Development of a conceptual framework for uncertainty and sensitivity analysis: Application to forest management under climate change

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Development of a Conceptual Framework for Uncertainty and Sensitivity Analysis: Application to Forest Management under Climate Change

by

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#### Abstract

Environmental model is use to predict the natural science system and provides information to decision maker for environmental management and decision making purposes. However, the important issue is not only to obtain information but is to get certain predicted output. As for decision maker, they should always question about how certain the model outputs are. At the some time, modeller should be able to answer this question. The different perspective of uncertainty from modeller and decision maker point of view has hindered the assessment of uncertainty to be effectively implemented. Thus, in order to create the common understanding of uncertainty between modellers and decision makers, an uncertainty conceptual framework is needed. To establish an uncertainty framework, one should understand the source and the propagation of uncertainty in an integrated model system. Managing forest under climate change is one of the examples which involve multiple models integration. Uncertainty and sensitivity analysis therefore is important to identify, to regconise and to assess uncertainty that occurs in the model chain. The uncertain outputs of regional climate model (RCM) in PRUDENCE are used as the site condition input (vegetation growing period, annual temperature ampltitude, mean temperature and precipitation during vegetation growing period) to SILVA to examine uncertainty propagation and conduct the sensitivity analysis. Tree input variable (tree height, tree height to crown base and crown diameter) are used to investigate uncertainty and sensitivity analysis in the SILVA modal. The sensitivity analysis revealed that the SILVA output: aggregation index, species profile index and species mingling index has very small impact from climate change. Sensitivity analysis also provides underlying information of the model and traces the uncertain inputs. Questionnaire analysis describes the uncertainty in decision making model by different experts. With all these analysis, an uncertainty conceptual framework is developed. However, the large uncertainty from different models has been "dismissed" by the classification system in habitat evaluation model. To conclude, the developed uncertainty framework is useful as a communication tool between modellers and decision makers to identify, recognise and analysis uncertainty in the model chain. However, the framework needs to be improved in terms of uncertainty assessment especially in the method of quantifying uncertainty.

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#### 1. INTRODUCTION

This chapter provides a brief introduction of the research background and significance and states the problems, objectives, questions, hypotheses, research approach and outlines of the thesis.

#### 1.1. Background and significance

An environmental model is the prediction of a natural science system. It provides an understanding of the environmental science and its complex interrelated physical processes. At the same time, the predicted model output can be used for environmental management and decision making purposes (Beven, 2008). However, decision maker must critically ask the following questions, "How certain of the predicted output would be"? "If the model output was uncertain, how can it be handled"? As for the modeller, he/she should be able to answer these questions.

Existence of uncertainty within the model and decision making process is generally understood by modeller and decision maker (Walker et al., 2003). Yet, they have different view of uncertainty (Walker et al., 2003; Liu et al., 2008). The concern of the modeller is about the accumulated uncertainty in the model output and the robustness of the output to decision support practice. For decision maker, uncertainty is about how to value the model output from the perspective of management's goal, priority and interest (Walker et al., 2003). Nevertheless, assessment and measurement of the effects of uncertainty for environmental modelling and decision support has started to be widely recognised by both parties (Helton and Davis, 2003; Walker et al., 2003; Brown, 2004; Refsgaard et al., 2007; Van der Sluijs et al., 2008). For example, the US National Research Council recommends that the US-Environmental Protection Agency should pay more attention to the systematic treatment and communication of uncertainties (Van der Sluijs et al., 2008).

Uncertainty assessment of model predictions is therefore important to be practically implemented in environmental modelling for policy and management. Communication across modellers, scientists, and decision makers is always a challenge in uncertainty assessment (Van der Sluijs, 2007). Assessment of uncertainty becomes more difficult when it involves multiple models integration. Adaptation of forest management under future climate change is one of the examples that need to apply the integrated uncertainty assessment. Integration of climate model, forest function model and forest management model carries large uncertainties and knowledge gaps between scientists and policy makers from various disciplines. Consequently, developing a framework to identify, categorise, communicate and assess uncertainty for integrated forest management under climate change is needed.

#### 1.2. Research problem

Forest growth model is useful to forest researcher and forest decision maker to predict future forest growth and assist silvacultural practice (Vanclay, 1994). The long production period of forest growth tends to engage unpredictability and uncertainty in forest management. Dynamic interactions in forestry ecosystem with future climate change would bring more uncertainties. (Hoogstra and Schanz, 2008). Due to that, modelling of forest growth becomes a challenge to modellers and the predicted model outputs are always questionable to decision makers.

Forests are critically influenced by climate because growth of forest plants is highly dependent on climate (Kirschbaum, 2000; Van der Meer et al., 2002). Response of forest to atmospheric and climate change is still a question mark to decision makers. Predictions of regional climate especially across European are also uncertain (Lasch et al., 2002). Policy-makers have been increasingly searching for information and strategy to help the adaptation of forest management under climate change. Thus, integration of forest growth models with regional climate model is essential (Lindner et al., 2002). Predictions from integrated models need to be carefully used and assessed by decision makers as the complexity of the models lead to great uncertainty of the model outputs (Böttcher et al., 2008).

Various types of uncertainty in models integration require an integrated uncertainty assessment for model outputs (Van der Sluijs, 2002; Van der Sluijs, 2005; Refsgaard et al., 2006). Before implementing the uncertainty assessment, one should understand the cause and effect of uncertainty to model predictions and to forest decision makers (Brown and Heuvelink, 2005). Moreover, confusion about the terminology, different mixture of interpretations and classifications of uncertainty in interdisciplinary science should be avoided (Walker et al., 2003). An uncertainty conceptual framework therefore needs to be developed to aid modellers and decision makers to understand, identify and manage uncertainty in a systematic way. However, most of the developed conceptual framework for climate change impacts are focused on single discipline (Lindner et al., 2002; Nitschke and Innes, 2008).

Single discipline might fail to perceive uncertainties in the models and restrict sufficient assistance to forestry decision maker (Nitschke and Innes, 2008). Consequently, adaptation of forest management under climate change needs an uncertainty conceptual framework to provide better understanding and communication of uncertainty between modellers, forest decision makers and policy makers.

#### **1.3.** Research objective

# 1.3.1. General objective

Establish an uncertainty conceptual framework to systematic identify, recognise and understand the uncertainty in forest management under climate change through the integration of climate model, forest growth model and decision support model.

#### **1.3.2.** Specific objective

- 1. To identify and recognise possible uncertainty in climate model, forest function model and decision making model.
- 2. To demonstrate sensitivity analysis of SILVA outputs to site condition and tree input variables.
- 3. To develop the uncertainty conceptual framework from the achievement of objective 1, 2 and 3.

Specific Objective			Research Questions			
1.	To identify and recognise possible uncertainty in climate model, forest function model and decision making model.	1.	How to identify uncertainty in the climate model, SILVA and decision making model?			
2.	To demonstrate sensitivity analysis of SILVA outputs to site condition and tree input variables.	1. 2.	How does the uncertain site condition and tree inputs variable contribute to SILVA output? The SILVA output is most sensitive to tree input variable or site condition variables?			
3.	To develop an uncertainty conceptual framework from the achievement of objective 1 and 2.	1.	How to compile, construct, analyse and develop the conceptual model from the impact of each objective to assess uncertainty?			

#### **1.4.** Research questions

#### **1.5.** Organisation of the thesis and outline

This thesis is organised and structured as follows

1.

Chapter 1 describes the introduction and background of uncertainty in integrated assessment modelling which includes the climatic model, forest

function model and decision making model. Research problem, research objective and research question are presented as well.

- 2. Chapter 2 focuses on the basic concept and interpretation of uncertainty and sensitivity analysis. This chapter also includes a brief description of the climatic model, forest function model and decision making model.
- 3. Chapter 3 provides information about study area, material and methodology that are used in the research.
- 4. Chapter 4 describes the results of uncertainty analysis and sensitivity analysis in climatic model, forest function model SILVA and decision making model. Development of uncertainty conceptual model is also explained.
- 5. Chapter 5 focuses on the discussion of the results for uncertainty and sensitivity analysis as well as the conceptual framework This chapter also comments the limitation of methodology
- 6. Chapter 6 provides a brief conclusion and recommendation to the future research.



#### 1.6. Research approach

Figure 1 Research approach overview

#### 2. LITERATURE REVIEW

This chapter begins with what is uncertainty (2.1), uncertainty analysis (2.2) and sensitivity analysis (2.3), uncertainty terminology and classification in the perspective of The W&H framework (2.4), comments and critiques of W&H framework (2.5). Description of individual model in integrated model chain is explained in section 2.6 for climatic model-PRUDENCE, section 2.7 for forest growth model-SILVA and section 2.8 for forest management model-habitat evaluation model. A summary of this chapter is presented in section 2.9.

#### 2.1. What is uncertainty

What men really want is not knowledge, but certainty.

#### Bertrand Russell, 1964

Knowledge is useful to improve and enhance our skill, awareness and understanding of something we do not know. Knowing how to interpret and evaluate the truth of the knowledge is more important than just having knowledge. According to Feynman (1988), scientific knowledge has different magnitudes of certainty, ranging from unknown, nearly sure and never absolutely certain. In order to identify and quantify uncertainty, we have to know something which gives a means of comparison. Uncertainty is impossible to be addressed when it is being completely ignored.

On the other hand, according to Van Asselt and Rotmans (2002) "uncertainty is not simply the absence of knowledge" but massive flow of information would cause confusion that might trigger uncertainty. Uncertainty can be reduced and increased by knowing more knowledge. This is because new knowledge brings more understanding to find out and to quantify uncertainties. Having more knowledge makes us realise the limitations and the complexity of the process that we have ignored in the past. Shackle (1955) in Van Asselt and Rotmans (2002) noted that "the fundamental imperfection of knowledge is the essence of uncertainty".

#### 2.2. Uncertainty analysis

Three key terms relate to uncertainty analysis are introduced in this section: bias, precision and accuracy. Bias is predicted by mean error, which measures the agreement between known value (expected) and predicted value. It is the systematic error that makes all measurement wrong by a certain amount,

$$ME = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)$$
(1.1)

Precision is predicted using measure of the spread of errors around the mean error which is the standard deviation of error. It describes how close the measured value to each other,

$$S_e = \sqrt{\frac{\sum_{i=1}^{n} (\bar{y}_i - \hat{y}_i)^2}{n-1}}$$
(1.2)

Accuracy is the sum of unbias and precision. It measures how close the measured value to the true value. Accuracy is quantified by root mean square error (RMSE),

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}$$
(1.3)

Accuracy, like bias and precision, depends on a statistical model. It is an expectation of the overall error.

#### 2.3. Sensitivity analysis

According to Saltelli et al. (2000) sensitivity analysis is the study about the relations between the input and the output of a model. It is used to determine the contribution of individual input factors to the uncertainty in model predictions (Lilburne et al., 2006). Sensitivity analysis is classed into global sensitivity analysis (GSA) and local sensitivity analysis (LSA). GSA quantifies sensitivity of model output to all inputs with combined variability of input simultaneously. It has the ability to counter the autocorrelation between inputs and outputs. LSA is the opposite of GSA where each input factor is varied at one time while other input factors fixed at nominal value. No interactions between inputs factors as as the analysis is limited to small area of the input space (Lilburne et al., 2006; Saltelli et al., 2006).

# 2.4. Uncertainty terminology and classification from the perspective of W&H Framework

W&H framework<sup>1</sup> is an integrated uncertainty conceptual framework developed by Walker et al (2003) to provide a basic concept and guidelines to systematically diagnose uncertainty in model-based decision support. The objective of W&H

<sup>&</sup>lt;sup>1</sup> The framework was named by the principal author Warren Walker and the central person within the group of authors, Poul Harremoës. The framework is the result of a collective effort by all of the co-authors of the Walker et al. (2003) paper.

framework is to establish a common terminology of various typology of uncertainty by using unified vocabulary in different scientific fields. It aims to bring the communication gap among the scientists as well as between policy makers and stakeholders (Walker et al., 2003). W&H framework described the concept of uncertainty into three dimensions: location, level and nature (Figure 2).



Figure 2 Three dimensions of uncertainty concept (source Walker et al., 2003)

#### Location of uncertainty

The location dimension or source of uncertainty depicts where uncertainty takes place within the model. Location of uncertainty is classified as follows

- *Model context* refers to the problem framing and boundary condition setting at the initial stage of the model development. External economic, environment, politics, social and technology are the key factors to structure the context of the problem.
- *Model uncertainty* relates to the model structure and model technical uncertainty. Uncertainty of model structure is lack of understanding about the system behaviour and the interactions of input, parameter, equation and assumptions in the system boundary. Model technical uncertainty is the uncertainty from the computer implementation in the model.
- *Uncertainty of input* is the uncertainty of system data that drives the model such as the measurement and observation data.
- *Parameter uncertainty* describes uncertainty of the factor that relates various part of a system and determines its performance such as used for model calibration. Parameters are usually constant in the model.
- *Uncertainty of model output* is the accumulation of various uncertainties from all the above locations.

Level of uncertainty

The level of uncertainty relates to the gradual scale of uncertainty ranges from "known" to "unknown" (Figure 3). The level of uncertainty provides information of "which" and "where" the uncertainty occurs in the range of uncertainty classification. In order to quantify the level of uncertainty, a quantitative scale was proposed to represent each level of uncertainty and further described by using the generic description (Figure 3) (Krayer von Krauss et al., 2004; Gillund et al., 2008).



Figure 3 The scale of levels of uncertainty range combined from Walker et al., 2003, Krayer von Krauss et al., 2004 and Gillund et al., 2008

The levels of uncertainty are:

- Determinism means knowing everything perfectly and absolute certainty.
- *Statistical uncertainty* is the measureable uncertainty which can be quantified statistically. The deviation of predicted values from true is quantifiable and the probabilities are assumed known.
- *Scenario uncertainty* is the uncertainty that beyond the measurement of statistical methods. The range of outcome is possibly known but its probability distribution is not formulated (known unknowns). This is because scenario uncertainty involves external environmental factors particularly in the future which might or might not happen.
- *The level of recognised ignorance* refers to the unknown outcome and the unknown probability of the outcome. This level of uncertainty is recognised and realised but it can not be estimated due to the deficit of knowledge and unpredictable process.
- *Total ignorance* is at the extreme end of uncertainty scale which means we do not even know what we do not know (unknown unknowns). The continuing arrow in the uncertainty scale indicates the infinite ignorance that is impossible to know.

Natural uncertainty

The third dimension of uncertainty concept, nature uncertainty is due to the intrinsic process and phenomena in the natural environment. Nature of uncertainty is divided into epistemic uncertainty and variability uncertainty.

- Epistemic uncertainty refers to uncertainty that caused by insufficient knowledge and can be improved by more studies.
- Variability uncertainty (ontological uncertainty) is primarily due to inherent variability such as the stochastic and unpredictable process in natural systems, the variability of human behaviour and external factors in economic and technology.

Three dimension classification of uncertainty in W&H framework was used to develop an uncertainty matrix. As shown in Figure 4, the vertical axis (row table) is used to identify where the uncertainties manifested and the horizontal axis (column table) explains how these uncertainties are categorised in dimension level and nature. Uncertainty at any location can occur in various levels of uncertainty and in different nature of uncertainty at the same time. For instance, uncertainty of input data might cause by statistical uncertainty and part of it might class as recognised ignorance.

			Level	Nature		
		Statistical	Scenario	Recognised	Epistemic	Variability
L	ocation	uncertainty	uncertainty	ignorance	uncertainty	uncertainty
Context	Natural, technological, economic, social and political					
Inputs	Input data					
	Driving force					
Model	Model structure					
Denometers						
Parameters						
Model out	put					

Figure 4 The Uncertainty Matrix (source from Walker et al., 2003)

#### 2.5. Comments and critiques of W&H framework

The W&H framework is commented by Norton et al. (2006) and replied by Krayer von Krauss et al. (2006). One of the major comments is the classification and terminology of uncertainty such as location, level and nature are uncommonly understandable if without any explicit explanation. Thus, classification of uncertainty should be more opened and varied to accommodate and to be adapted by

different disciplines. The major comments and evaluation from Norton et al. (2006) and Krayer von Krauss et al. (2006) can be summarised as following,

- W&H framework is not able to relate the classification of uncertainty to the real situation in the model and the method for assessing uncertainty.
- The framework takes no account of interactions between different sources of uncertainty which excludes sources of uncertainty that might be occurred before or after the model application.
- The concept of uncertainty is more on modeller point of view rather than decision maker and it does not consider the link to decision making.
- Linguistic uncertainty should be included.
- Structural uncertainty should be divided into the precision of model prediction (low deviation from observed data) and the capability of model to predict the real processes (knowledge of the underlying process).
- The framework did not include the uncertainty propagation analysis especially on the qualitative elements.

#### 2.6. Climate model: regional climate ensemble model PRUDENCE

Regional climate models (RCMs) have gained high interest in investigating the impacts of climate change to human and terrestrial ecosystems. This is because the horizontal resolution of general circulation models (GCMs) are too coarse to resolve detailed climate variables for regional impact studies (Olesen et al., 2007). Individual simulation of regional climate model is claimed inadequate to assess future climate change phenomena and its impacts to different sectors. The use of ensembles approach by integrating multi-climate models can provide more comprehensive uncertainties of the potential future climate change (Palmer and RaÈisaÈnen, 2002; Murphy et al., 2004; Stainforth et al., 2005; Christensen and Christensen, 2007)..

Prediction of Regional scenario and Uncertainties for Defining EuropeaN Climate change risks and Effects project (PRUDENCE) is the European Commission funded project which aimed to provide large ensemble of high resolution future regional climate change for Europe. At the same time, it was designated to analyse the uncertainty propagate from the GCM to RCMs (Christensen and Christensen, 2007). PRUDENCE produced a set of nine RCMs with horizontal resolution about 50km under two IPCC Special Report on Emission Scenarios (SRES) A2<sup>2</sup> and B2<sup>3</sup>.

<sup>&</sup>lt;sup>2</sup> A2 scenario depicts the future world with more regional oriented development in economic and technological growth. Green house gases emission will be higher in this scenario compared to B2. See: http://www.grida.no/publications/other/ipcc\_sr/?src=/climate/ipcc/emission/094.htm

All the RCM outputs were driven by two different GCMs, HadAM3H and ECHAM4/OPYC3. HadAM3H is the atmospheric general circulation model (AGCM) which is developed by the Hadley Centre, United Kingdom with 140 km horizontal resolution. ECHAM4/OPYC3 is an atmospheric ocean general circulation model (AOGCM) provided by Max-Planck Institute for Meteorology (MPI) with the horizontal resolution of 300 km (Christensen and Christensen, 2007; Déqué et al., 2007; Jacob et al., 2007). The simulations of PRUDENCE RCMs were run for 30 years which covered current period 1961-1990 and projected period 2071-2100. A short description of the PRUDENCE RCMs together with information about the GCMs is listed in Appendix 1.

#### 2.7. Forest growth model: single tree growth SILVA model

Single tree forest growth model SILVA is one of the forest growth models developed by Chair of Forest Yield Science in Munich, Germany (Pretzsch et al., 2002a). It is a semi-empirical and environmentally sensitive model. It has been developed and parameterised mainly based on forest inventory data from Germany. Simulation of SILVA is initialised with tree key variables, information about management and site condition (Pretzsch et al., 2002a; Schmid et al., 2006). SILVA simulates pure and mixed forests based on single tree approach. Each tree is described by a set of tree variables: tree species, diameter at breast height, tree height, height to crown base, crown diameter and tree coordinates. Management information about different types of thinning, the intensity and frequency of thinning can be set before the simulation. Site condition input variables are used to calculate competition index (competition between neighbouring trees) which determines the single tree growth. The site condition variables are: soil nutrient supply (NUT), atmospheric NO<sub>x</sub> and CO<sub>2</sub> concentration, duration of the vegetation period (DT<sub>10</sub>), annual temperature amplitude (Tvar), mean temperature during vegetation period (Tv), aridity index of vegetation growing period (Mv), total precipitation during vegetation period (Pv) and soil moisture (MOIST) (Pretzsch et al., 2002a).

SILVA uses a time step of five years to simulate the forest growth. At each time step, the simulation starts with inter-tree competition analysis follows by tree growth (height, diameter and crown dimension growth) and mortality of single tree calculation. After the removal of tree from mortality and thinning practices, competition of the tree and tree growth of each tree are recalculated (Pretzsch et al., 2002a). Due to the underlying environmental and biological processes of trees,

<sup>&</sup>lt;sup>3</sup> B2 scenario is the storyline of IPCC which emphasis on environmental concern and social sustainability. See: http://www.grida.no/publications/other/ipcc\_sr/?src=/climate/ipcc/emission/095.htm

SILVA incorporates stochastic elements in mortality and tree height calculations (Pretzsch et al., 2002b). SILVA produces three kinds of output (Pretzsch et al., 2002a). The first output is the classical growth and yield data of the stand and individual tree. Secondly, SILVA provides information about the monetary values and development of the stand. The third output describes the ecological value of the stand and individual tree. Indices of structure and diversity of forest can be calculated, for example, aggregation index by Clark and Evan (1954).

#### 2.8. Forest management model: habitat evaluation model

Decision support model in environmental management needs to deal with various objectives and multiple criteria of the problem (van Herwijnen, 1999). Thus, multicriteria evaluation model is essential to assist decision maker to investigate possible choices based on the criteria priority (Voogd, 1983). The Central Services Department of National Forests of Rhineland-Palatinate, Germany has established a multi-criteria evaluation model to assess habitat and species protection (Appendix 2). This evaluation model started to use since 1998. It is still operating to serve as a communication tool between forester and environmentalist in environmental protection. Operation scale of these evaluation models is on a community basis. The assessment is focused in area where three to four communities are found in the same area with the purposed of land use planning. The objective, criteria and indicator in the model are evaluated based on the weight summation technique. Each objective, criteria and indicator is attached to a weight in percentage. The weight for objectives, criteria and indicators is assigned depending on their priorities level to the evaluation score. Detail description of the evaluation model is shown in Appendix 3.

# 2.9. Summary

Studies from various literature sources establish the understanding of the basic concept and different types of uncertainty and sensitivity analysis. W&H framework gives more explicit classification and terminology of uncertainty. Shortcomings of W&H framework can be improved from the comments and critiques made by Norton et al. (2006) and Krayer von Krauss et al. (2006). Exploration of climate model, forest growth model and forest management model helps to establish the link between models in the integrated model chain.

# 3. MATERIAL AND METHODOLOGY

An overview of the materials and methodologies used for this research is described in Figure 6.



# 3.1. Study area

Figure 5 Location map of forest demonstration sites.

The study areas of the research are two demonstration sites in the National Forests of Rhineland-Palatinate (Landesforsten Rheinland-Pfalz), Germany (Figure 5). 150,000 hectares of National Forests Rhineland-Palatinate will be used as the new site surveying practices for forest planning and sustainable forestry measures in the context of climate change. It covers both deciduous and coniferous forest with range of species such as oak, pine, douglas fir, spruce, beech, birch and larch. This national forest is under the control of Research Institute for Forest Ecology and Forestry Germany (FAWF)<sup>4</sup>.

The two forest demonstration sites were named as forest stand number 3 ( $BE^53$ ) and forest stand number 4 (BE4). They are located in the south-western part of Germany. The location of BE3 is at 49°16'N and 7°48'E in Merzalben area and BE4 is situated at 49°18'N and 7°51'E in Johanniskreuz. The average elevation range in this region is about 550m above mean sea level. This area consists mainly of reddish sandstone with low soil moisture content. The climatic condition of BE3 and BE4 is

<sup>&</sup>lt;sup>4</sup> Information about FAWF: http://www.wald-rlp.de/index.php?id=1750&L=2

<sup>&</sup>lt;sup>5</sup> BE is the abbreviation of bestands in German which means forest stand.

summarised in Table 1. This climatic data was collected from 1971 to 2000 by Institute of Climate Impact Research (IFOM), Potsdam in the framework of the project "concepts and feasibility studies for the integrated analysis of data of forest environmental monitoring".

Climatic condition	BE3	BE4
Temperature (yearly)	7.9°C	8.6°C
Temperature (May to September)	14.3°C	15.1°C
Total precipitation (yearly)	1067 mm	967 mm
Total precipitation (May to September)	423 mm	389 mm
Annual potential evapotranspiration	598 mm	611 mm
Annual actual evapotranspiration	562 mm	545 mm

Table 1 Summary of Climatic condition for BE3 and BE4 from 1971 to 2000

The tree species composition of BE3 and BE4 is respectively oak and beech and pine and beech. The trees are mature with on average 204-year-old oak, 100-year-old beech and 133-year-old pine. The area of the stand is 0.57 hectares (107 x 53.5m) for BE3 and 0.25 hectares (50 x 50m) for BE4. These forest stands are usually functioning as the sample plots to estimate forest resource for forest inventory in forestry management.

#### **3.2.** General methodology overview

The main focus of the research was to develop an uncertainty conceptual framework in the models chain which consists of PRUDENCE RCMs, SILVA and habitat evaluation. An experimental design was designed to practically examine uncertainty chain from the input data to the model output throughout three models. One-at-atime (OAT) sensitivity analysis was applied and focused on the effect of input variables used in SILVA to the model output. This was aimed to observe which input variable contributes the most to SILVA outputs. Two set of input variables were used to run sensitivity analysis, they are site condition and tree input variables. The site condition input variables were obtained from PRUDENCE RCMs outputs. Tree input variables were computed from allometric regression model. The uncertainty of SILVA outputs were linked to habitat evaluation model. Uncertainty in habitat evaluation model was investigated through the questionnaire survey of expert judgement for criteria weight estimation. Eventually, the source, the linkage and the relation of input/output uncertainty in three models were compiled, analysed and incorporated with W&H framework to establish an uncertainty conceptual framework (Figure 6).



Figure 6 General methodology overview

#### 3.3. Climate model: PRUDENCE regional climate model (RCM)

#### **3.3.1. PRUDENCE RCM outputs: precipitation and temperature**

PRUDENCE RCMs output, 2-m temperature (t2m) and precipitation (precip) were used to compute the site condition input variables to SILVA. For the experimental design in this research, only four site condition inputs were used to run OAT sensitivity analysis. This was due to the limitation of obtaining the complete set of

site condition inputs from PRUDENDE RCMs' output. The four site condition input variables were listed in Table 2

Table 2 Description of four site condition inputs of SILVA

-	-		
Site condition input variables	Abbreviation	Description	unit
Duration of vegetation growing period	$DT_{10}$	number of days with mean temperature more than 10°C	day
Mean temperature during vegetation growing period	Tv	Mean temperature with $DT_{10}$	°C
Annual temperature amplitude	Tvar	difference between then highest and the lowest monthly mean temperature of the year	°C
Precipitation during vegetation growing period	Pv	Precipitation with DT <sub>10</sub>	mm

#### **3.3.2. Processing of site condition input variables**

Two output variables from PRUDENCE, t2m and precip were downloaded from PRUDENCE official webpage <u>http://prudence.dmi.dk/</u>. T2m was presented in monthly means in unit Kelvin (k) and precip was available in daily means (mm/day) throughout the entire 30 years (1961-1990 and 2071-2100). PRUDENCE output variables were computed based on a 360-day calendar with 30 days per month. These data were downloaded in the format of interpolated CRU<sup>6</sup> grid with  $0.5^{\circ} \times 0.5^{\circ}$  spatial resolution. CRU grid covered the European area ranging from -14.75°W-32.75°E and 35.25°S-74.75°N. The studied forest stands in this research were in one grid box, 7.75°E and 49.25°N. Downloaded t2m and precip data were processed and computed based on the site condition requirement input in SILVA (Table 2).

Computation and processing of four site condition input variables to SILVA is shown in Figure 7. The computation steps were performed in Microsoft Excel. Tv and Pv were computed based on vegetation growing period with temperature more than 10°C. This was different with the initial standard vegetation growing period from May to September. This was because the rising of temperature will increase the vegetation growing duration from April to October or even longer (Menzel et al., 2003; Fronzek and Carter, 2007). Thus, computation of precipitation in vegetation growing period should not be limited only in the standard vegetation growing period but should take into consideration of the temperature.

<sup>&</sup>lt;sup>6</sup> CRU is the common grid for climatic data that produced by the Climatic Research Unit, School of Environmental Sciences University of East Anglia, United Kingdom.



Figure 7 Computation and processing steps of PRUDENCE data to SILVA required site condition inputs

#### **3.3.3.** Selection of site condition variables from PRUDENCE RCMs

Computed site condition variables from multiple RCMs need to be selected to use in SILVA. However, according to Déqué et al. (2007), selection of the plausible model outputs is a difficult task as there is no recognised method about the proper selection. In addition, different models performed differently and have varied model setups. Investigation of climate models in PRUDENCE was aimed to examine the uncertainty driven by emission scenarios A2 and B2 in different RCMs. Thus, the multiple choices of RCMs were categorised into current, scenario A2 and S2 (Table 3). The RCMs were selected accordingly in current, scenario A2 and B2. RCMs with different driven AGCM boundary condition (HadAM and ECHAM) were not taken into considerations.

Table 3 List of	<b>PRUDENCE</b>	RCMs based	on current.	scenario	A2 and B	32
Tuble 5 List of	TRODUCE	items bused	on current,	Sconario	112 und D	

urrent	Driving GCM	SRES emissions scenarios	Horizontal Resolution	Institute	PRUDENCE RCM	RCM Acronym
0	HadAM	A2	50km	DMI	HIRHAM	HC1

	Driving	SRES	Horizontal	Institute	PRUDENCE	
	GCM	emissions	Resolution		RCM	RCM
		scenarios				Acronym
				ETH	CHRM	HC_CTL
				GKSS	CLM	CTL
					CLM (improved)	CTLsn
				ICTP	RegCM	ref
				KNMI	RACMO	HC1
				METNO	HIRHAM	HADCN
				MPI	REMO	REMO3003
				SMHI	RCAO	HCCTL
				UCM	PROMES	Control
	ECHAM			DMI	HIRHAM	ECC
						ecctrl
				SMHI	RCAO	MPICTL
	HadAM	A2	50km	DMI	HIRHAM	HS1
				ETH	CHRM	HC_A2
				GKSS	CLM	SA2
					CLM (improved)	SA2sn
<b>F</b>				ICTP	RegCM	A2
rio				KNMI	RACMO	SA2
nai				METNO	HIRHAM	HADA2
Sce				MPI	REMO	KEMO3006
•1				SMIII	RCAU	A2
	FCHAM	۸2	50km	DMI	HIRHAM	A2 FCS
	Lennin	112	JOKIII	Divit		ecscA2
				SMHI	RCAO	MPIA2
	HadAM	B2	50km	DMI	HIRHAM	HB1
2				ICTP	RegCM	B2
0 B				METNO	HIRHAM	B2
ari				SMHI	RCAO	HCB2
cen				UCM	PROMES	b2
Š	ECHAM	B2		DMI	HIRHAM	ecscB2
				SMHI	RCAO	MPIB2

Uncertainty in climate change literature was interpreted as the spread of the predicted values (Déqué et al., 2007). Multiple PRUDENCE RCMs driven by different AGCMs and emission scenarios produced wide range of the predicted precipitation and temperature. This caused the computed site condition variables have large spread of predicted. The uncertainty of the predicted site condition variables propagated into the SILVA model. The wide spread of predicted site conditions in different RCMs was presented in four different scales as illustrated in Figure 8. Different RCMs were assigned in different colours. RCMs in current, scenario A2 and B2 were differentiated by different symbols. However, same RCMs presented in current, scenario A2 and B2 were given the same colour. In order to

establish the uncertainty range between the models and between the variable values, selections of RCMs were divided into:

- Selections based on the same RCMs where the four site condition variables were chosen from the same RCMs in same level of extremeness. The extremeness level was divided into minimum, average and maximum (black lines in Figure 8)
- Selections based on the variability value of site condition variables in minimum, average and maximum extreme (red lines in Figure 8)



Figure 8 Method used to select RCMs by model and variable

#### 3.4. Forest growth model: SILVA

#### 3.4.1. Tree input variables for SILVA

SILVA uses a list of tree input variables in Table 4 to represent each tree in the stand (Pretzsch et al., 2002a). The tree input variables used in the research were measured in 2003 for BE3 and BE4. This was due to the incompleteness of measurements during field work. The high density of beech leaves in autumn during the field visit hindered the measurement of tree height and tree height to crown base. As a result, tree inputs variables measured in 2003 were used to substitute the incomplete measurement of the above two variables.

Та	ble 4	Tree	inputs	used	in S	ILVA	to	generate	forest	stand
----	-------	------	--------	------	------	------	----	----------	--------	-------

Variable	unit	Abbreviation
Diameter at breast height	cm	DBH
Tree height	m	Н
Tree height to the base of the crown	m	Hcb
Crown diameter	m	Cd

The tree input variables in BE3 and BE4 were not from the actual measurement but they were predicted from the allometric regression. According to Huxley (1932),

"allometric regression is used to express the relationship between the relative growth rate of one organ to another organ within the same organism". The allometric regression was developed by measuring the four tree input variables in the neighbouring trees which surrounded BE3 and BE4. The neighbouring trees have same species composition, similar age and stand structure as in BE3 and BE4. The surrounded environmental conditions such as soil moisture and soil nutrient are comparable to the two demonstrations stands as well. These similarities were important to establish the allometric regression because it can make more precise prediction of tree variable values based on the similarities mentioned above. This statement was supported by Ponce-Hernandez (2004), where "selection of regression model approach needs to consider the similarity of the site".

The measurement and calculation process of the tree variables in BE3 and BE4 is illustrated in Figure 9. Measurement in BE3 and BE4 was completed only for DBH. H, Hcb and Cd were predicted from the allometric regression which relates the relationship between DBH-H, DBH-Hcb and DBH-Cd. The allometric regression was calculated based on the power regression function (equation 3.1). According to the forestry expert at FAWF Dr. Dong Phan Hoang, power regression function is the best model to fit the relation of DBH-H and DBH-Cd. This statement was supported by Hemery et al. (2005) where there is a close relationship between crown size and DBH. As shown in Table 5 and Table 6, the coefficient of determination ( $\mathbb{R}^2$ ) of DBH-H and DBH-Cd were strongly correlated. However, DBH-Hcb has low correlation of  $\mathbb{R}^2$  and this function is not commonly used in forestry. Due to the limitations of time and that Cd was one of the key variables to generate stand in SILVA, the DBH-Hcb allometric regression was still used to predict Hcb.

$$Y=ax^b \tag{3.1}$$

Where Y is predicted H, Hcb or Cd. a is intercept b is slope x is DBH

Relationship	Beech			Oak		
	Regression	$\mathbf{R}^2$	SE	Regression	$\mathbf{R}^2$	SE
	equation			equation		
DBH-H	$y = 4.3159x^{0.4952}$	0.8097	1.00252	$y = 11.076 x^{0.2466}$	0.2348	1.00153
DBH-Hcb	$y = 4.0213x^{0.2979}$	0.2576	1.02303	$y = 71.108x^{-0.3987}$	0.0905	1.01226

Table 5 Allometric regression for BE3 (source from FAWF)

DBH-Cd	$y = 0.6636x^{0.6801}$	0.7726	1.00723	$y = 0.0543 x^{1.2716}$	0.6866	1.00564
--------	------------------------	--------	---------	-------------------------	--------	---------

Table 6 Allometric regression model for BE4 (source from FAWF)

Relationship	Beech			Pine		
	Regression	$\mathbf{R}^2$	SE	Regression	$\mathbf{R}^2$	SE
	equation			equation		
DBH-H	$y = 9.0363x^{0.2583}$	0.6549	1.00238	$y = 13.222x^{0.1823}$	0.0936	1.00211
DBH-Hcb	$y = 5.051 x^{-0.1186}$	0.0158	1.06124	$y = 32.111 x^{-0.1378}$	0.0527	1.00227
DBH-Cd	$y = 1.4955 x^{0.5918}$	0.7933	1.00619	$y = 0.1762x^{0.9645}$	0.559	1.00489



Figure 9 Measurement and calculation process of tree variables in BE3 and BE4

#### 3.4.2. Uncertainty of tree input variables

To quantify the uncertainty of predicted tree input variables H, Hcb and Cd, standard error (SE) of the regression equations was computed (Equation 3.2). SE of the regression equation was applied to the estimated tree variable ( $\hat{Y}_{BE3}$ ) for BE3 and ( $\hat{Y}_{BE4}$ ) BE4 in order to define the interval for each tree variable. This was to assume the interval of lower limit (potential minimum uncertainty) and upper limit (potential maximum uncertainty) of predicted tree input variables. Assigning the minimum and maximum value for uncertain input variable has been practised in many uncertainty and sensitivity analysis approaches. (Beven, 2008; Wramneby et al., 2008; Xenakis et al., 2008).

$$SE = \sqrt{\frac{\sum (\hat{Y} - Y)^2}{(n-2)}}$$
(3.2)

In order to establish the upper and lower bound of the (95%) interval, factor *t* need to be multiplied by SE. *t* gives the critical value for certain degree of freedom and selected significance level.

$$\hat{Y}_{BEi} \pm SE \times t \tag{3.3}$$

# 3.5. One-at-a-Time (OAT) sensitivity analysis

To demonstrate the sensitivity analysis in this research, the simple one-at-a-time (OAT) sensitivity analysis technique was used. This was due to the restriction of using batch mode of SILVA to process repeated batch simulations and provide the distributions information of model variables. Generation of random sample across the entire input variables was unable to carry out in SIMLAB<sup>7</sup>. Alternatively, simulations in SILVA have to carry out manually by repeating the simulations in interactive mode. Hence, only OAT sensitivity analysis was applicable to suit the constraint of manual simulations in SILVA. OAT sensitivity analysis investigates the effects of changing one input variable at a time to the output whilst other input variables are kept at a nominal value. The changing rate of the output is relative to the changing magnitude of the input (Saltelli et al., 2004). The limitation of this approach is it takes no account of the interactions or correlations between the input variables (Hamm et al., 2006).

Two set of input variables, site condition inputs (Table 2) and tree inputs (Table 4) were used to run the OAT sensitivity analysis. The stand development was simulated over a 30-years period to suit the future site condition time window. Each input was varied across two levels of variations which were the minimum and maximum value while the other inputs variables were held constant at their average value. The intention of varying the input in minimum and maximum value was to produce the uncertainty range with the possible situation of underestimate or overestimate the input variables.

Two types of experiments were carried out for OAT sensitivity analysis. First experiment used the tree inputs and site condition input variables that selected from the same RCMs in same level of extremeness. For example, maximum extreme RCMs (Figure 10) represented all the site conditions variables in maximum extreme from the same RCM. Thus, only a set of four site condition variables from same RCMs was varied at one time. The objective of the first experiment was to examine

<sup>&</sup>lt;sup>7</sup> SIMLAB stands for Simulation Laboratory. It is a software designed to learn, to use and exploit uncertainty and sensitivity analysis techniques. See: http://simlab.jrc.ec.europa.eu/

the impact of the uncertain value of tree inputs and site condition inputs from different RCMs. The second experiment was to investigate the sensitivity of tree inputs and site condition inputs based on variability of variable values (Figure 11). For these two experiments, only one input from tree and site condition input variables was varied and the other inputs were held constant at average value. These experiments were carried out for current, scenario A2 and scenario B2. This approach required 2k+1 model runs where k is the number of input variables and one is the mean. Number of model runs for first experiment was 9 (3 tree inputs and 1 set of site condition variable from same RCM) (Figure 10). Second experiment has 15 model runs for 7 input variables (Figure 11). Total model runs for second experiment. The experiments were carried out for two demonstration stands. Hence, the grand total model runs for BE3 and BE4 was 144.



Figure 10 First experiment of OAT sensitivity analysis: varying tree inputs and site condition inputs from same RCMs



Figure 11 Second experiment of OAT sensitivity analysis: varying tree inputs and site condition inputs based on variability of variable values

#### 3.6. Linking SILVA output to habitat evaluation model

Linkage of SILVA outputs to habitat evaluation model was aimed to examine the propagation of uncertain site condition inputs and tree inputs to habitat evaluation model. SILVA outputs were linked to evaluation model based on the explanation from the model main user, Miss Astrid Tesch and Miss Ulrike Raible from FAWF. Besides, information from literature review was use to establish the possible link. The linkage of SILVA output to evaluation model was shown in Table 7. Three ecological indices, species profile index by Pretzsch, mingling index and aggregation index from SILVA outputs were matched with habitat criteria. These indices were used to examine the effect of uncertain SILVA input to SILVA outputs in sensitivity analysis. The three indices are mainly used to quantify spatial stand structure diversity in the forest. The calculations of the indices are based on distance-dependent measures (neighbour relations) (Pretzsch, 1998; Pommerening, 2002). The detailed information of the indices can be found in Appendix 4.

Table 7 Linkage of SILVA outputs to habitat and timber production model

Silva output	Criteria of habitat model
Species profile index by Pretzsch (1996) (Index A) <sup>8</sup>	Stratification
Mingling index (Index M)	mixed tree species number
Aggregation index by Clark Evan, (1954) (Index R) <sup>9</sup>	mosaic diversity

# 3.7. Questionnaire survey on criteria weights for habitat evaluation model

A questionnaire survey to assign and estimate criteria weight for habitat evaluation model was conducted at Research Institute for Forest Ecology and Forestry Rheinland-Pfalz (FAWF), Germany during the field visit. The objective of the questionnaire survey was to determine the uncertainty associated with weight estimating from various experts compared to the existing criteria weights. The experts expressed the criteria weights in percentage with the total value of 100% for the sum of the weight. The original criteria weights (Appendix 2) were used for more than 10 years by FAWF Central office of the Forest Services Department. This method was based on expert judgement approach as according to Meyer and Booker (2001) expert judgement is practised to interpret multiple experts judgement on existing data. Generally, judgement from various experts is based on their education background, working history, personal experience, understanding of the problem and personality. Thus, they would most probably interpret a subject or an issue

<sup>&</sup>lt;sup>8</sup> Source from Pretzsch (1998)

<sup>&</sup>lt;sup>9</sup> Source from Pretzsch (1998)

differently with diverse opinion and judgement (Gillund et al., 2008; Krayer von Krauss et al., 2008).

This survey was administrated with the help of ForeStClim project coordinators to 35 FAWF's experts at Trippstadt and Neustadt office in Germany. These experts were mainly from the department of Forest Growth, Forest Ecology and Forest Plant Production, Forest Protection and Forest Health, Forest Operations and Forest Products, Forest and Wildlife Ecology and Central Services. The questionnaire is enclosed as in appendix 5.

#### **3.8.** Construction of uncertainty conceptual framework

Uncertainty analysis throughout the integrated model chain in this research required an understanding of fundamental concept of uncertainty in order to analytically deal with various types of uncertainty. Thus, an uncertainty conceptual framework is needed to recognise, to classify and to assess uncertainty throughout forestry management in the context of climate change. W&H framework developed by Walker et al. (2003) was chosen to be adapted in this research. Modifications of the framework by Van der Sluijs et al.(2003), Refsgaard et al. (2007) and Krayer von Krauss et al. (2008) were taken into considerations. The conceptual framework was also enhanced by using the critiques and comments from Norton et al. (2006) and Krayer von Krauss et al. (2006) (Section 2.5).

Summary of the adaptations of W&H framework by Van der Sluijs et al.(2003), Refsgaard et al. (2007) is shown in Table 8. The main modifications of Van der Sluijs et al.(2003) approach was in dimension and location uncertainty. Van der Sluijs (2005) has integrated quantitative and qualitative element in model uncertainty analysis. Changes made by Refsgaard et al. (2007) were mainly in terminology uncertainty and level uncertainty. Consequently, a new conceptual uncertainty framework was developed by adapting the modifications, comments and critiques (Table 9) to suit into the research objective and research problem of this study.

and Reisguard et al. (2007) frame work						
Classification W&H framewo		Van der Sluijs et al.	Refsgaard et al. (2007)			
of uncertainty	(Walker et al., 2003)	(2003)				
Dimension	<ul> <li>Location</li> </ul>	<ul> <li>Location</li> </ul>	Source of			
uncertainty	Level	• Level	uncertainty			
	Nature	Nature	Taxonomy			

Table 8 Comparison of W&H framework, Van der Sluijs et al. (2003) framework and Refsgaard et al. (2007) framework

		Qualification of the knowledge base Value-ladennes of choice	Nature
Location of uncertainty	<ul> <li>Context of model</li> <li>Model input</li> <li>Parameter</li> <li>Model output</li> </ul>	<ul> <li>Context of model</li> <li>Model</li> <li>Model input</li> <li>Parameter</li> <li>Model output</li> <li>Expert judgement</li> <li>Data</li> </ul>	Changed in terminology of <u>location uncertainty</u> to <u>source of uncertainty</u> • Context of model • Model • Model input • Parameter • Model output
Level of uncertainty	<ul> <li>statistical uncertainty</li> <li>scenario uncertainty</li> <li>recognised ignorance</li> </ul>	<ul> <li>statistical uncertainty</li> <li>scenario uncertainty</li> <li>recognised ignorance</li> </ul>	Changed in terminology of <u>level uncertainty</u> to <u>taxonomy</u> • statistical uncertainty • scenario uncertainty • <u>qualitative</u> <u>uncertainty</u> • recognised ignorance
Nature of uncertainty	<ul> <li>Epistemic uncertainty</li> <li>Variability uncertainty</li> </ul>	<ul><li>Knowledge related</li><li>Variability related</li></ul>	<ul> <li>Epistemic uncertainty</li> <li>Stochastic uncertainty</li> </ul>

# Table 9 Development of new uncertainty conceptual framework

Classification	Description of new uncertainty	Remarks		
of uncertainty	framework			
Dimension uncertainty • Level of uncertainty • Nature of uncertainty • Qualification of the know		<ul> <li>Adapted from Refsgaard et al. (2007)</li> <li>Adapted from Van der Sluijs et al. (2003)</li> </ul>		
	<ul> <li><u>Value-ladennes of choice</u></li> <li><u>Spatial uncertainty</u></li> <li><u>Temporal uncertainty</u></li> </ul>	• Adaptation from experimental design in climate model and SILVA		
Location of uncertainty	<ul> <li>Context and framing</li> <li>Model         <ul> <li>Model structure</li> <li>Model technical</li> <li>Model parameter</li> <li>Model input</li> <li>Model output</li> <li>Expert judgement</li> </ul> </li> </ul>	<ul> <li>Adaptation from experimental design</li> <li>Adapted from Refsgaard et</li> </ul>		
		al. (2007)		
--------------------------	---	--		
Level of uncertainty	<ul><li>Statistical uncertainty</li><li>Scenario uncertainty</li><li>Recognised ignorance</li></ul>	• Adapted the level of uncertainty scale from Krayer von Krauss et al.(2004) and Gillund et al.(2008)		
Nature of uncertainty	<ul> <li>Epistemic uncertainty</li> <li>Variability uncertainty         <ul> <li>Linguistic uncertainty</li> <li>Natural uncertainty</li> </ul> </li> </ul>	<ul> <li>Comments from Norton et al. and Krayer von Krauss et al. (2006)</li> <li>Adaptation from experimental design</li> </ul>		

# 3.9. Summary

The uncertainty in model chain was recognised from the PRUDENCE, SILVA to habitat evaluation model throughout the whole exercise. The uncertainty in model chain started from PRUDENCE RCMs outputs, precipitation and temperature. Uncertainty from RCMs propagated into the SILVA model by the computed site conditions input variables. Besides uncertainty from RCMs, tree input variables for the SILVA model found to have certain range of uncertainty. The OAT sensitivity analysis was carried out to examine which uncertain input variables contributed the most to the SILVA outputs. Three uncertain SILVA output, species profile index, mingling index and aggregation index were linked to habitat evaluation model. The uncertainty in habitat evaluation model was found in the criteria weights by examining the questionnaire survey. Finally, the uncertainty throughout the model chain was recognised and it provided practical information to construct an uncertainty conceptual model.

# 4. **RESULTS**

This chapter shows the results of the uncertainty and sensitivity analysis throughout the model chain. Firstly, the uncertainty of PRUDENCE regional climate model is described. Then, the results from OAT-sensitivity analysis in the forest growth model, SILVA is presented. Uncertainty of decision making process in forest management by using the habitat suitability evaluation model as an example is shown. Finally, the focus is on the uncertainty conceptual framework.

### 4.1. Uncertainty of site condition variable from PRUDENCE RCMs

Figure 12, 13 and 14 shows the spread of site condition variables and the selection results of RCMs in current, scenario A2 and scenario B2. According to selection based on extremity between models, PROMES was selected as the minimum extreme for current, scenario A2 and scenario B2. For average case, HS1 and HB1 were selected for scenario A2 and scenario B2. MPIA2 and MPIB2 were selected for maximum extreme case in scenario A2 and scenario B2. However, model ECC was chosen for current condition. The selected maximum extreme RCMs tend to have low Pv in three climate conditions. RCMs selected by variables were found to be inconsistent where the selected RCMs were from a mixture of different models.



Figure 12 Distribution of site condition variables and selected PRUDENCE RCMs for current condition



Figure 13 Distribution of site condition variables and the selected PRUDENCE RCMs for scenario A2



Figure 14 Distribution of site condition variables and the selected PRUDENCE RCMs for scenario B2

Table 10 and Table 11 show the range of variability of site condition variables in current for selected RCMs by models and selected RCMs by variables. Tvar has similar uncertainty magnitude to both selection methods of RCMs. Variation of Pv for selected RCMs by variables was large compared to RCMs selected by model. This was contributed by the RCMs, ECC in maximum case with low precipitation.

Table 10 Distribution range of site condition variables for RCMs selected by model in current condition

Site condition variables	Minimum	average	Maximum
DT <sub>10</sub> (day)	137	157	179

Tv (°c)	14.80	15.63	16.66
Tvar (°c)	17.28	18.75	21.25
Pv (mm)	216.76	400.53	475.45

 Table 11 Distribution range of site condition variables for RCMs selected by

 variables in current condition

Site condition variables	Minimum	average	Maximum
DT <sub>10</sub> (day)	137	157	179
Tv (°c)	14.74	15.63	16.66
Tvar (°c)	17.28	19.36	21.25
Pv (mm)	216.76	400.53	626.73

Table 12 presents the distribution range of site condition variables for scenario A2 and scenario B2 for selected RCMs by model. Distribution range of site condition variables for scenario A2 and B2 for RCMs selected by variables is described in Table 13. The spread of site condition variables in scenario A2 and B2 for RCMs selected by model and RCMs selected by variable was generally analogous. Interestingly, substantial difference was found in variable Pv for scenario A2 and B2. For In general, RCMs driven by scenario B2 shows lower value in all site condition variables compared to RCMs driven by scenario A2.

Table 12 Distribution range of site condition variables for RCMs selected by same model in scenario A2 and B2

	A2			B2		
Site condition variables	Minimum	Average	Maximum	Minimum	Average	Maximum
DT <sub>10</sub> (day)	187	206	247	177	187	226
Tv (°c)	17.66	18.25	20.00	17.47	17.88	18.5
Tvar (°c)	19.31	20.31	24.28	19.31	20.31	20.92
Pv (mm)	264.38	599.38	387.23	234.69	556.27	420.3

Table 13 Distribution range of site condition variables for RCMs selected by different model in scenario A2 and B2

	A2			B2		
Site condition variables	Minimum	average	Maximum	Minimum	average	Maximum
DT <sub>10</sub> (day)	187	220	247	177	198	226
Tv (°c)	17.54	18.37	20.00	17.15	17.88	18.84
Tvar (°c)	19.17	20.81	24.28	18.93	20.31	22.05
Pv (mm)	236.10	494.5	702.18	234.69	420.3	698.54

Another attention that can be drawn was the difference of RCMs site condition values driven by two differences GCM, HadAM and ECHAM. From the selection result, RCMs driven by ECHAM found to have more extreme estimation than RCMs driven by HadAM for current, scenario A2 and B2. Selection of RCMs by model with GCM HadAM (H) and ECHAM (E) is summarised in Table 14. For RCMs selected by variable value, RCMs driven by HadAM and ECHAM were varied for minimum and average case in current, scenario A2 and B2 (Table 15).

Table 14 Selection of RCMs by model with GCM HadAM and ECHAM

RCMs	RCMs with degree of variability					
Category	Minimum extreme	Average	Maximum extreme			
Current	Н	Н	Е			
H/EA2	Н	Н	Е			
H/EB2	Н	Н	Е			

Table 15 Selection of RCMs by variable with GCM HadAM and ECHAM

Site condition	RCMs with degree of variability for variables value					
variable	Minimum extreme	Average	Maximum extreme			
$DT_{10}$	Н	Н	Е			
Tv	H,E	Н	E			
Tvar	H,E	H,E	E			
Pv	Н	H,E	E			

### 4.2. OAT Sensitivity analysis of SILVA

Results from Figure 15 show that the sensitivity of index R, index A and index M to tree variables and site condition variables was varied in a forest stand, species oak and beech. Sensitivity of index R, index A and index M to RCMs site condition did not reveal information about the contributions of each site condition inputs variable. Table 16 shows the indices value from sensitivity analysis by using site condition variable from same RCMs at lower and upper bound in BE3.





Figure 15 Sensitivity of index R, index A and index M to tree variables and site condition for RCMs selected by model under current condition, scenario A2 and B2 in BE3

Table 16 Results from OAT sensitivity analysis for index R, index A and index M by using site condition variables from same RCMs under a)current condition, b) scenario A2 and c)scenario B2 in BE3

a) Current						
Input variables	Inde	ex R	Inde	x A	Inde	ex M
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	0.99	0.98	1.05	0.91	0.5	0.39
Hcb	0.97	0.88	0.99	0.93	0.44	0.39
Cd	1.02	0.98	0.87	0.89	0.44	0.44
RCM site condition	0.94	1	0.91	0.97	0.38	0.43
b)Scenario A2						
Input variables	Inde	ex R	Index A		Index M	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	0.96	0.95	1.08	0.95	0.46	0.41
Hcb	0.93	0.95	0.93	0.97	0.4	0.39
Cd	0.93	0.92	0.87	0.9	0.4	0.39
RCM site condition	0.95	0.93	0.92	1.08	0.4	0.43
b)Scenario B2						
Input variables	Inde	ex R	Inde	x A	Index M	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	0.96	0.95	1.02	0.99	0.44	0.4
Hcb	0.97	1.03	0.95	1	0.43	0.46

Cd	0.93	0.93	0.92	0.92	0.43	0.4
RCM site condition	0.91	0.98	0.89	0.85	0.43	0.41

Sensitivity results in Figure 16 depict more information about the explicit sensitivity effects from individual input variable. Sensitivity of the indices to the input variables behaved differently in forest stand and different tree species. Sensitivity of index A tends to have similar response in forest stand and beech for three climate conditions. OAT sensitivity results for different RCMs revealed individual index value for each site condition variables explicitly.



Figure 16 Sensitivity of index R, index A and index M to tree variables and site condition for RCMs selected by variables under current condition, scenario A2 and B2 in BE3

Table 17 Results from OAT sensitivity analysis for index R, index A and index M by using site condition variables from different RCMs under a)current condition, b) scenario A2 and c)scenario B2 in BE3

a) Current						
Input	Index R		Inde	x A	Index M	
variables	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	0.94	0.91	1.02	0.92	0.44	0.39

b)Scenario A2						
Pv	0.92	0.93	0.91	1.08	0.41	0.43
Tvar	0.92	0.97	0.98	0.98	0.43	0.36
Tv	0.92	1	0.96	0.92	0.43	0.46
$DT_{10}$	1.01	0.92	0.97	0.95	0.43	0.41
Cd	1	0.94	0.89	0.89	0.42	0.4
Hcb	0.92	0.95	0.94	0.99	0.41	0.39

Input	Inc	lex R	Inde	x A	Index M				
variables	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound			
Н	1.01	0.95	1.07	0.91	0.45	0.41			
Hcb	1.03	0.95	0.9	0.93	0.45	0.45			
Cd	0.94	0.99	0.8	0.91	0.41	0.42			
$DT_{10}$	1.03	0.96	0.93	0.93	0.45	0.39			
Tv	1.05	0.9	0.98	1.06	0.48	0.4			
Tvar	1.05	0.93	0.97	1.08	0.48	0.43			
Pv	0.96	0.96	0.93	0.9	0.42	0.35			
b)Scenario B2									

Input	Inc	lex R	Inde	x A	Ind	ex M
variables	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	0.98	0.99	0.97	1.03	0.44	0.41
Hcb	0.97	1.02	0.96	0.96	0.48	0.49
Cd	0.99	0.93	0.81	0.88	0.4	0.4
$DT_{10}$	0.97	0.97	0.98	1.03	0.48	0.45
Tv	0.97	0.98	0.94	0.85	0.41	0.41
Tvar	0.95	1	0.92	0.91	0.4	0.39
Pv	0.94	0.9	0.9	1.01	0.43	0.41

OAT Sensitivity analysis was conducted for BE4 with the composition of beech and pine. Results of OAT sensitivity analysis for BE4 with input variable from same RCM is shown in Figure 17. For this experiment, only variable height and variables of RCM were found to be most sensitive to index A, index R and index M in three climate conditions for both types of tree and forest stand. Generally, sensitivity of index R, index A and index M for pine was much lower than beech and forest stand. As shown in Table 18, changes of RCMs site condition produced very different results than tree input variables.



Figure 17 Sensitivity of index R, index A and index M to tree variables and site condition for RCMs selected by RCMs under current condition, scenario A2 and B2 in BE4

Table 18 Results from OAT sensitivity analysis for index R, index A and index M by using site condition variables from same RCMs under a)current condition, b) scenario A2 and c)scenario B2 in BE4

<u>a) Current</u>						
Input variables	Ind	ex R	Inde	x A	Inde	ex M
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	1.09	1.05	0.97	1.06	0.52	0.47
Hcb	1.07	1.07	1.07	1.07	0.51	0.51
Cd	1.07	1.07	1.07	0.99	0.51	0.51
RCM site condition	0.99	1.07	0.88	1.07	0.49	0.51
b)Scenario A2						
Input variables	Inde	ex R	Inde	x A	Inde	ex M
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	1.1	1.06	0.96	1.1	0.52	0.52
Hcb	1.07	1.07	1.06	1.06	0.51	0.51
Cd	1.07	1.07	1.06	0.99	0.51	0.51

RCM site condition	0.99	0.99	0.85	0.87	0.49	0.49
b)Scenario B2						
Input variables	Inde	ex R	Inde	x A	Inde	ex M
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	1.1	1.05	0.96	1.09	0.52	0.47
Hcb	1.07	1.07	1.07	1.07	0.51	0.51
Cd	1.07	1.07	1.07	1.07	0.51	0.51
RCM site condition	0.99	1.07	0.85	1.04	0.49	0.51

Results of sensitivity analysis for BE4 by using variables from different RCMs are shown in Figure 18. Generally, three predicted indices showed less effect on the selected input variables in BE4. Under scenario B2, the sensitivity effect was very low for index R, index A and index M. As shown in Table 19, the range of indices results mostly increased by variable Pv which tend to generate lower indices value.



Figure 18 Sensitivity of index R, index A and index M to tree variables and site condition for RCMs selected by variables under current condition, scenario A2 and B2 in BE4

a) Current						
Input	Inc	lex R	Inde	x A	Inde	ex M
variables	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	1.09	1.05	0.97	1.06	0.52	0.47
Hcb	1.07	1.07	1.07	1.07	0.51	0.51
Cd	1.07	1.07	1.07	0.99	0.51	0.51
DT10	1.07	1.07	1.07	1.07	0.51	0.51
Tv	1.07	1.07	1.07	1.07	0.51	0.51
Tvar	1.09	1.07	0.97	1.06	0.51	0.51

0.85

0.69

0.49

0.51

Table 19 Results from OAT sensitivity analysis for index R, index A and index M by using site condition variables from different RCMs under a)current condition, b) scenario A2 and c)scenario B2 in BE4

b)Scenario A2						
Input	Inc	lex R	Inde	x A	Inde	ex M
variables	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	1.1	1.05	0.94	1.1	0.52	0.47
Hcb	1.07	1.07	1.05	1.05	0.51	0.51
Cd	1.07	1.07	1.05	1.05	0.51	0.51
DT <sub>10</sub>	1.07	1.07	1.04	1.06	0.51	0.51
Tv	1.07	0.99	1.07	0.87	0.51	0.49
Tvar	1.07	0.99	1.06	0.87	0.51	0.49
Pv	0.99	1.07	0.83	0.93	0.49	0.51
b)Scenario B2						

1.07

Input	Inc	lex R	Inde	x A	Inde	ex M
variables	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Н	1.1	1.05	0.94	1.1	0.52	0.47
Hcb	1.07	1.07	1.06	1.06	0.51	0.51
Cd	1.07	1.07	1.06	1.06	0.51	0.51
$DT_{10}$	1.07	1.07	1.06	1.06	0.51	0.51
Tv	1.07	1.07	1.07	1.04	0.51	0.51
Tvar	1.07	1.07	1.04	1.04	0.51	0.51
Pv	0.99	1.07	0.85	0.93	0.49	0.51

# 4.3. Results of questionnaires

0.99

Pv

14 questionnaires were collected from the total of 35 experts. The number of collected questionnaires did not achieve the expected number which should be half of the total in order to get more concrete representation of the expert judgement. Distribution of the estimated criteria weights for individual criteria was showed in

Figure 19. The estimated criteria weights from 14 respondents have high variation and inconsistency. For example, the estimated weight for close to nature has high number of equal proportion of experts in assigning different weight. Criteria for rarity, age diversity and number of tree species have more significant proportion of experts in expressing the same weight. On average, only four to six experts estimated the same weight for each criterion.







Figure 19 Histogram of estimated criteria weights from 14 experts to criteria and indicators of habitat evaluation model

Table 20 shows the descriptive statistic of the weight from 14 experts. Two respondents assigned zero weight to the criteria number of tree species, water and nutrient supply. This caused the high standard deviation in criteria water supply. One respondent did not assign the criteria weight to the sum of 100% in criteria structural diversity.

				Standard	Standard
	Min	Max	Mean	Deviation	Error
Close_to_nature	20	50	36.07	12.43	3.322
Structural diversity	20	70	39.29	12.84	3.431
<ul> <li>spatial structure</li> </ul>	20	80	41.07	15.00	3.998
o vertical structure	10	40	21.14	10.55	2.820
stratification	40	70	54.29	10.16	2.716
step range	30	60	45.71	10.16	2.716
o stock structure	10	60	30.00	13.59	3.631
tree species diversity	30	90	51.79	15.89	4.245
mixed tree species number	10	40	25.36	9.70	2.592
number of tree species	0	50	22.86	12.04	3.219
o age diversity	10	40	24.21	8.29	2.214

Table 20 Mean and standard deviation of the criteria weights from 14 experts

o mosaic diversity	10	50	24.64	12.32	3.293
• habitat feature	10	70	35.71	14.92	3.987
0 stocking	10	30	21.43	6.91	1.848
o heavy wooden share	10	60	32.50	15.41	4.119
o location potential	20	80	46.07	17.34	4.634
water supply	0	80	56.43	22.05	5.893
nutrient supply	0	70	36.43	18.23	4.873
<ul> <li>special structure</li> </ul>	10	40	21.79	8.68	2.321
o dead wood	10	50	33.21	14.36	3.838
o location diversity	10	70	40.36	16.7	4.462
o special local structure	10	40	26.43	10.08	2.695
Rarity	10	50	24.64	11.84	3.165
<ul> <li>biotope des LUWG</li> </ul>	20	50	37.14	9.35	2.498
<ul> <li>protected area</li> </ul>	50	80	62.86	9.35	2.498

#### 4.4. Uncertainty conceptual framework and uncertainty matrix

The new uncertainty conceptual framework was expanded to seven dimensions of uncertainty for characterising source of uncertainty in this research and projected in Figure 20. The rows in the matrix indicate the sources of uncertainty that occur in the model chain. The columns are used to further categorise the sources of uncertainty into level of uncertainty, nature of uncertainty, qualification of knowledge base, value ladenness of choice, spatial uncertainty and temporal uncertainty. In order to facilitate the model chain approach, the new matrix was rearranged and combined the uncertainty of input, parameter, expert judgement, data and model outcome into the category of model uncertainty.

The model uncertainty was sub-divided into four divisions which included general circulation model, regional circulation model, SILVA and habitat evaluation model. Each model was examined separately based on the above source of uncertainty but uncertainty of each model output was accumulated from one model to another and summed as the total uncertainty output at the end for model chain. Expert judgement was added as the source of uncertainty in habitat evaluation model because the assessment score and criteria weight for the model were contributed mainly from interpretation and judgement from mental model. Data uncertainty was added to facilitate the usage of forest inventory data in SILVA and habitat evaluation model. Uncertainty of data refers to uncertainty of monitoring and observation data which was used as the empirical data and inventory data in the model development.

Level of uncertainty was categorised into scale of 1 to 5 as explained in Figure 3. One source of uncertainty can be categorised into different level of uncertainty and different dimensions of uncertainty. For example, model technical of global circulation model can be expressed as statistical uncertainty and recognise ignorance. The model technical error can be quantified from model result relative to the effects of parameter variation (Knight et al., 2007). Yet, bugs from software, different processor and RAM size used in the model have shown unclear association to the predicted results variation. Technical uncertainty was found in epistemic uncertainty as the software and hardware problem in the model can be improved by understanding and knowledge.

Besides, variability uncertainty was further sub-divided into linguistic uncertainty and natural uncertainty. Linguistic uncertainty<sup>10</sup> was added as it was occurred in system data of SILVA. It expressed the ambiguity of verbal communication among forest workers during the tree measurement in the forest. This was examined during the field measurement in field work especially when measurement value was not pronounced precisely to other co-workers. Besides, linguistic uncertainty also occurred in criteria weights estimation from questionnaire exercise for habitat evaluation model. As claimed by some of the experts, the terminology of the criteria was vague and incomprehensible to estimate the weight. This caused misinterpretation of the criteria and obscured precise weight estimation.

Qualification of knowledge base and value ladenness of choice were added to reflect the underpinning and reliability of the employed knowledge and the different views and perspectives in the choice. For example, all source of uncertainty in general circulation models tend to have strong qualification of knowledge base. This was because GCM was developed and investigated by wide range of scientist and climate experts with large scale of numerical methods and information for global circulation modelling (Houghton, 2001). Expert judgement for criteria score and criteria weight found to have strong value ladenness of choice as they contained many different views and assumptions from different experts.

Spatial uncertainty can be discussed at GCM and RCM level. As for GCM, coarse spatial resolution of climatic data is unable to capture fine-scale of climate variations for impact assessment studies (Giorgi et al., 2001). Besides, spatial uncertainty occurs due to the downscaling process of GCM output to RCM from 300 km spatial resolutions to 50 km spatial resolutions. Temporal uncertainty concerned about the wide range of temporal scale from sub-daily to century for climate prediction in GCMs and RCMs (Heal and Kriström, 2002).

<sup>&</sup>lt;sup>10</sup> It is the uncertainty related to communication of science resulted from vague, context dependent, ambiguous and underspecific of scientific vocabulary (Gillund et al., 2008).

Eventually, the matrix was filled by marking the tick symbol in the relevant uncertainty columns for any occurrences of uncertainty. The total uncertainty was the chain of uncertainty propagated and accumulated from GCM, RCM, SILVA and habitat evaluation model. The uncertainty in GCM has to carry forward to RCM, accumulated to SILVA, habitat evaluation model and sum in the total output of uncertainty. From the total output of uncertainty, all the sources of uncertainty in model chain can be identified and further categorised. In level of uncertainty, statistical uncertainty found to be the highest uncertainty in the model chain. In nature uncertainty, natural uncertainty has the highest occurrences of uncertainty, followed by epistemic uncertainty. The model chain has strong qualification of knowledge base with low quantity of large value ladenness of choice. Spatial and temporal uncertainty have high occurrence in model chain as well.

y	y uncertainty	Natural uncertainty	~	~		7	ددد		~	22	دد	~ ~	7	~~	√ (16)	7
of uncertaint	Variabilit	Linguistic uncertainty														
Nature	Epistemic uncertainty		٨	7	7	7	ددد	~~~							(6) M	7
	orance	w													0	
certainty	Recognised ign	4	7		7										√ (2)	
Level of und	nario tainty	£												7	γ (1)	
I	In Scer	7	^										7	-	V (2)	
	Statistical uncertainty	1		~	~	~	د د د	~~~	^	77	دد	~~			√ (14)	~
urce of uncertainty			Future adaptation of forest management in social-economic, technology and ecology context under climate change.	Model structure System behaviour- interactions between input, parameter in system boundary	<u>Model technical</u> Software/ hardware	Model parameter • Physical parameter	<ul> <li>Atmospheric parameter</li> <li>Sea surface parameters</li> </ul>	<ul> <li>Land surface parameter</li> <li>Hydrological parameter</li> <li>Soil input parameter</li> </ul>	Model <u>System data</u> input • Physics control input	Atmospheric input variable     Sea curface innut variable	Land surface input variable	• Soil input variable • Hydrological input variable	Driving force	Emissions scenarios	Model output	Model structure System behaviour- interactions between input, parameter in system boundary
So			Context and framing	General circulation model <sup>11</sup>												Regional climate model <sup>13</sup>

<sup>11</sup> Source can be found in Appendix 2: Summary and description of PRUDENCE models <sup>12</sup> See: http://en.wikipedia.org/wiki/Radiative\_forcing

ertaintv	P	ariability uncertainty	uistic Natural tainty uncertainty			~	~	~ ~	>-	> -	>		2	~	~	~ ~	~ ~	~	-	~	_	>	_	7	1.	~	) V (33)	-	~		~
Nature of unc	Epistemic	uncertainty Va	Ling	~		~	2.		2	27	~																又(17) (17) (17) (17) (17) (17) (17) (17)		7		~
	orance		2																								0				
ertaintv	Recognised ign		4	7																							V (3)				7
evel of unce	ario	tainty	3																						17	>	√ (2)				
	Scer	uncer	7																	>	-	>	-	>			V (5)				
	Statistical	uncertainty	1	7		7	>.	7	>`	> 7	>		2.	7	>-	>-	~~	٨									マ (28)	_	7		
Source of uncertainty				Model technical Software/ hardware	Model parameter	Physical parameter	Atmospheric parameter	Sea surface parameters	<ul> <li>Land surface parameter</li> </ul>	<ul> <li>Hydrological parameter</li> </ul>	<ul> <li>Soil input parameter</li> </ul>	Model System data	inputs	Atmospheric input variable	<ul> <li>Sea surface input variable</li> </ul>	<ul> <li>Land surface input variable</li> </ul>	Soil input variable	<ul> <li>Hydrological input variable</li> </ul>	Driving force	Global atmospheric	circulation model	Global atmospheric ocean	circulation model	Local scale of topography	and land use characteristic	Emissions scenarios	Model output	SILVA <sup>14</sup> Model structure	System behaviour- interactions	between input, parameter in system	boundary

<sup>13</sup> Source can be found in Appendix 2: Summary and description of PRUDENCE models

Source of uncertainty		I	revel of un	certainty		Nature	of uncertainty	
	Statistical uncertainty	Scen uncer	nario taintv	Recognised ign	orance	Epistemic uncertainty	Variability	uncertaintv
	1	2	3	4	5	3	Linguistic uncertainty	Natural uncertainty
Model technical Software /hardware	7			7		7		
<u>Model parameter</u>	-					-		-
• Species-specific parameter $(a_0, \ldots, a_{n-1})$	7					7		7
, add for mortality model	7					~		7
• Species-specific parameter $(p_0, \ldots, p_2)$ for probability value of single	*					*		*
tree mortality	-					-		
Species-specific parameter (c <sub>0</sub> ,,c <sub>5</sub> )	7					Ż		7
for tree height growth model	1					_		-
• Species-specific parameter (j1, j2, j3)	7					~		7
for potential diameter growth model	14					10		1
• Species-specific parameter (k <sub>0</sub> ,,k <sub>5</sub> )	>					>		٨
for potential basal area growth	1.					1		1.5
Species-specific parameter (l <sub>0</sub> ,,l <sub>2</sub> )	>					>		*
for height to crown base growth	1.					-		14
Species-specific parameter (m <sub>0</sub> ,m <sub>3</sub> )	>					~		~
crown dimensions growth								
Model <u>System data</u> inputs • DBH (cm)	~					7	7	7
• H (m)	7					~	7	7
• Hcb (m)	~					_ ک	7	2
$\bullet$ Cd (m)	٧					٨	٨	٨
Driving force								-
Inut	~							>`
NO <sub>X</sub> (ppm)	>`							27
<ul> <li>CO<sub>2</sub> (ppm)</li> </ul>	>`							27
DT <sub>10</sub> (day)	>7							>7
TVAR (°C)	> ~							> _,
• TV (°C)	~~							~~
• Pv (mm)	~							~~
MOISI								

<sup>14</sup> Source from Pretzsch et al., 2002a; Pretzsch et al., 2002b

	Source of uncertainty		Γ	evel of unce	ertainty		Nature	of uncertainty	
		Statistical	Scen	ario	Recognised ign	orance	Epistemic		
		uncertainty	uncert	ainty			uncertainty	Variability	uncertainty
		1	2	3	4	S		Linguistic	Natural
	Data								
	Forest inventory data	7			7		~		7
	Model output	√ (50)	√ (5)	√ (2)	√(5)	0	v (32)	ν (4)	V (55)
Habitat	Model structure								
evaluation	<sup>1</sup> Algorithm formulation	7							7
model	Model technical								
	Software /hardware	7			~				
	Model parameter	7					~		۲
	Expert judgement								
	Criteria score	~							>-
	<ul> <li>Criteria weight</li> </ul>	7							7
	Model System data	7					~		۲
	input Driving force	7					7		7
	Data						-		
	Forest inventory data	~			~		~		
	Model output	√ (58)	ν (5)	V (2)	v (7)	0	√ (36)	イ (4)	V (61)
Total output		√ (58)	γ (5)	V (2)	γ (L)	0	v (36)	V (4)	√ (61)

Figure 20 New uncertainty matrix Part 1

 rrce of uncertainty	Qualifica	tion of knowl	edge base	Value	-ladenness of c	choice	Spatial	Temporal
	Weak	Fair	Strong	Small	Medium	Large	uncertainty	uncertainty
Future adaptation of forest management		~				٨		$^{}$
in social-economic, technology and								
ecology context under climate change								
Model structure								
System behaviour- interactions between			7				~	~
 input, parameter in system boundary								
<u>Model technical</u>								
Software/ hardware			7					~
<u>Model parameter</u>							-	
<ul> <li>Physical parameter</li> </ul>			7				>-	~
<ul> <li>Atmospheric parameter</li> </ul>			>				~	>

	Source of unce	ertainty	Qualifics	ation of knowle	edge base	Value	ladenness of	choice	Spatial	Temporal
			Weak	Fair	Strong	Small	Medium	Large	uncertainty	uncertainty
	<ul> <li>Sea surf.</li> </ul>	face parameters			~				~	~
	<ul> <li>Land sui</li> </ul>	uface parameter			7				7	>-
	• Hydrolo	ogical parameter			7				>-	>-
	<ul> <li>Soil inp</li> </ul>	out parameter			٨				2	٧
	Model	System data			-				-	-
	inputs	<ul> <li>Physics control input</li> </ul>			>				7	>-
		<ul> <li>Atmospheric input variable</li> </ul>			~				>	>-
		<ul> <li>Sea surface input variable</li> </ul>			>				~	>-
		<ul> <li>Land surface input variable</li> </ul>			2.				7	~
		<ul> <li>Soil input variable</li> </ul>			>.				2	>
		<ul> <li>Hydrological input variable</li> </ul>			7				7	Ż
	1	Driving force								
		<ul> <li>Global atmosphere</li> </ul>			~				~	
		circulation model								
		<ul> <li>Global atmosphere ocean</li> </ul>			7				~	
		circulation model								
		<ul> <li>Local scale of tonography</li> </ul>			7				~	
		and land use characteristic			-					-
		<ul> <li>Emissions scenarios</li> </ul>			7					Ż
	Model out	put	0	م (I) کر	√ (18)	0	0	√ (1)	$\sqrt{(16)}$	$\sqrt{(16)}$
Regional	Model stri	ucture							-	-
climate	System bel	haviour- interactions between			7				~	~
model	input, para	meter in system boundary								
	Model tech	hnical								
	Software/ t	hardware			~					V
	Model par	rameter								
	<ul> <li>Physical</li> </ul>	l parameter			2.				7	
	<ul> <li>Atmospi</li> </ul>	heric parameter			~				7	
	<ul> <li>Sea surf.</li> </ul>	face parameters			7				>-	
	<ul> <li>Land sur</li> </ul>	urface parameter			~				>-	
	• Hydrolo	ogical parameter			27				~~	
	<ul> <li>Soil inpr</li> </ul>	ut parameter			>				7	
	Model	System data							-	
	inputs	<ul> <li>Physics control input</li> </ul>			2				~	~
		<ul> <li>Atmospheric input variable</li> </ul>			2.				7	
		<ul> <li>Sea surface input variable</li> </ul>			>				7	
		<ul> <li>Land surface input variable</li> </ul>			7				7	
-	-									

S	ource of uncertainty	Qualifics	ation of knowl	edge base	Value	ladenness of	choice	Spatial	Temporal
		Weak	Fair	Strong	Small	Medium	Large	uncertainty	uncertainty
	<ul> <li>Soil input variable</li> <li>Hydrological input variable</li> </ul>			~ ~				77	
	Driving force • Radiative forcing		7	۲					
	Model output	0	\ \(2)	v (33)	0	0	م (1) ا	√ (29)	√ (19)
SILVA	Model structure System behaviour- interactions between input, parameter in system boundary			~					7
	<u>Model technical</u> Software/hardware			Y					7
	Model parameter     Species-specific parameter (a0,			~				7	7
	<ul> <li><i>a</i><sub>4</sub>) for mortanty model</li> <li>Species-specific parameter (b<sub>0</sub>,, b<sub>2</sub>) for probability value of single tree</li> </ul>			7				7	7
	<ul> <li>mortality</li> <li>Species-specific parameter (c<sub>0</sub>,,c<sub>5</sub>) for tree height growth model</li> </ul>			7				7	7
	• Species-specific parameter ( <i>j</i> <sub>1</sub> , <i>j</i> <sub>2</sub> , <i>j</i> <sub>3</sub> ) for potential diameter growth model			7				7	7
	• Species-specific parameter (k <sub>0</sub> ,,k <sub>5</sub> ) for potential basal area growth			~				7	7
	<ul> <li>Species-specific parameter (l<sub>0</sub>,l<sub>2</sub>) for height to crown base growth</li> <li>Species-two-rific parameter (m<sub>2</sub>, m<sub>4</sub>)</li> </ul>			77				7	7
	crown dimensions growth							7	7
	Model         System data           inputs         • DBH (cm)           • H (m)         • H (m)           • Heb (m)         • Cd (m)		2222						7777
	Driving force           • NUT           • NO <sub>X</sub> (ppm)           • CO <sub>2</sub> (ppm)			222				~ ~	52

	So	ource of uncertain	nty	Qualifics	ation of knowl	edge base	Value	-ladenness of	choice	Spatial	Temporal	
				Weak	Fair	Strong	Small	Medium	Large	uncertainty	uncertainty	
		• D,	T <sub>10</sub> (day)			7				~	~	
		Í.	VAR (°C)			2				~	~	
		ť.	V (°C)			. ć				~	~	
		•	v (mm)			2.				~	~	
		•	IOIST .			7				<i>ج</i> .	~ ~	
		Data										
		Forest inventor	y data			7				~	~	
		Model output		0	م (9)	V (51)	0	0	√ (1)	√ (44)	$\sqrt{(40)}$	
1	Habitat	Model structur										
	evaluation	Algorithm forn	nulation			7						
	model	Model technics	le			~					Ś	
		Model parame	ater			٨						
		Expert judgem	<u>ient</u>			-			-	-	-	
		<ul> <li>Criteria sco</li> </ul>	ore			2			~~	Ż	Ż	
		<ul> <li>Criteria we</li> </ul>	eight			>			>			
		Model inputs	System data			^				~	~	
			Driving force			~				~	~	
		Data										
		Forest inventory	y data			~				~	~	
		Model output		0	م (9)	V (59)	0	0	V (3)	v (48)	V (45)	
Total outpr	ıt			0	<b>(9)</b> ∧	√ <b>(59</b> )	0	0	√ ( <b>3</b> )	√ <b>(48)</b>	√ ( <b>45</b> )	
Ei anno 1	O Naw in	cartainty me	striv nart J									

Figure 20 New uncertainty matrix part 2

### 5. DISCUSSION

### 5.1. Uncertainty of site condition variable from PRUDENCE RCMs

Prediction of future climate change involves various sources of uncertainty (Déqué et al., 2007). The sources of uncertainty include uncertainty of emission scenario, uncertainty of the driving GCM, uncertainty of RCM formulation and uncertainty of natural variability (Déqué et al., 2007; Jacob et al., 2007). Through the RCMs selection exercise and the results from RCMs selection, uncertainty caused by emission scenarios and uncertainty from driving GCM can be discussed.

The computed site condition input variables are generally higher for scenario A2 compared to scenario B2 (Table 12 and Table 13). This is because scenario A2 developed under the economic oriented storyline with high emissions. But, B2 was developed under environmental protection storyline with low emissions (IPCC, 2007). Yet, the variation of predicted site conditions was found to be small between RCMs under scenario A2 and RCMs under scenario B2. This can be concluded that uncertainty introduced by different scenario is not enormous (Fowler et al., 2007).

The uncertainty introduced by choice of driving GCM was larger than different emission scenario (Fowler et al., 2007; Fronzek and Carter, 2007). This can be shown by the wide spread of the predicted site condition value driven by HadAM and ECHAM. RCMs driven by ECHAM, generated the maximum extreme value of all the site condition inputs (Figure 12, 13 and 14). As claimed by Fronzek and Carter (2007), RCMs driven by ECHAM produced greater temperature changes compared to RCMs driven by HadAM. This is due to the different behaviour of atmospheric moisture in HadAM and ECHAM. Besides, projection of site condition from RCMs with same GCM ECHAM showed large variation especially in Pv. This can be explained that RCMs has more influences to Pv variation during summer compared to GCM (Christensen and Christensen, 2007; Déqué et al., 2007; Fowler et al., 2007). Exploration and selection of RCMs outputs by inter-comparison of RCMs driven by different emission scenario and GCMs gave an insight of sources of the uncertainty.

# 5.2. OAT sensitivity analysis

The results of OAT sensitivity analysis to index R, index A and index M were not

consistent to the same input variables. The sensitivity of the indices to the input variables differed between three climate conditions. Therefore, it is not possible to identify that the indices are most sensitive to which particular input variables. However, this might due to the complexity of SILVA model structure coupled with multiple sub-models in it. The interactions of tree inputs and site conditions input to the index R, index A and index M are non-linear. The indices are calculated from three dimensional structure model (Pretzsch, 1998; Pretzsch et al., 2002a). The three-dimensional structure model is constructed from stem position, tree height, diameter, crown length, crown diameter and species related crown model (Pretzsch, 1998). Index R, index A and index M used the 3-D stand as the basis platform to derive the index value.

The large change of indices value does not make a difference if the change of the indices is between the ranges of index classification. For example, index R is classified into: R < 1 represents the stand with high clustered distribution, R=1 has random distribution and R>1 has the regular distribution pattern (Pretzsch, 1998). This can be discussed in the changes of index R to Cd and Hcb in scenario B2 (Table 17). The change of index R to Cd was larger than Hcb, but, this did not give much difference to the classification of index R. This was because the change of index to Cd from 0.93 to 0.99 was still under the same category of index R classification. However, change of index R to Hcd from 0.97 to 1.02 revealed that the change of index classification. To conclude, the inputs which contribute the most to the index change do not make much difference it has been classified to certain classification.

Two different mixed stands, BE3 with oak and beech and BE4 with pine and beech also behaved differently in this analysis. Generally, sensitivity of the indices to the tree input variables and site condition for BE4 is much lower than BE3. The reason for this might cause by the low coefficient of determination ( $R^2$ ) of Hcb to DBH in the allometric regression (Table 6). The predicted value of Hcb was not compatible to the size of tree crown diameter. As a result, the generated 3D stand structure in SILVA for BE4 was occupied by large crown diameter and short tree height to crown base. This strange shape and dimension of stand structure might cause the calculation of the spatial structure indices to be deviated.

To conclude, the sensitivity analysis under different climate scenario showed that the effect of climate change to three indices was very small. This reveals that SILVA might be not sensitive to the change of climate. The OAT sensitivity analysis in this research does not reveal that the indices are most sensitive to which particular input variables. This is because the interpretation of the changing magnitude of the indices resulted from varying the input variable is difficult to infer and varied between different experiments. Nevertheless, this analysis gives the underlying information and broad picture of the problems in the research. This is because OAT sensitivity analysis takes no accounts of the interactions between different inputs.

#### 5.3. Uncertainty conceptual framework and uncertainty matrix

The uncertainty framework was designed to deal with multiple integrated models in the form of model chain. The expansion and modifications of the framework were needed to cover all dimensions of uncertainty in the model chain. To achieve this, new sources of uncertainty and dimensions of uncertainty were added (Figure 20. One important changed in the matrix was to establish the linkage between model outputs. This aimed to trace and accumulate the source of uncertainty from each model to total model output. Expert judgement was another important source of uncertainty in the chain because it was the shift of quantitative uncertainty to qualitative uncertainty.

The level of uncertainty was further determined by the score of 1 to 5 to explicitly classify level of uncertainty. Linguistic uncertainty was needed to address the uncertainty in science communication (Gillund et al., 2008). Besides, the model chain required the information about the level of quality and underpinning of the various uncertainties. This was helpful to identify to which extent the uncertainty can be reduced by better underpinning (Van der Sluijs et al., 2003; Walker et al., 2003). Since the model chain included the decision support model, values and biases in the choices were unavoidable. Spatial and temporal uncertainty was needed to facilitate the spatial and temporal variability in climate models.

The result from the total output of uncertainty in Figure 20shows that natural uncertainty and statistical uncertainty occurred the most in the model chain. However, the focus of the framework was not on how many times the uncertainty occurs. It was more relevant to investigate how this result could help decision makers. The marking of the uncertainty in the matrix could help the policy makers to identify and trace the uncertainty in each model. This identification can be used as the communication tool between modellers, decision makers and policy makers to understand the underlying uncertainty in the models (Walker et al., 2003). For example, climate modeller can explain to SILVA developer and decision makers that what, why and how system data and driving forces are classified as statistical uncertainty (Figure 20. Furthermore, based on the uncertainty scale of uncertainty

level, GCM modeller can explain which source of uncertainty can be reduced or vice versa. With this information, RCM modeller and decision makers can use this explanation and the accumulated model output uncertainty to investigate uncertainty before using them.

The matrix also revealed the uncertainty from the normative perspective especially in habitat evaluation model. For example, criteria score and criteria weights in the model were basically contributed by the experts. As for criteria score, experts played a major role in determining the criteria score to three standardised class which is bad, medium and good (Appendix 3). For criteria weights, the uncertainty came from the questionnaire survey of the weight estimation by different experts. These two sources of uncertainty can be classified as statistical uncertainty as they can be measured based on the range of the weight distribution from the experts (section 4.1.3). At the same time, the criteria score and criteria weights were considered full of value ladennes of choice. This was resulted from the estimated weights by experts with full of different views and interpretations. Together with this, the accumulated model output from GCM, RCM and SILVA can be incorporated to examine the total output model chain. This is the place where uncertainty from descriptive model can be combined with normative model.

To conclude, the total output model can reveal two messages. Firstly, the accumulated model chain output was surrounded by large uncertainty. But, "large uncertainty" did not mean as a disaster to modeller, decision maker and policy maker. This is because, on top of this, the total output model of uncertainty also revealed that most of these large uncertainties were quantifiable (statistical uncertainty and spatial uncertainty) and unavoidable (nature uncertainty and temporal uncertainty). But quantifiable uncertainty can be improved and reduced by further investigation and research (epistemic uncertainty). At the same time, the results from the matrix explained that the degree of underpinning of the information about the various uncertainties were strong and with large value ladenness of choice. Therefore, it provided more information about the meaning of uncertainty.

Secondly, in the management point of view, one can argue that was the large accumulated uncertainty from different models has enormous effects to decision maker in the future? This might not be true. Because the large accumulated uncertainty was "dismissed" when the uncertain results from GCM, RCM and SILVA were classified into three standardised of the criteria score in habitat evaluation model. As a result, the uncertain results from the chain made no

difference to decision maker as the uncertainty might have been "demolished" by the classes of criteria score.

### 6. CONCLUSIONS AND RECOMMENDATIONS

#### 6.1. Conclusions

Model based decision support is a useful too to assist decision makers to make decision. However, what more important to decision makers is not only the predicted model output, but it is the certainty. Therefore, to address the uncertainty in a systematic way, an uncertainty framework for model-based decision support is essentially needed particularly for integrated model-based decision support. In this context, this study aimed to construct an integrated uncertainty conceptual framework to assist decision makers in forest management under climate change.

The objectives of the study have principally been addressed. The first objective was to identify and recognise possible uncertainty in climate model, forest function model and decision making model. Three major uncertainties in climate model were addressed: uncertainty from GCM, uncertainty from emission scenario and uncertainty of RCM formulation. In forest function model, SILVA, uncertainty analysis was focused on uncertainty of input variable. Therefore, tree input variables were used to analyse uncertainty input by using standard error on prediction. For decision making model, the uncertainty was recognised in expert judgement of the criteria score and criteria weights. The uncertainty of the criteria score was analysed by questionnaire survey to different experts.

The following objective was to demonstrate sensitivity and uncertainty analysis for site condition and tree inputs of forest function model, SILVA. Two set of input variables, site condition inputs (duration of vegetation growing period, mean temperature in vegetation growing period) and tree inputs (tree input variable, tree height, tree height to crown base and crown diameter) were used to run the OAT sensitivity analysis in SILVA. The sensitivity of index R, index A and index M to these input variables does reveal useful information about the research and model. The analysis showed a broad picture about how the outputs change for a specific change in any given input variable.

The final objective was to develop the uncertainty conceptual framework from the achievement of objective 1 and 2. The uncertainty conceptual framework was mainly adapted from the W&H framework and comments from Norton et al. (2006) to systematically address the uncertainty in the model chain of GCM, RCM, SILVA and habitat evaluation model. The framework managed to identify and categorise

source of uncertainty and the linkage uncertainty from one model output to another model. The framework was able to incorporate the quantitative and qualitative uncertainty in habitat evaluation model. The total output of uncertainty revealed that the uncertainty should take into account of the uncertainty from modellers' point of view and decision maker/policy makers' point of view. By doing this, the "real" uncertainty can be identified and revealed by both parties especially to decision maker in making certain decision

# 6.2. Recommendations

- Climate model with more extreme emission scenario such as A1, A1B and B1 should be included to investigate the effect of more extreme future climate change in forest management.
- More detail information about the underlying model structure and calculation of the habitat evaluation model should be explored. The class of the criteria score should be substituted with more meaningful value to precisely assess the evaluation score.
- The matrix should be distributed and filled by the relevant modeller, developer and policy maker in an interview form. This is because they have better understanding and knowledge to identify and characterize the source of uncertainty
- The matrix should be further extended to the method of how to assess and quantify uncertainty in the model chain.

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## Appendices

Appendix	1: Summary	and description	of PRUDENCE	RCMs

Model	Research Centre or Institution of Origin	Description	Reference
HadAM3H	Met Office Hadley Centre (HC)	HadRM3H was developed to provide realistic simulation of regional climate globally. configuration as HadRM3P. It can calculate large scale of cloud and make assumption of the radiative effects of convective clouds.	(Hudson and Jones, 2002; Buonomo et al., 2007)
ECHAM4/O PYC3	Max-Planck-Institute for Meteorology (MPI) and Deutsches Klimarechenzentrum (DKRZ)	ECHAM is the atmospheric general circulation model and OPYC is the ocean general circulation model	(Roeckner et al., 1999)
HIRHAM	Danish Meteorological Institute (DMI)	Incorporates new high resolution physiographical sets of surface topography and land use classification in the model.	(Christensen and Meijgaard, 1992)
CHRM	Swiss Federal Institute of Technology (ETH)	The model quality has been improved the ability to represent the continental and Alpine-scale water cycle.	(Vidale et al., 2003)
CLM	Geesthacht Institute for Coastal Research (GKSS)	It is a non-hydrostatic regional climate model. CLM is using the same dynamic and physical core as local weather forecast model of the German Weather Services (DWD)	(Steppeler et al., 2003)
RegCM2	International Centre for Theoretical Physics (ICTP)	(- ·· )	(Giorgi and Mearns, 1999)
RACMO	Koninklijk Nederlands Meteorologisch Instituut (KNMI)	It combines the land surface characteristics and the dynamical core of the HIRLAM Numerical Weather Prediction System with the physical parameterisation of the European Centre for Medium-range Weather Forecasting (ECMWF), version of 40-year reanalysis (ERA40). The model increases the soil hydrological reservoir and reduces the sensitivity of canopy evaporation to drought conditions.	(Lenderink et al., 2003)
HIRHAM	The Norwegian Meteorological Institute (met.no)	1 0	(Christensen et al., 1996)
REMO	Max-Planck Institute for Meteorology (MPI)	REMO is developed from the Europa-Modell (EM) and Deutschland-Modell (DM) model of the German Weather Service. The physical parameterisation schemes have been modified by ECHAM4.	(Jacob, 2001)
RCAO	Swedish Meteorological and Hydrological Institute (SMHI)	Simulation of RCAO is based on the combination of atmospheric (Rossby Centre Atmospheric 2) model and ocean model (Rossby Centre Ocean).	(Döscher et al., 2002; Meier et al., 2003; Jones et al., 2004)
PROMES	University Complutense of Madrid (UCM)	···· ( ···· j ··· · · · · · · · · · · ·	(Castro et al., 1993)



 Objective
 Criteria
 Indicator

Objective	Criteria	Indicator	Indicator	Unit
Close to nature	Naturalness of	Proportion of		Percentage of tree
- closeness of	forest stand	natural trees		species sharing the
tree to nature				same soil type and
indicated by				moisture content
naturally growth				1 = < 40%
of tree species in				2 = 40% - 80%
that particular				3 = 80%
soil type and				
moisture content				
of the area				
Structural	Spatial	Vertical	Stratification	Index ranges from
diversity	structure	structure	number of vertical	1(no layer) to 5 (all
	-horizontal and		layers/ stratum	aged of trees)
	vertical diversity		Step range	Index ranges from 0
	of forest		Area within the	(<20% of the area in
			stand with	the stand have the
			difference height	8m difference of
			which is more than	height) to 3 (>60%)
			8m	
		Stock	Tree species	Percentage of area
		structure	diversity	covered by dominant
			proportion of	tree.
			dominant tree	
			species at the upper	
			layer of the stand	
			Mixed tree species	< 5% of mixed tree
			number	species in the stand
			Number of different	do not take into
			tree species with	consideration
			area coverage $\geq 5\%$	> 5% of tree species
			of the total stand	
			area	
			number of tree	The code range from
			spacias	$<1$ to $\geq 6$ trees
			Total number of	$<4 \text{ to} \ge 0 \text{ trees}$
			tree species	
		Age diversity	number of different	The Code range from
		Age unversity	age groups in the	$\sim$ ages to $\sim$ ages
			stand covering >	<5 ages to >4 ages
			5% of total area	
		Mosaic	Distribution or	index with values
		diversity	composition of tree	from 1.0
		urversity	species	(homogeneous) _
			species	30 (clustered)
	Habitat features		Stand density (the	1  bad outcome > 1.0
	manat reatures	Stocking	value obtained from	r < 0.3
			university) which	2 medium Score <
			depends on	$2 \text{ meanum Score} \leq 1.0 \text{ and } \geq 0.7$
			intervention and	3  Good Score > 0.4
			type of tree	and $\leq 0.6$
		Honyy wooder	Resed on DRU size	$\frac{\text{and} \ge 0.0}{\text{Percentage of the}}$
		share	The higher the	share
1	1	snare	The nigher the	share

Appendix 3: Habitat evaluation model summary (source FAWF)

			value the more the	1 badly $\leq 10\%$
			share.	2 medium 11% -
				30%
		Location	Water supply	Water supply
		notential	water suppry	1 (extremely dry) to
		potential		12  (wet)
			Nutrient supply	Nutrient supply
				1 to 9
	Special	Dead wood	Number of dead	Index ranges from 0
	structure		wood in the stand	(a lot of dead wood)
			including standing	to 3 (less dead wood)
			and lying dead	and based on the
			wood	cubic meter value of
			D 11	dead wood.
		Location	Rare soil type	
		diversity	-11 It occurs < 5%	
			But if $>10\%$ then it	
			is good	
			Diversity of the soil	
			-if more than 2 soil	
			types in the stand,	
			then it is very good	
		Special local	Description of the	Yes or no
		structure	structure of the	
			landscape such as	
			rock, lake, cave	
Darit	Distance of the	Diadama.	grassland.	The mene of a second
Rarity	Biotopes of the	вюторе	The area coverage	The percentage
	LUWG		valuable area such	areas
			as biotope	1 - bad area < 25%
			us biotope	2  medium surface
				proportion>25% and
				<50%
				3 Good surface share
				$\geq 50\%$
	Protected areas		The area coverage	The percentage
			of nature protected	coverage of these
			areas, forest nature	areas
			reserve, nuclear	
			zona NWP 100	
1		1	ZOIIC, IN WIK 100	

Reference	(Pretzsch, 1998; Pommerening, 2002)	(Pommerening, 2002; Kint et al., 2004)	(Pretzsch, 1998; Pommerening, 2002)
SILVA output score	Varied between 0 (mono-layered) and > 1 (strong vertical differentiation) Index A increases with the number of tree species appearing in a forest stand and the degree of their vertical distribution. Values of A range from 0 (pure stands) until about 2.0 (BIBER, 1997)	0.0 = all the individuals of the group belong to the same species 0.25 = one of the neighbours of the reference tree belongs to other species; 0.50 = if two of the neighbouring trees belong to other species 0.75 = if three of the neighbours of the reference tree belongs to other species and 1.00 = if the neighbouring four of the reference tree belong to different species	Range between 0 (greatest clustering) and 2.1491. <1 - clustering formation or distribution =1 - random distribution >1 - regular distribution
Description	Denoted as Index A Tree species portions divide in to three height zones:0-50% , 50%-80% and 80%-100%. It defines as	Denoted as M	Denoted as R
SILVA Matched	Species profile index (by Pretzsch) -measures the vertical species mingling within the stand. -quantify species diversity vertically -one-storied pure stands give lowest value of index A and it rises with two or more layers. -mixture of several species in the stand increases the index. -different layering of one-storied pure stand to another will increase the index differently.	Mingling index -proportion of the nearest neighbour tree to the reference tree with different species-)	Aggregation index by Clark, Evans (1954) - variability of tree location/ clustering of tree species -describes the horizontal tree distribution pattern where observed average distance of the nearest neighbour tree to the average distance of the expected tree when trees are randomly distributed.
Habitat evaluation criteria	Stratification	Mixed tree species number	mosaic diversity

## Appendix 4 Description of Ecological indices

Appendix 5 Habitat evaluation criteria weight estimation questionnaire

Survey to Establish Priorities on Criteria for

	Habitat Suitability Function Assessment Biotope and Species Protection by Point Distribution
Name	
Institution	
Department	
Position	

according to their level of importance. The sum of distribution points of criteria, indicator and characteristic has Please distribute points for criteria, indicator and characteristic of habitat suitability function assessment to be in 100 as indicated on the form.

Waldbeständen in Bezug auf ihre Bedeutung für den Biotop- und Artenschutz. Die Summe der Punkte sollte Bitte vergeben Sie Punkte für die Hauptweiser, Teilindikatoren und Erhebungsmerkmale zur Einstufung von innerhalb der Abschnitte 100 ergeben.

	Rangordnung					100				100						
Erhebungsmerkmale	Erhebungsmerkmale		Schichtung (stratification)		Stufung (step range)		Baumartenvielfalt (tree species diversity)	Mischbaumartenanzahl (mixed tree species number)	Baumartenanzahl (number of tree species)							
rkmale	Rangordnung													100		
Erhebungsme	Erhebungsmerkmale		Vertikalstruktur	(vertical structure)			Bestandesstruktur (stock structure)				Mosaikvielfalt	(mosaic diversity)	Altersvielfalt (age diversity)		Bestockungsgrad	(Stocking)
oren	Rangordnung															
Teilindika	Teilindikatoren		Raumstruktur	(spatial structure)											Habitatsmerkmale	(habitat teature)
iser	Rangordnung															
Hauptwe	Hauptweiser	Naturnähe (close to nature)	Strukturvielfalt	(structural diversity)												

			100												
	Wasserversorgung	Nährstoffversorgung (nutrient supply)													
			100					100							
Starkholzanteil (heavy wooden share)	Standortspotential			Totholz (dead wood)	Standortsvielfalt (location diversity)	örtliche Sonderstrukturen	(special local stuctures)								
									100			100			
				Sonderstrukturen (special structure)						Biotope des LUWG	Schutzgebiete	(protected area) z.B.	Naturwaldreservate,	Kernzonen des	Biosphärenreservats, NSG
													100		
										Seltenheit (Darity)	(Autor)				