM**

PS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**28.3**	3.7	**55.0**	7.8	**-**	**-**	**26.2**	3.7	**60.3**	10.4	**39.9**	9.3
soilpar	-	-	**13.7**	3.5	**-0.4**	3.0	-	-	**12.5**	3.3	**-4.7**	2.4	**-4.5**	2.5
p2epar	**-**	**-**	**1.7**	2.9	**-1.2**	2.4	**-**	**-**	**9.7**	3.4	**-4.2**	3.0	**-5.5**	2.2
p2eusv	**-**	**-**	**1.7**	2.9	**-1.2**	2.4	**-**	**-**	**7.2**	3.1	**-4.2**	3.0	**-3.7**	1.5
ntmusv	**-**	**-**	**1.7**	2.9	**-1.2**	2.4	**-**	**-**	**4.1**	3.1	**-4.2**	3.0	**-1.4**	1.3
ntmpar	**-**	**-**	**1.7**	2.9	**-1.2**	2.4	**-**	**-**	**4.1**	3.1	**-4.2**	3.0	**-1.4**	1.3

EC-BU **with USV P2E and with USV NTM**

RS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**30.4**	4.5	**64.7**	8.0	**-**	**-**	**13.0**	3.3	**64.7**	8.0	**28.3**	8.2
soilpar	**-**	**-**	**46.4**	4.2	**6.4**	3.3	**-**	**-**	**12.4**	3.2	**6.4**	3.3	**-3.0**	2.5
p2epar	**-**	**-**	**-3.7**	3.1	**4.3**	3.0	**-**	**-**	**23.5**	3.5	**4.3**	3.0	**-0.8**	2.5
p2eusv	**-**	**-**	**-3.7**	3.1	**4.3**	3.0	**-**	**-**	**27.0**	4.4	**4.3**	3.0	**13.8**	2.2
ntmusv	**-**	**-**	**-3.7**	3.1	**4.3**	3.0	**-**	**-**	**-0.6**	3.0	**4.3**	3.0	**1.0**	1.7
ntmpar	**-**	**-**	**-3.7**	3.1	**4.3**	3.0	**-**	**-**	**-0.6**	3.0	**4.3**	3.0	**0.1**	1.7

EC-BU **with USV P2E and with USV NTM**

RS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**22.4**	4.2	**41.2**	4.6	**-**	**-**	**16.1**	3.7	**38.2**	4.2	**32.5**	6.2
soilpar	**-**	**-**	**42.9**	5.4	**20.9**	3.5	**-**	**-**	**34.4**	5.5	**21.2**	3.4	**-2.0**	3.0
p2epar	**-**	**-**	**-0.7**	3.6	**3.7**	3.3	**-**	**-**	**8.6**	4.0	**5.0**	2.9	**2.0**	3.1
p2eusv	**-**	**-**	**-0.7**	3.6	**3.7**	3.3	**-**	**-**	**7.2**	3.7	**5.0**	2.9	**11.3**	3.4
ntmusv	**-**	**-**	**-0.7**	3.6	**3.7**	3.3	**-**	**-**	**1.6**	3.6	**5.0**	2.9	**-0.6**	2.9
ntmpar	**-**	**-**	**-0.7**	3.6	**3.7**	3.3	**-**	**-**	**1.6**	3.6	**5.0**	2.9	**-1.5**	2.8

EC-BU **with USV P2E and with USV NTM**

RS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**22.2**	4.3	**42.1**	7.1	**-**	**-**	**18.2**	4.0	**58.6**	8.8	**36.2**	7.7
soilpar	**-**	**-**	**10.3**	3.4	**-0.9**	3.0	**-**	**-**	**5.7**	3.4	**-0.2**	2.3	**3.6**	3.6
p2epar	**-**	**-**	**5.2**	3.0	**4.1**	2.9	**-**	**-**	**7.5**	3.1	**2.6**	2.7	**4.5**	3.4
p2eusv	**-**	**-**	**5.2**	3.0	**4.1**	2.9	**-**	**-**	**6.5**	3.0	**2.6**	2.7	**5.8**	3.8
ntmusv	**-**	**-**	**5.2**	3.0	**4.1**	2.9	**-**	**-**	**4.2**	3.0	**2.6**	2.7	**4.5**	3.1
ntmpar	**-**	**-**	**5.2**	3.0	**4.1**	2.9	**-**	**-**	**4.2**	3.0	**2.6**	2.7	**4.2**	3.0

Table V: Estimates of mean and standard deviation (s.d.) for the BU-scenario and succession 2 (succession of current vegetation) on rich sand; with and without USV

Bu_S2 **with USV P2E and with USV NTM**

		msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
				-		mol ha-1 a-1		-		-		-		-	
		mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
RS	1995	3	0	4.04	0.30	3830	429	2.99	0.78	3.60	1.57	2.80	0.37	10.2	1.7
	2005	3	0	4.07	0.29	4840	884	2.99	0.78	3.62	1.57	3.67	0.76	9.9	1.7
	2025	3	0	4.09	0.27	6670	1572	2.99	0.78	3.64	1.57	5.23	1.29	9.6	1.7
	2095	3	0	4.13	0.26	11000	2583	2.99	0.78	3.67	1.57	8.09	1.20	9.6	1.8

Bu_S2 **without USV P2E and without USV NTM**

		msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
				-		mol ha-1 a-1		-		-		-		-	
		mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
RS	1995	3	0	4.04	0.30	3830	429	2.99	0.15	3.56	0.37	2.80	0.37	10.2	0.4
	2005	3	0	4.07	0.29	4840	884	2.99	0.15	3.67	0.76	3.67	0.76	9.9	0.3
	2025	3	0	4.09	0.27	6670	1572	2.99	0.15	3.60	0.36	5.23	1.29	9.7	0.4
	2095	3	0	4.13	0.26	11000	2583	2.99	0.15	3.63	0.35	8.09	1.20	9.7	0.6

Table VI: Estimates of the % top-marginal variances of the predictions from Table V; with and without USV

BU_S2 **with USV P2E and with USV NTM**
RS 1995

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**1.4**	3.1	**88.1**	4.9	**-0.6**	3.2	**-2.9**	3.2	**88.1**	4.9	**3.3**	3.0
soilpar	**-**	**-**	**96.2**	5.3	**9.4**	3.5	**-0.6**	3.2	**-1.6**	3.3	**9.4**	3.5	**0.2**	3.1
p2epar	**-**	**-**	**-2.5**	3.1	**-0.8**	3.2	**3.5**	3.1	**0.4**	3.2	**-0.8**	3.2	**0.2**	3.1
p2eusv	**-**	**-**	**-2.5**	3.1	**-0.8**	3.2	**96.3**	4.2	**94.8**	3.8	**-0.8**	3.2	**21.2**	3.1
ntmusv	**-**	**-**	**-2.5**	3.1	**-0.8**	3.2	**-0.7**	3.2	**-3.0**	3.2	**-0.8**	3.2	**74.7**	4.1
ntmpar	**-**	**-**	**-2.5**	3.1	**-0.8**	3.2	**-0.7**	3.2	**-3.0**	3.2	**-0.8**	3.2	**1.3**	3.1

BU_S2 **with USV P2E and with USV NTM**
RS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**2.2**	3.1	**87.5**	5.2	**-0.6**	3.2	**-2.9**	3.2	**87.5**	5.2	**1.8**	3.0
soilpar	**-**	**-**	**96.2**	5.4	**12.8**	3.4	**-0.6**	3.2	**-1.7**	3.2	**12.8**	3.4	**-0.5**	3.0
p2epar	**-**	**-**	**-2.3**	3.1	**1.3**	3.2	**3.5**	3.1	**0.4**	3.2	**1.3**	3.2	**-0.3**	3.1
p2eusv	**-**	**-**	**-2.3**	3.1	**1.3**	3.2	**96.3**	4.2	**95.0**	3.8	**1.3**	3.2	**19.1**	3.1
ntmusv	**-**	**-**	**-2.3**	3.1	**1.3**	3.2	**-0.7**	3.2	**-3.0**	3.2	**1.3**	3.2	**77.6**	4.2
ntmpar	**-**	**-**	**-2.3**	3.1	**1.3**	3.2	**-0.7**	3.2	**-3.0**	3.2	**1.3**	3.2	**1.8**	3.2

BU_S2 **with USV P2E and with USV NTM**
RS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**2.9**	3.1	**87.9**	5.8	**-0.6**	3.2	**-2.8**	3.2	**87.7**	4.2	**0.3**	3.1
soilpar	**-**	**-**	**93.8**	5.4	**14.0**	3.5	**-0.6**	3.2	**-1.9**	3.2	**13.7**	3.3	**-1.7**	3.0
p2epar	**-**	**-**	**-3.3**	3.1	**2.0**	3.0	**3.5**	3.1	**0.3**	3.2	**2.0**	3.0	**-1.2**	3.0
p2eusv	**-**	**-**	**-3.3**	3.1	**2.0**	3.0	**96.3**	4.2	**95.3**	3.8	**2.0**	3.0	**14.5**	3.1
ntmusv	**-**	**-**	**-3.3**	3.1	**2.0**	3.0	**-0.7**	3.2	**-3.0**	3.2	**2.0**	3.0	**79.6**	4.3
ntmpar	**-**	**-**	**-3.3**	3.1	**2.0**	3.0	**-0.7**	3.2	**-3.0**	3.2	**2.0**	3.0	**2.5**	3.2

BU_S2 **with USV P2E and with USV NTM**
RS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**10.9**	3.1	**93.1**	4.5	**-0.6**	3.2	**-2.6**	3.3	**94.4**	4.9	**-1.6**	2.9
soilpar	**-**	**-**	**79.7**	5.0	**-2.6**	3.2	**-0.6**	3.2	**-2.0**	3.2	**0.2**	3.1	**-2.0**	2.9
p2epar	**-**	**-**	**-4.8**	3.1	**-5.4**	3.4	**3.5**	3.1	**0.6**	3.2	**-1.5**	3.1	**-2.1**	3.0
p2eusv	**-**	**-**	**-4.8**	3.1	**-5.4**	3.4	**96.3**	4.2	**95.3**	3.8	**-1.5**	3.1	**13.7**	3.2
ntmusv	**-**	**-**	**-4.8**	3.1	**-5.4**	3.4	**-0.7**	3.2	**-3.0**	3.3	**-1.5**	3.1	**74.7**	4.1
ntmpar	**-**	**-**	**-4.8**	3.1	**-5.4**	3.4	**-0.7**	3.2	**-3.0**	3.3	**-1.5**	3.1	**10.6**	3.0

RS_S2 **without USV P2E and without USV NTM**
CN 1995

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**1.4**	3.1	**88.1**	4.9	**4.4**	**3.2**	**-1.8**	2.9	**88.1**	4.9	**50.3**	3.6
soilpar	-	-	**96.2**	5.3	**9.4**	3.5	**4.4**	**3.2**	**32.5**	2.9	**9.4**	3.5	**2.8**	2.8
p2epar	-	-	**-2.5**	3.1	**-0.8**	3.2	**100**	**4.6**	**57.7**	3.7	**-0.8**	3.2	**30.6**	2.9
p2eusv	-	-	**-2.5**	3.1	**-0.8**	3.2	**4.6**	**3.2**	**-3.3**	2.8	**-0.8**	3.2	**-2.2**	3.0
ntmusv	-	-	**-2.5**	3.1	**-0.8**	3.2	**4.6**	**3.2**	**-3.3**	2.8	**-0.8**	3.2	**-2.2**	3.0
ntmpar	-	-	**-2.5**	3.1	**-0.8**	3.2	**4.6**	**3.2**	**-3.3**	2.8	**-0.8**	3.2	**8.5**	3.1

BU_S2 **without USV P2E and without USV NTM**
RS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	-	-	**2.2**	3.1	**87.5**	5.2	**4.4**	**3.2**	**-1.4**	2.9	**87.5**	5.2	**32.2**	3.9
soilpar	-	-	**96.2**	5.4	**12.8**	3.4	**4.4**	**3.2**	**31.5**	2.9	**12.8**	3.4	**2.3**	2.8
p2epar	-	-	**-2.3**	3.1	**1.3**	3.2	**100**	**4.6**	**59.2**	3.7	**1.3**	3.2	**33.1**	2.9
p2eusv	-	-	**-2.3**	3.1	**1.3**	3.2	**4.6**	**3.2**	**-3.1**	2.8	**1.3**	3.2	**1.3**	3.0
ntmusv	-	-	**-2.3**	3.1	**1.3**	3.2	**4.6**	**3.2**	**-3.1**	2.8	**1.3**	3.2	**1.3**	3.0
ntmpar	-	-	**-2.3**	3.1	**1.3**	3.2	**4.6**	**3.2**	**-3.1**	2.8	**1.3**	3.2	**17.7**	3.1

BU_S2 **without USV P2E and without USV NTM**

RS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**2.9**	3.1	**87.9**	5.8	**4.4**	**3.2**	**-1.5**	2.9	**87.7**	4.2	**16.1**	3.6
soilpar	**-**	**-**	**93.8**	5.4	**14.0**	3.5	**4.4**	**3.2**	**28.6**	2.9	**13.7**	3.3	**-1.3**	2.7
p2epar	**-**	**-**	**-3.3**	3.1	**2.0**	3.0	**100**	**4.6**	**61.0**	3.8	**2.0**	3.0	**13.7**	2.7
p2eusv	**-**	**-**	**-3.3**	3.1	**2.0**	3.0	**4.6**	**3.2**	**-3.6**	2.8	**2.0**	3.0	**0.9**	2.7
ntmusv	**-**	**-**	**-3.3**	3.1	**2.0**	3.0	**4.6**	**3.2**	**-3.6**	2.8	**2.0**	3.0	**0.9**	2.7
ntmpar	**-**	**-**	**-3.3**	3.1	**2.0**	3.0	**4.6**	**3.2**	**-3.6**	2.8	**2.0**	3.0	**41.0**	3.7

BU_S2 **without USV P2E and without USV NTM**

RS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**10.9**	3.1	**93.1**	4.5	**4.4**	**3.2**	**1.0**	2.8	**94.4**	4.9	**1.2**	2.7
soilpar	**-**	**-**	**79.7**	5.0	**-2.6**	3.2	**4.4**	**3.2**	**23.3**	2.9	**0.2**	3.1	**-4.6**	2.7
p2epar	**-**	**-**	**-4.8**	3.1	**-5.4**	3.4	**100**	**4.6**	**61.2**	3.8	**-1.5**	3.1	**-0.6**	2.9
p2eusv	**-**	**-**	**-4.8**	3.1	**-5.4**	3.4	**4.6**	**3.2**	**-4.5**	2.8	**-1.5**	3.1	**-2.7**	2.8
ntmusv	**-**	**-**	**-4.8**	3.1	**-5.4**	3.4	**4.6**	**3.2**	**-4.5**	2.8	**-1.5**	3.1	**-2.7**	2.8
ntmpar	**-**	**-**	**-4.8**	3.1	**-5.4**	3.4	**4.6**	**3.2**	**-4.5**	2.8	**-1.5**	3.1	**75.4**	3.9

Table VII: Estimates of mean and standard deviation (s.d.) for the difference between the two scenarios (EC-BU) and succession 2 (succession of current vegetation) on rich sand; with and without USV

EC-BU_S2 with USV P2E and with USV NTM

		msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
				-		mol ha-1 a-1		-		-		-		-	
		mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
RS	1995	0	0	0.00	0.00	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	2005	0	0	0.07	0.01	-341	50	0.00	0.00	0.05	0.02	-0.29	0.04	0.12	0.10
	2025	0	0	0.17	0.04	-716	218	0.00	0.00	0.12	0.05	-0.61	0.19	0.12	0.15
	2095	0	0	0.27	0.12	-988	860	0.00	0.00	0.20	0.11	-0.43	0.52	0.03	0.19

EC-BU_S2 without USV P2E and without USV NTM

		msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
				-		mol ha-1 a-1		-		-		-		-	
		mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
RS	1995	0	0	0.00	0.00	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	2005	0	0	0.07	0.01	-341	50	0.00	0.00	0.06	0.02	-0.29	0.04	0.14	0.10
	2025	0	0	0.17	0.04	-716	218	0.00	0.00	0.13	0.04	-0.61	0.19	0.15	0.14
	2095	0	0	0.27	0.12	-988	860	0.00	0.00	0.21	0.10	-0.43	0.52	0.05	0.18

Table VIII: Estimates of the % of top-marginal variances of the predictions from Table VII; with and without USV

EC-BU_S2 with USV P2E and with USV NTM

RS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**56.7**	5.0	**93.3**	4.6	**-**	**-**	**14.8**	3.2	**93.3**	4.6	**47.8**	3.3
soilpar	**-**	**-**	**25.2**	3.1	**1.7**	2.9	**-**	**-**	**2.4**	3.1	**1.7**	2.9	**10.1**	3.0
p2epar	**-**	**-**	**-4.3**	3.1	**0.0**	2.9	**-**	**-**	**28.6**	3.9	**0.0**	2.9	**3.2**	3.1
p2eusv	**-**	**-**	**-4.3**	3.1	**0.0**	2.9	**-**	**-**	**31.6**	4.9	**0.0**	2.9	**25.1**	3.1
ntmusv	**-**	**-**	**-4.3**	3.1	**0.0**	2.9	**-**	**-**	**1.2**	3.0	**0.0**	2.9	**1.0**	3.0
ntmpar	**-**	**-**	**-4.3**	3.1	**0.0**	2.9	**-**	**-**	**1.2**	3.0	**0.0**	2.9	**9.1**	3.2

EC-BU_S2 with USV P2E and with USV NTM

RS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**50.2**	17.7	**78.6**	5.2	**-**	**-**	**19.3**	6.0	**76.2**	5.0	**24.1**	3.4
soilpar	**-**	**-**	**34.0**	7.3	**5.1**	4.0	**-**	**-**	**10.6**	2.8	**2.5**	3.5	**-2.3**	2.7
p2epar	**-**	**-**	**3.9**	3.3	**-0.7**	3.4	**-**	**-**	**25.6**	3.6	**-0.2**	3.0	**1.3**	2.8
p2eusv	**-**	**-**	**3.9**	3.3	**-0.7**	3.4	**-**	**-**	**26.5**	4.4	**-0.2**	3.0	**13.6**	3.1
ntmusv	**-**	**-**	**3.9**	3.3	**-0.7**	3.4	**-**	**-**	**5.0**	2.9	**-0.2**	3.0	**3.2**	2.8
ntmpar	**-**	**-**	**3.9**	3.3	**-0.7**	3.4	**-**	**-**	**5.0**	2.9	**-0.2**	3.0	**24.9**	3.1

EC-BU_S2 **with USV P2E and with USV NTM**
RS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**29.6**	5.8	**85.4**	3.0	**-**	**-**	**21.2**	4.0	**75.2**	3.8	**20.3**	4.3
soilpar	**-**	**-**	**18.0**	4.9	**-1.0**	3.1	**-**	**-**	**10.6**	4.2	**7.3**	3.3	**-4.2**	3.1
p2epar	**-**	**-**	**1.8**	3.0	**0.9**	3.0	**-**	**-**	**15.5**	4.1	**1.1**	3.1	**-4.6**	2.8
p2eusv	**-**	**-**	**1.8**	3.0	**0.9**	3.0	**-**	**-**	**15.2**	3.7	**1.1**	3.1	**3.0**	3.1
ntmusv	**-**	**-**	**1.8**	3.0	**0.9**	3.0	**-**	**-**	**5.2**	3.3	**1.1**	3.1	**-5.4**	3.3
ntmpar	**-**	**-**	**1.8**	3.0	**0.9**	3.0	**-**	**-**	**5.2**	3.3	**1.1**	3.1	**14.3**	3.1

EC-BU_S2 **without USV P2E and without USV NTM**
RS 2005

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**56.7**	5.0	**93.3**	4.6	**-**	**-**	**23.2**	3.5	**93.3**	4.6	**77.3**	3.5
soilpar	**-**	**-**	**25.2**	3.1	**1.7**	2.9	**-**	**-**	**7.0**	3.2	**1.7**	2.9	**6.7**	3.1
p2epar	**-**	**-**	**-4.3**	3.1	**0.0**	2.9	**-**	**-**	**61.6**	3.9	**0.0**	2.9	**-0.1**	3.1
p2eusv	**-**	**-**	**-4.3**	3.1	**0.0**	2.9	**-**	**-**	**-0.8**	3.5	**0.0**	2.9	**-1.6**	3.1
ntmusv	**-**	**-**	**-4.3**	3.1	**0.0**	2.9	**-**	**-**	**-0.8**	3.5	**0.0**	2.9	**-1.6**	3.0
ntmpar	**-**	**-**	**-4.3**	3.1	**0.0**	2.9	**-**	**-**	**-0.8**	3.5	**0.0**	2.9	**10.4**	3.2

EC-BU_S2 **without USV P2E and without USV NTM**
RS 2025

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**50.2**	17.7	**78.6**	5.2	**-**	**-**	**25.0**	7.3	**76.2**	5.0	**35.3**	4.1
soilpar	**-**	**-**	**34.0**	7.3	**5.1**	4.0	**-**	**-**	**15.4**	2.9	**2.5**	3.5	**-1.7**	3.1
p2epar	**-**	**-**	**3.9**	3.3	**-0.7**	3.4	**-**	**-**	**47.8**	3.4	**-0.2**	3.0	**0.5**	2.9
p2eusv	**-**	**-**	**3.9**	3.3	**-0.7**	3.4	**-**	**-**	**2.8**	3.5	**-0.2**	3.0	**-1.5**	3.0
ntmusv	**-**	**-**	**3.9**	3.3	**-0.7**	3.4	**-**	**-**	**2.8**	3.5	**-0.2**	3.0	**-1.5**	3.0
ntmpar	**-**	**-**	**3.9**	3.3	**-0.7**	3.4	**-**	**-**	**2.8**	3.5	**-0.2**	3.0	**28.5**	3.2

EC-BU_S2 **without USV P2E and without USV NTM**
RS 2095

	msgl		pH		N_{av}		e_F		e_R		e_N		PCV	
	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.	est.	s.d.
vegpar	**-**	**-**	**29.6**	5.8	**85.4**	3.0	**-**	**-**	**21.4**	4.1	**75.2**	3.8	**32.2**	4.2
soilpar	**-**	**-**	**18.0**	4.9	**-1.0**	3.1	**-**	**-**	**11.6**	4.6	**7.3**	3.3	**-3.6**	3.5
p2epar	**-**	**-**	**1.8**	3.0	**0.9**	3.0	**-**	**-**	**22.8**	4.0	**1.1**	3.1	**-6.6**	3.2
p2eusv	**-**	**-**	**1.8**	3.0	**0.9**	3.0	**-**	**-**	**2.9**	3.3	**1.1**	3.1	**-8.1**	3.3
ntmusv	**-**	**-**	**1.8**	3.0	**0.9**	3.0	**-**	**-**	**2.9**	3.3	**1.1**	3.1	**-8.1**	3.3
ntmpar	**-**	**-**	**1.8**	3.0	**0.9**	3.0	**-**	**-**	**2.9**	3.3	**1.1**	3.1	**15.3**	3.1