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)[8]	Stratification
Mingling index (Index M)	mixed tree species number
Aggregation index by Clark Evan, (1954) (Index R)[9]	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

---

[8] Source from Pretzsch (1998)

[9] 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.

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

Classification of uncertainty	**W&H framework (Walker et al., 2003)**	**Van der Sluijs et al. (2003)**	**Refsgaard et al. (2007)**
Dimension uncertainty	• Location • Level • Nature	• Location • Level • Nature	• Source of uncertainty • Taxonomy

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

Table 9 Development of new uncertainty conceptual framework

Classification of uncertainty	Description of new uncertainty framework	Remarks
Dimension uncertainty	• Source of uncertainty • Level of uncertainty • Nature of uncertainty • **Qualification of the knowledge base** • **Value-ladennes of choice** • **Spatial uncertainty** • **Temporal uncertainty**	• Adapted from Refsgaard et al. (2007) • Adapted from Van der Sluijs et al. (2003) • Adaptation from experimental design in climate model and SILVA
Location of uncertainty	• Context and framing • Model o Model structure o Model technical o Model parameter o Model input o Model output o **Expert judgement**	• Adaptation from experimental design • Adapted from Refsgaard et

		al. (2007)
Level of uncertainty	• Statistical uncertainty • Scenario uncertainty • Recognised ignorance	• Adapted the level of uncertainty scale from Krayer von Krauss et al.(2004) and Gillund et al.(2008)
Nature of uncertainty	• **Epistemic uncertainty** • **Variability uncertainty** o **Linguistic uncertainty** o **Natural uncertainty**	• Comments from Norton et al. and Krayer von Krauss et al. (2006) • Adaptation from experimental design

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.

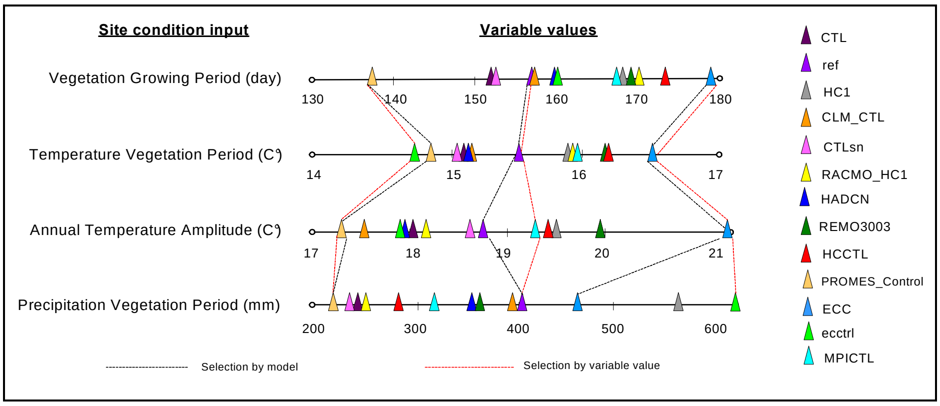


Figure 12 Distribution of site condition variables and selected PRUDENCE RCMs for current condition

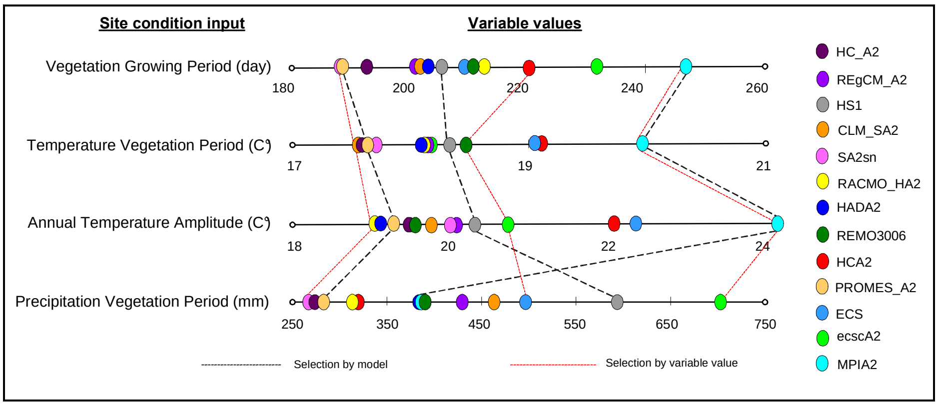


Figure 13 Distribution of site condition variables and the selected PRUDENCE RCMs for scenario A2

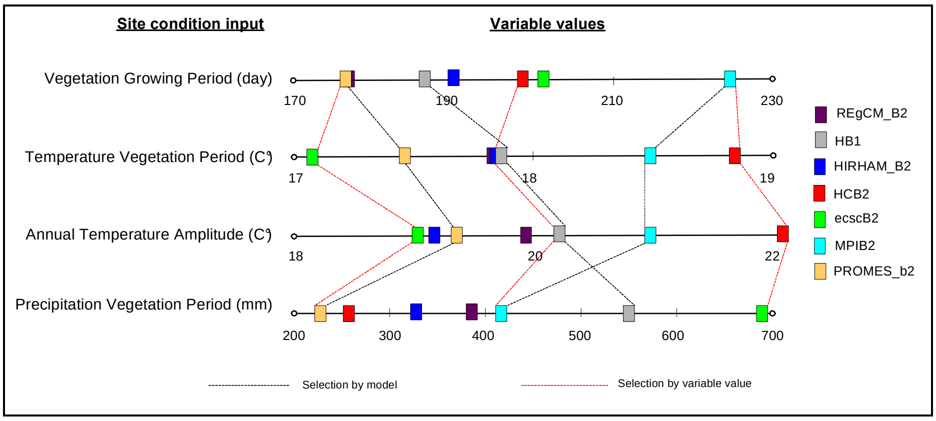


Figure 14 Distribution of site condition variables and the selected PRUDENCE RCMs for scenario B2

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_{10} (day)	137	157	179

Tv (^{o}c)	14.80	15.63	16.66
Tvar (^{o}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_{10} (day)	137	157	179
Tv (^{o}c)	14.74	15.63	16.66
Tvar (^{o}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_{10} (day)	187	206	247	177	187	226
Tv (^{o}c)	17.66	18.25	20.00	17.47	17.88	18.5
Tvar (^{o}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_{10} (day)	187	220	247	177	198	226
Tv (^{o}c)	17.54	18.37	20.00	17.15	17.88	18.84
Tvar (^{o}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 Category	**RCMs with degree of variability**		
	Minimum extreme	**Average**	**Maximum extreme**
Current	H	H	E
H/EA2	H	H	E
H/EB2	H	H	E

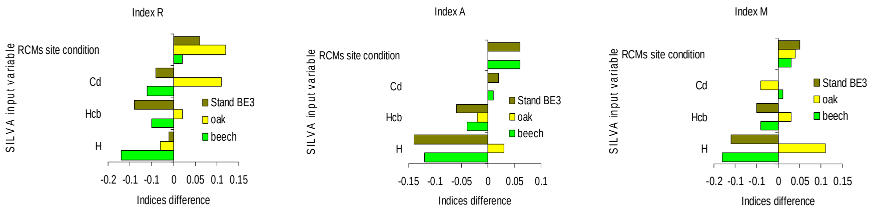
Table 15 Selection of RCMs by variable with GCM HadAM and ECHAM

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

Current



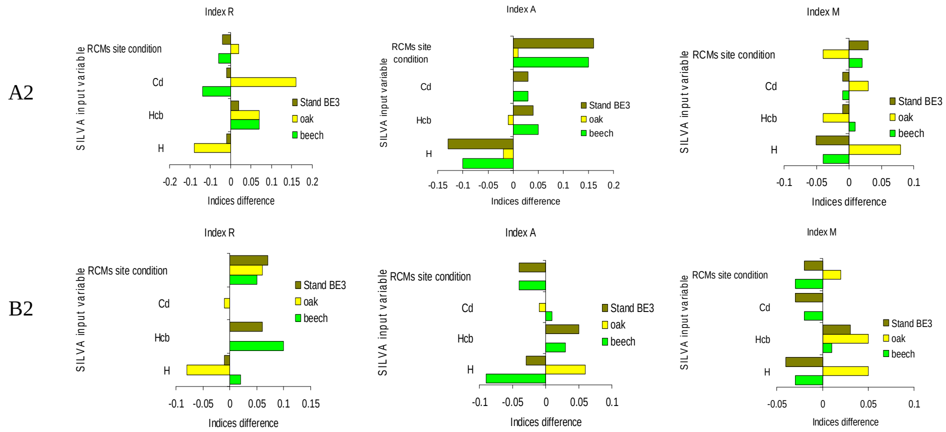


Figure 15 Sensitivity of index R, index A and index M to tree variables and site condition for RCMs selected by model under current condition, scenario A2 and B2 in BE3

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	**Index R**		**Index A**		**Index M**	
	Lower bound	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**
H	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	**Index R**		**Index A**		**Index M**	
	Lower bound	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**
H	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	**Index R**		**Index A**		**Index M**	
	Lower bound	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**
H	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.

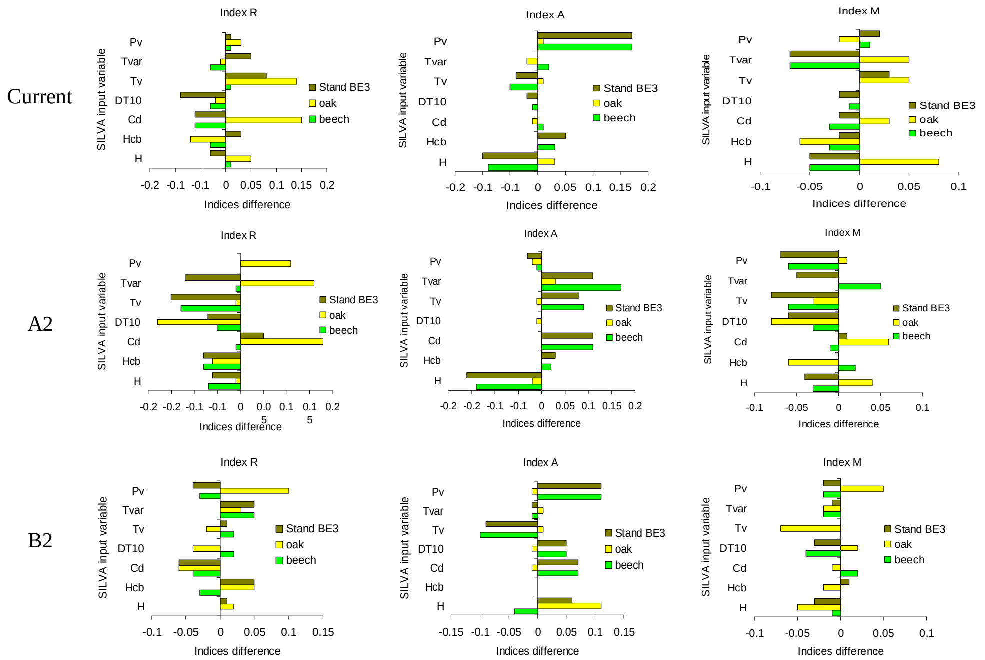


Figure 16 Sensitivity of index R, index A and index M to tree variables and site condition for RCMs selected by variables under current condition, scenario A2 and B2 in BE3

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 variables	**Index R**		**Index A**		**Index M**	
	Lower bound	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**
H	0.94	0.91	1.02	0.92	0.44	0.39

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

b)Scenario A2

Input variables	Index R		Index A		Index M	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
H	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 variables	Index R		Index A		Index M	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
H	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.

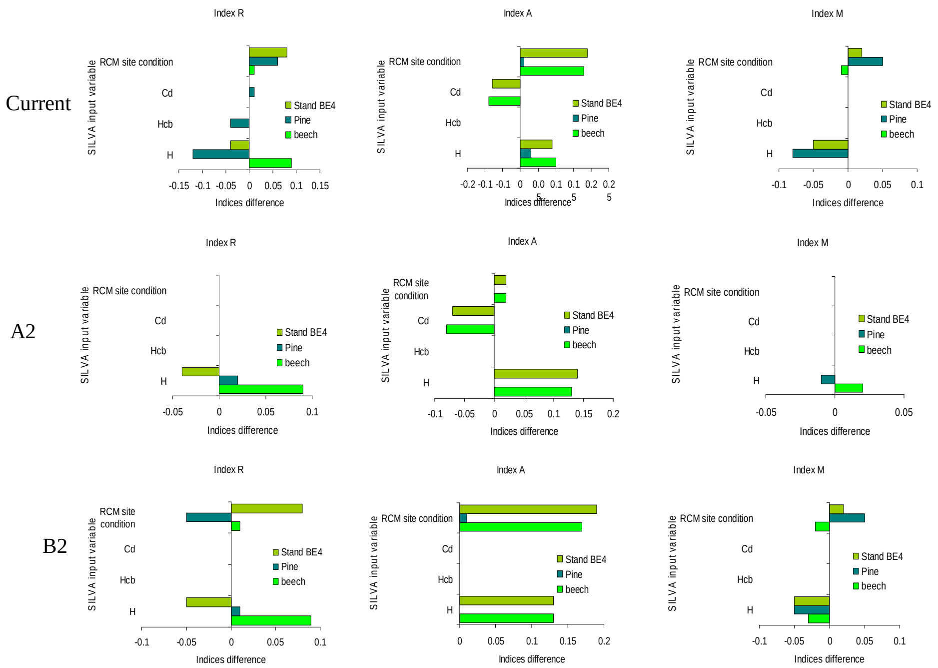


Figure 17 Sensitivity of index R, index A and index M to tree variables and site condition for RCMs selected by RCMs under current condition, scenario A2 and B2 in BE4

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

a) Current						
Input variables	**Index R**		**Index A**		**Index M**	
	Lower bound	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**
H	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	**Index R**		**Index A**		**Index M**	
	Lower bound	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**
H	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	Index R		Index A		Index M	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
H	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.

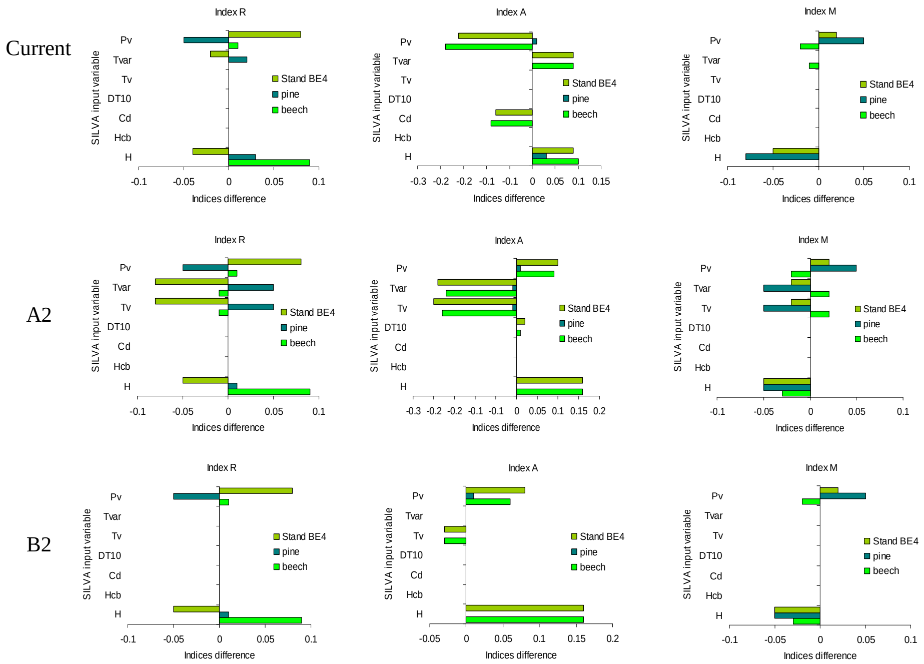


Figure 18 Sensitivity of index R, index A and index M to tree variables and site condition for RCMs selected by variables under current condition, scenario A2 and B2 in BE4

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

a) Current

Input variables	Index R		Index A		Index M	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
H	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
DT_{10}	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
Pv	0.99	1.07	0.85	0.69	0.49	0.51

b)Scenario A2

Input variables	Index R		Index A		Index M	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
H	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_{10}	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

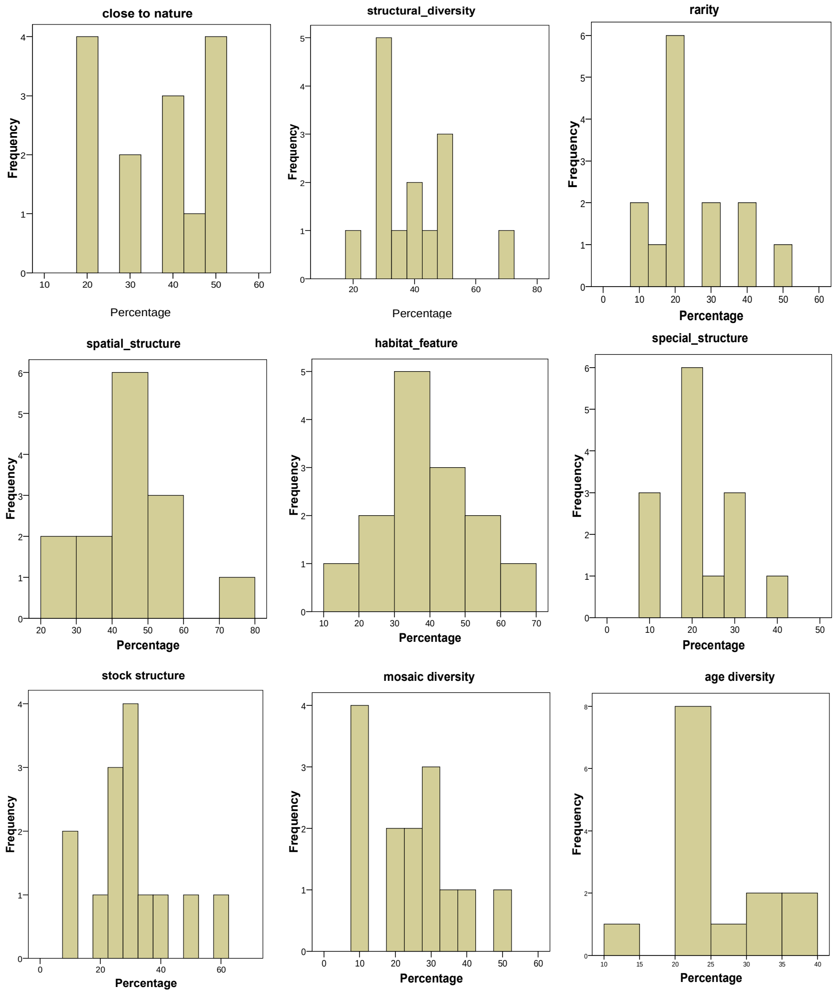
b)Scenario B2

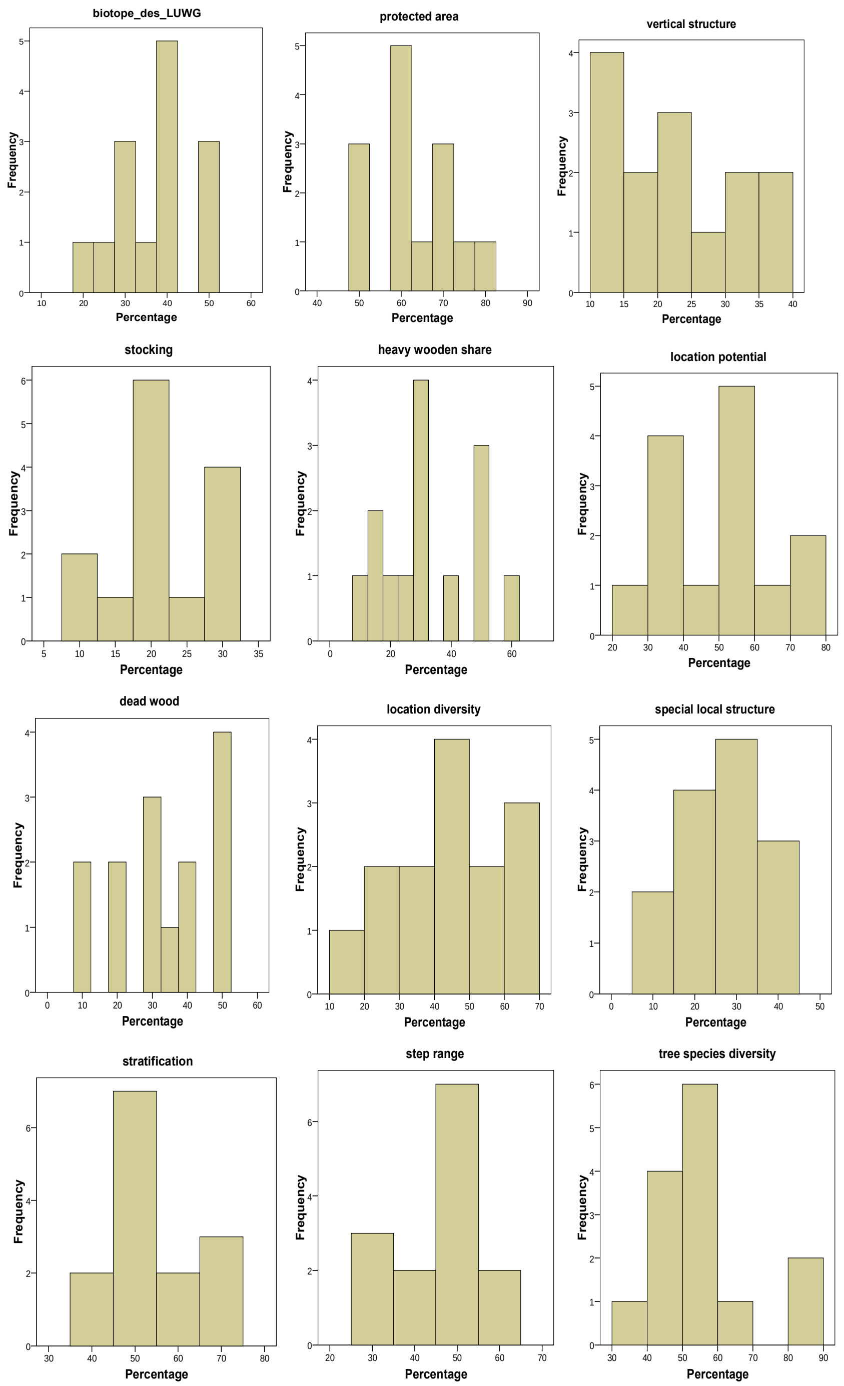
Input variables	Index R		Index A		Index M	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
H	1.1	1.05	0.94	1.1	0.52	0.47
Hcb	1.07	1.07	1.06	1.06	0.51	0.51
Cd	1.07	1.07	1.06	1.06	0.51	0.51
DT_{10}	1.07	1.07	1.06	1.06	0.51	0.51
Tv	1.07	1.07	1.07	1.04	0.51	0.51
Tvar	1.07	1.07	1.04	1.04	0.51	0.51
Pv	0.99	1.07	0.85	0.93	0.49	0.51

4.3. Results of questionnaires

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.




biotope_des_LUWG
protected area
vertical structure
stocking
heavy wooden share
location potential
dead wood
location diversity
special local structure
stratification
step range
tree species diversity
Frequency
Percentage

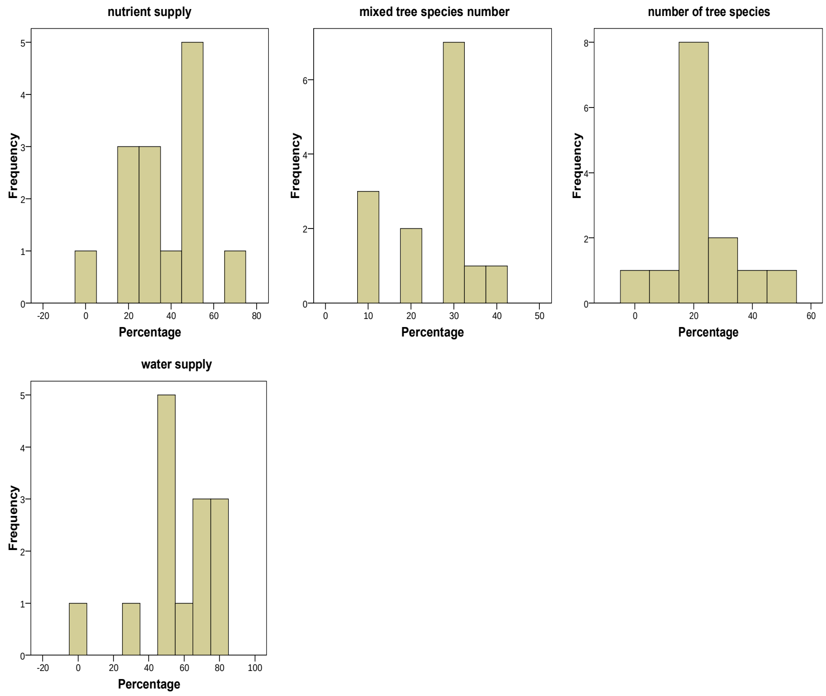


Figure 19 Histogram of estimated criteria weights from 14 experts to criteria and indicators of habitat evaluation model

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.

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

	Min	Max	Mean	Standard Deviation	Standard Error
Close_to_nature	20	50	36.07	12.43	3.322
Structural diversity	20	70	39.29	12.84	3.431
• spatial structure	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

o mosaic diversity	10	50	24.64	12.32	3.293
• habitat feature	10	70	35.71	14.92	3.987
o 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
• special structure	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
• biotope des LUWG	20	50	37.14	9.35	2.498
• protected area	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[10] 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).

[10] 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.

Source of uncertainty			Level of uncertainty					Nature of uncertainty		
			Statistical uncertainty	Scenario uncertainty		Recognised ignorance		Epistemic uncertainty	Variability uncertainty	
			1	2	3	4	5		Linguistic uncertainty	Natural uncertainty
Context and framing		Future adaptation of forest management in social-economic, technology and ecology context under climate change.		√		√		√		√
	General circulation model[11]	**Model structure** System behaviour- interactions between input, parameter in system boundary	√					√		√
		Model technical Software/ hardware	√			√		√		
		Model parameter • Physical parameter • Atmospheric parameter • Sea surface parameters • Land surface parameter • Hydrological parameter • Soil input parameter	 √ √ √ √ √ √					 √ √ √ √ √ √		 √ √ √ √ √ √
		Model input — **System data** • Physics control input • Atmospheric input variable • Sea surface input variable • Land surface input variable • Soil input variable • Hydrological input variable	 √ √ √ √ √ √							 √ √ √ √ √ √
		Model input — **Driving force** • Radiative Forcing [12] • Emissions scenarios		 √ 	 √					 √ √
		Model output	√ (14)	√ (2)	√ (1)	√ (2)	0	√ (9)		√ (16)
	Regional climate model[13]	**Model structure** System behaviour- interactions between input, parameter in system boundary	√					√		√

[11] Source can be found in Appendix 2: Summary and description of PRUDENCE models

[12] See: http://en.wikipedia.org/wiki/Radiative_forcing

Source of uncertainty			Level of uncertainty					Nature of uncertainty		
			Statistical uncertainty	Scenario uncertainty		Recognised ignorance		Epistemic uncertainty	Variability uncertainty	
			1	2	3	4	5		Linguistic uncertainty	Natural uncertainty
		Model technical								
		Software/ hardware	√			√		√		
		Model parameter								
		• Physical parameter	√					√		√
		• Atmospheric parameter	√					√		√
		• Sea surface parameters	√					√		√
		• Land surface parameter	√					√		√
		• Hydrological parameter	√					√		√
		• Soil input parameter	√					√		√
	Model inputs	**System data**								
		• Physics control input	√							√
		• Atmospheric input variable	√							√
		• Sea surface input variable	√							√
		• Land surface input variable	√							√
		• Soil input variable	√							√
		• Hydrological input variable	√							√
		Driving force								
		• Global atmospheric circulation model		√						√
		• Global atmospheric ocean circulation model		√						√
		• Local scale of topography and land use characteristic		√						√
		• Emissions scenarios			√					√
		Model output	√ (28)	√ (5)	√ (2)	√ (3)	0	√ (17)	0	√ (33)
SILVA[14]		**Model structure**								
		• System behaviour- interactions between input, parameter in system boundary	√					√		√
		• Stochastic				√		√		√

[13] Source can be found in Appendix 2: Summary and description of PRUDENCE models

Source of uncertainty			Level of uncertainty					Nature of uncertainty		
			Statistical uncertainty	Scenario uncertainty		Recognised ignorance		Epistemic uncertainty	Variability uncertainty	
			1	2	3	4	5		Linguistic uncertainty	Natural uncertainty
		Model technical								
		Software /hardware	√			√		√		
		Model parameter								
		• Species-specific parameter (a_0, . . . ,a_4) for mortality model	√					√		√
		• Species-specific parameter (b_0, . . ,b_2) for probability value of single tree mortality	√					√		√
		• Species-specific parameter (c_0,….c_5) for tree height growth model	√					√		√
		• Species-specific parameter (j_1, j_2, j_3) for potential diameter growth model	√					√		√
		• Species-specific parameter (k_0,….k_5) for potential basal area growth	√					√		√
		• Species-specific parameter (l_0,….l_2) for height to crown base growth	√					√		√
		• Species-specific parameter (m_0,….m_3) crown dimensions growth	√					√		√
	Model inputs	**System data**								
		• DBH (cm)	√					√	√	√
		• H (m)	√					√	√	√
		• Hcb (m)	√					√	√	√
		• Cd (m)	√					√	√	√
		Driving force								
		• NUT	√							√
		• NO_X (ppm)	√							√
		• CO_2 (ppm)	√							√
		• DT_{10} (day)	√							√
		• TVAR (°C)	√							√
		• TV (°C)	√							√
		• Pv (mm)	√							√
		• MOIST	√							√

[14] Source from Pretzsch et al., 2002a; Pretzsch et al., 2002b

Source of uncertainty			Statistical uncertainty 1	Scenario uncertainty 2	Scenario uncertainty 3	Recognised ignorance 4	Recognised ignorance 5	Epistemic uncertainty	Linguistic uncertainty	Natural uncertainty
			Level of uncertainty					**Nature of uncertainty**	**Variability uncertainty**	
		Data Forest inventory data	√			√		√		√
		Model output	√ (50)	√ (5)	√ (2)	√(5)	0	√ (32)	√ (4)	√ (55)
	Habitat evaluation model	**Model structure** Algorithm formulation	√							√
		Model technical Software /hardware	√			√				
		Model parameter	√					√		√
		Expert judgement • Criteria score • Criteria weight	√ √							√ √
		Model input – **System data**	√					√		√
		Model input – **Driving force**	√					√		√
		Data Forest inventory data	√			√		√		
		Model output	√ (58)	√ (5)	√ (2)	√ (7)	0	√ (36)	√ (4)	√ (61)
Total output			√ (58)	√ (5)	√ (2)	√ (7)	0	√ (36)	√ (4)	√ (61)

Figure 20 New uncertainty matrix Part 1

Source of uncertainty			Qualification of knowledge base: Weak	Qualification of knowledge base: Fair	Qualification of knowledge base: Strong	Value-ladenness of choice: Small	Value-ladenness of choice: Medium	Value-ladenness of choice: Large	Spatial uncertainty	Temporal uncertainty
Context and framing		Future adaptation of forest management in social-economic, technology and ecology context under climate change		√				√		√
Model	General circulation model	**Model structure** System behaviour- interactions between input, parameter in system boundary			√				√	√
		Model technical Software/ hardware			√					√
		Model parameter • Physical parameter • Atmospheric parameter			√ √				√ √	√ √

Source of uncertainty			Qualification of knowledge base: Weak	Fair	Strong	Value-ladenness of choice: Small	Medium	Large	Spatial uncertainty	Temporal uncertainty
		• Sea surface parameters			√				√	√
		• Land surface parameter			√				√	√
		• Hydrological parameter			√				√	√
		• Soil input parameter			√				√	√
	Model inputs	**System data**								
		• Physics control input			√				√	√
		• Atmospheric input variable			√				√	√
		• Sea surface input variable			√				√	√
		• Land surface input variable			√				√	√
		• Soil input variable			√				√	√
		• Hydrological input variable			√				√	√
		Driving force								
		• Global atmosphere circulation model			√				√	
		• Global atmosphere ocean circulation model			√				√	
		• Local scale of topography and land use characteristic			√				√	
		• Emissions scenarios			√					√
	Model output		0	√ (1)	√ (18)	0	0	√ (1)	√ (16)	√ (16)
Regional climate model	**Model structure**	System behaviour- interactions between input, parameter in system boundary			√				√	√
	Model technical	Software/ hardware			√					√
	Model parameter	• Physical parameter			√				√	
		• Atmospheric parameter			√				√	
		• Sea surface parameters			√				√	
		• Land surface parameter			√				√	
		• Hydrological parameter			√				√	
		• Soil input parameter			√				√	
	Model inputs	**System data**								
		• Physics control input			√				√	√
		• Atmospheric input variable			√				√	
		• Sea surface input variable			√				√	
		• Land surface input variable			√				√	

Source of uncertainty				Qualification of knowledge base			Value-ladenness of choice			Spatial uncertainty	Temporal uncertainty
				Weak	Fair	Strong	Small	Medium	Large		
			• Soil input variable			√				√	
			• Hydrological input variable			√				√	
			Driving force								
			• Radiative forcing		√						
			• Emissions scenarios			√					
		Model output		0	√ (2)	√ (33)	0	0	√ (1)	√ (29)	√ (19)
	SILVA	**Model structure** System behaviour- interactions between input, parameter in system boundary				√					√
		Model technical Software/ hardware				√					√
		Model parameter									
		• Species-specific parameter (a_0, . . . ,a_4) for mortality model				√				√	√
		• Species-specific parameter (b_0, . . ,b_2) for probability value of single tree mortality				√				√	√
		• Species-specific parameter (c_0,….c_5) for tree height growth model				√				√	√
		• Species-specific parameter (j_1, j_2, j_3) for potential diameter growth model				√				√	√
		• Species-specific parameter (k_0,….k_5) for potential basal area growth				√				√	√
		• Species-specific parameter (l_0,….l_2) for height to crown base growth				√				√	√
		• Species-specific parameter (m_0,….m_3) crown dimensions growth				√				√	√
		Model inputs	**System data**								
			• DBH (cm)		√						√
			• H (m)		√						√
			• Hcb (m)		√						√
			• Cd (m)		√						√
			Driving force								
			• NUT			√				√	√
			• NO_X (ppm)			√				√	√
			• CO_2 (ppm)			√					

Source of uncertainty			Qualification of knowledge base			Value-ladenness of choice			Spatial uncertainty	Temporal uncertainty
			Weak	Fair	Strong	Small	Medium	Large		
		• DT_{10} (day)			√				√	√
		• TVAR (°C)			√				√	√
		• TV (°C)			√				√	√
		• Pv (mm)			√				√	√
		• MOIST			√				√	√
	Data	Forest inventory data			√				√	√
	Model output		0	√ (6)	√ (51)	0	0	√ (1)	√ (44)	√ (40)
Habitat evaluation model	**Model structure**	Algorithm formulation			√					
	Model technical				√					√
	Model parameter				√					
	Expert judgement	• Criteria score			√			√	√	√
		• Criteria weight			√			√		
	Model inputs	System data			√				√	√
		Driving force			√				√	√
	Data	Forest inventory data			√				√	√
	Model output		0	√ (6)	√ (59)	0	0	√ (3)	√ (48)	√ (45)
Total output			**0**	**√ (6)**	**√ (59)**	**0**	**0**	**√ (3)**	**√ (48)**	**√ (45)**

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 stand 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, annual temperature amplitude and precipitation 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.

Reference

Beven, K., 2008, Environmental Modelling: An Uncertainty Future? Routledge, UK, London and New York

Böttcher, H., Freibauer, A., Obersteiner, M. and Schulze, E.D., 2008, Uncertainty Analysis of Climate Change Mitigation Options in the Forestry Sector Using a Generic Carbon Budget Model. Ecological Modelling, 213: 45-62.

Brown, J.D., 2004, Knowledge, Uncertainty and Physical Geography: Towards the Development of Methodologies for Questioning Belief. Transactions of the Institute of British Geographers, 29: 367-381.

Brown, J.D. and Heuvelink, G.B.M., 2005, Assessing Uncertainty Propagation through Physically Based Models of Soil Water Flow and Solute Transport. Encyclopedia of Hydrological Science-20 ences, edited by: Andersen, M., John Wiley & Sons, Ltd.

Buonomo, E., Jones, R., Huntingford, C. and Hannaford, J., 2007, On the Robustness of Changes in Extreme Precipitation over Europe from Two High Resolution Climate Change Simulations. QUARTERLY JOURNAL-ROYAL METEOROLOGICAL SOCIETY, 133: 65.

Castro, M., Fernández, C. and Gaertner, M.A., 1993, Description of a Mesoscale Atmospheric Numerical Model. Mathematics, Climate and Environment. Rech. Math. Appl. Ser. Mason: 230–253.

Christensen, J.H., Christensen, O.B., Lopez, P., van Meijgaard, E. and Botzet, M., 1996, The Hirham4 Regional Atmospheric Climate Model. DMI Scientific Report, 4: 51.

Christensen, J.H. and Christensen, O.B., 2007, A Summary of the PRUDENCE Model Projections of Changes in European Climate by the End of This Century. Climatic Change, 81: 7-30.

Christensen, O.B. and Meijgaard, E., 1992, On the Construction of a Regional Atmospheric Climate Model. Dmi Technical Report 92–14., Report, Available from DMI, Lyngbyvej 100, Copenhagen Ø, Denmark

Clark, P.J. and Evans, F.C., 1954, Distance to Nearest Neighbor as a Measure of Spatial Relationships in Populations. Ecology, 35: 445-453.

Déqué, M., Rowell, D.P., Lüthi, D., Giorgi, F., Christensen, J.H., Rockel, B., Jacob, D., Kjellström, E., de Castro, M. and van den Hurk, B., 2007, An Intercomparison of Regional Climate Simulations for Europe: Assessing Uncertainties in Model Projections. Climate Change, 81: 53-70.

Döscher, R., Willén, U., Jones, C., Rutgersson, A., Meier, H.E.M., Hansson, U. and Graham, L.P., 2002, The Development of the Regional Coupled Ocean-Atmosphere Model Rcao. Boreal Environ. Res, 7: 183-192.

Fowler, H.J., Blenkinsop, S. and Tebaldi, C., 2007, Linking Climate Change Modelling to Impacts Studies: Recent Advances in Downscaling Techniques for Hydrological Modelling. International Journal of Climatology, 27: 1547.

Fronzek, S. and Carter, T.R., 2007, Assessing Uncertainties in Climate Change Impacts on Resource Potential for Europe Based on Projections from Rcms and Gcms. Climatic Change, 81: 357-371.

Gillund, F., Kjølberg, K.A., Krayer von Krauss, M. and Myhr, A.I., 2008, Do Uncertainty Analyses Reveal Uncertainties? Using the Introduction of DNA Vaccines to Aquaculture as a Case. Science of The Total Environment, 407: 185-196.

Giorgi, F. and Mearns, L.O., 1999, Introduction to Special Section: Regional Climate Modeling Revisited. Journal of geophysical research, 104: 6335-6352.

Giorgi, F., Hewitson, B., Christensen, J., Hulme, M., Von Storch, H., Whetton, P., Jones, R., Mearns, L., Fu, C. and Arritt, R., 2001, Chapter 10, Regional Climate Information–Evaluation and Projections. Climate Change: 583–638.

Hamm, N.A.S., Hall, J.W. and Anderson, M.G., 2006, Variance-Based Sensitivity Analysis of the Probability of Hydrologically Induced Slope Instability. Computers and Geosciences, 32: 803-817.

Heal, G. and Kriström, B., 2002, Uncertainty and Climate Change. Environmental and Resource Economics, 22: 3-39.

Helton, J.C. and Davis, F.J., 2003, Latin Hypercube Sampling and the Propagation of Uncertainty in Analyses of Complex Systems. Reliability Engineering and System Safety, 81: 23-69.

Hemery, G.E., Savill, P.S. and Pryor, S.N., 2005, Applications of the Crown Diameter-Stem Diameter Relationship for Different Species of Broadleaved Trees. Forest Ecology and Management, 215: 285-294.

Hoogstra, M.A. and Schanz, H., 2008, The Future Orientation of Foresters: An Exploratory Research among Dutch Foresters into the Prerequisite for Strategic Planning in Forestry. Forest Policy and Economics, 10: 220-229.

Houghton, J.T., 2001, Climate Change 2001: The Scientific Basis. Cambridge University Press Cambridge

Hudson, D.A. and Jones, R.G., 2002, Regional Climate Model Simulations of Present-Day and Future Climates of Southern Africa. Hadley Centre Technical Note, 39.

Huxley, J.S., 1932, Problems of Relative Growth: 1-276. Methuen, London.

IPCC, 2007, Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M. and Miller, H.L. (eds.), Summary for Policymakers. Cambridge University Press, Cambridge, United Kingdom and New York, USA.

Jacob, D., 2001, A Note to the Simulation of the Annual and Inter-Annual Variability of the Water Budget over the Baltic Sea Drainage Basin. Meteorology and Atmospheric Physics, 77: 61-73.

Jacob, D., Bärring, L., Christensen, O.B., Christensen, J.H., de Castro, M., Déqué, M., Giorgi, F., Hagemann, S., Hirschi, M. and Jones, R., 2007, An Inter-Comparison of Regional Climate Models for Europe: Model Performance in Present-Day Climate. Climatic Change, 81: 31-52.

Jones, C.G., Willén, U., Ullerstig, A. and Hansson, U., 2004, The Rossby Centre Regional Atmospheric Climate Model Part I: Model Climatology and

Performance for the Present Climate over Europe. AMBIO: A Journal of the Human Environment, 33: 199-210.
Kint, V., Robert, D.W. and Noël, L., 2004, Evaluation of Sampling Methods for the Estimation of Structural Indices in Forest Stands. Ecological Modelling, 180: 461-476.
Kirschbaum, M.U., 2000, Forest Growth and Species Distribution in a Changing Climate. Tree Physiol, 20: 309-322.
Knight, C.G., Knight, S.H.E., Massey, N., Aina, T., Christensen, C., Frame, D.J., Kettleborough, J.A., Martin, A., Pascoe, S., Sanderson, B., Stainforth, D.A. and Allen, M.R., 2007, Association of Parameter, Software, and Hardware Variation with Large-Scale Behavior across 57,000 Climate Models. Proceedings of the National Academy of Sciences, 104: 12259-12264.
Krayer von Krauss, M.P., Casman, E.A. and Small, M.J., 2004, Elicitation of Expert Judgments of Uncertainty in the Risk Assessment of Herbicide-Tolerant Oilseed Crops. Risk Analysis, 24: 1515-1527.
Krayer von Krauss, M.P., Walker, W.E., van der Sluijs, J.P., Janssen, P., van Asselt, M.B.A. and Rotmans, J., 2006, Response To "To What Extent, and How, Might Uncertainty Be Defined" By Norton, Brown, and Mysiak. Integrated Assessment, 6: 89-94.
Krayer von Krauss, M.P., Kaiser, M., Almaas, V., van der Sluijs, J. and Kloprogge, P., 2008, Diagnosing and Prioritizing Uncertainties According to Their Relevance for Policy: The Case of Transgene Silencing. Science of The Total Environment, 390: 23-34.
Lasch, P., Lindner, M., Erhard, M., Suckow, F. and Wenzel, A., 2002, Regional Impact Assessment on Forest Structure and Functions under Climate Change—the Brandenburg Case Study. Forest Ecology and Management, 162: 73-86.
Lenderink, G., van den Hurk, B., van Meijgaard, E., van Ulden, A.P. and Cuijpers, J.W.M., 2003, Simulation of Present-Day Climate in Racmo2: First Results and Model Developments, Knmi-Tr 252, 24 Pp. Koninklijk Nederlands Meteorol. Inst., De Bilt, Netherlands.
Lilburne, L., Gatelli, D. and Tarantola, S., Year, Sensitivity Analysis on Spatial Models: A New Approach. International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences
Lindner, M., Sohngen, B., Joyce, L.A., Price, D.T., Bernier, P.Y. and Karjalainen, T., 2002, Integrated Forestry Assessments for Climate Change Impacts. Forest Ecology and Management, 162: 117-136.
Liu, Y.Q., Gupta, H., Springer, E. and Wagener, T., 2008, Linking Science with Environmental Decision Making: Experiences from an Integrated Modeling Approach to Supporting Sustainable Water Resources Management. Environmental Modelling & Software, 23: 846-858.
Meier, H.E.M., Döscher, R. and Faxén, T., 2003, A Multiprocessor Coupled Ice-Ocean Model for the Baltic Sea: Application to Salt Inflow. J. Geophys. Res, 108: 3273.

Menzel, A., Jakobi, G., Ahas, R., Scheifinger, H. and Estrella, N., 2003, Variations of the Climatological Growing Season (1951-2000) in Germany Compared with Other Countries. International Journal of Climatology, 23: 793-812.
Meyer, M.A. and Booker, J.M., 2001, Eliciting and Analyzing Expert Judgement : A Practical Guide. ASA-Society for Individual and Applied Mathematics (SIAM), LOs Alamos, New Mexico
Murphy, J.M., Sexton, D.M.H., Barnett, D.N., Jones, G.S., Webb, M.J., Collins, M. and Stainforth, D.A., 2004, Quantification of Modelling Uncertainties in a Large Ensemble of Climate Change Simulations. Nature, 430: 768-772.
Nitschke, C.R. and Innes, J.L., 2008, Integrating Climate Change into Forest Management in South-Central British Columbia: An Assessment of Landscape Vulnerability and Development of a Climate-Smart Framework. Forest Ecology and Management, 256: 313-327.
Norton, J.P., Brown, J.D. and Mysiak, J., 2006, To What Extent, and How, Might Uncertainty Be Defined? Integrated Assessment, 6: 83-88.
Olesen, J.E., Carter, T.R., Díaz-Ambrona, C.H., Fronzek, S., Heidmann, T., Hickler, T., Holt, T., Minguez, M.I., Morales, P. and Palutikof, J.P., 2007, Uncertainties in Projected Impacts of Climate Change on European Agriculture and Terrestrial Ecosystems Based on Scenarios from Regional Climate Models. Climatic Change, 81: 123-143.
Palmer, T.N. and RaÈisaÈnen, J., 2002, Quantifying the Risk of Extreme Seasonal Precipitation Events in a Changing Climate. Nature, 415: 512-514.
Pommerening, A., 2002, Approaches to Quantifying Forest Structures. Forestry, 75: 305-324.
Ponce-Hernandez, R., 2004, Assessing Carbon Stocks and Modelling Win-Win Scenarios of Carbon Sequestration through Land-Use Changes, Report, Food and Agriculture Organization of the United Nations, Rome
Pretzsch, H., 1998, Structural Diversity as a Result of Silvicultural Operations. Lesnictvi-UZPI (Czech Republic), 44: 429-439.
Pretzsch, H., Biber, P. and Durský, J., 2002a, The Single Tree-Based Stand Simulator Silva: Construction, Application and Evaluation. Forest Ecology and Management, 162: 3-21.
Pretzsch, H., Biber, P., Grote, R., Meier, H., Moshammer, R., Seifert, S. and Sodtke, R., 2002b, Silva 2.2 User Manual. Chair for Forest Yield Science, Technischen Universität München.
Refsgaard, J.C., Van der Sluijs, J.P., Brown, J. and Van der Keur, P., 2006, A Framework for Dealing with Uncertainty Due to Model Structure Error. Advance in Water Resources, 29: 1586-1597.
Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L. and Vanrolleghem, P.A., 2007, Uncertainty in the Environmental Modelling Process - a Framework and Guidance. Environmental Modelling & Software, 22: 1543e1556.
Roeckner, E., Bengtsson, L., Feichter, J., Lelieveld, J. and Rodhe, H., 1999, Transient Climate Change Simulations with a Coupled Atmosphere–Ocean Gcm Including the Tropospheric Sulfur Cycle. Journal of Climate, 12: 3004-3032.

Saltelli, A., Chan, K. and Scott, E.M., 2000, Sensitivity Analysis. Wiley, Chichester; New York

Saltelli, A., Tarantola, S., Campolongo, F. and Ratto, M., 2004, Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models. Halsted Press New York, NY, USA

Saltelli, A., Ratto, M., Tarantola, S. and Campolongo, F., 2006, Sensitivity Analysis Practices: Strategies for Model-Based Inference. Reliability Engineering & System Safety, 91: 1109-1125.

Schmid, S., Zingg, A., Biber, P. and Bugmann, H., 2006, Evaluation of the Forest Growth Model Silva Along an Elevational Gradient in Switzerland. European Journal of Forest Research, 125: 43-55.

Shackle, G.L.S., 1955, Uncertainty in Economics and Other Reflections. Cambridge University Press, Cambridge, UK

Stainforth, D.A., Aina, T., Christensen, C., Collins, M., Faull, N., Frame, D.J., Kettleborough, J.A., Knight, S., Martin, A. and Murphy, J.M., 2005, Uncertainty in Predictions of the Climate Response to Rising Levels of Greenhouse Gases. Nature, 433: 403-406.

Steppeler, J., Doms, G., Schättler, U., Bitzer, H.W., Gassmann, A., Damrath, U. and Gregoric, G., 2003, Meso-Gamma Scale Forecasts Using the Nonhydrostatic Model Lm. Meteorology and Atmospheric Physics, 82: 75-96.

Van Asselt, M.B.A. and Rotmans, J., 2002, Uncertainty in Integrated Assessment Modelling—from Positivism to Pluralism. Climatic Change, 54: 75–105.

Van der Meer, P.J., Jorritsma, I.T.M. and Kramer, K., 2002, Assessing Climate Change Effects on Long-Term Forest Development: Adjusting Growth, Phenology, and Seed Production in a Gap Model. Forest Ecology and Management, 162: 39-52.

Van der Sluijs, J.P., 2002, Integrated Assessment. Encyclopedia of Global Environmental Change, 4: 250-253.

Van der Sluijs, J.P., Risbey, J.S., Kloprogge, P., Ravetz, J.R., Funtowicz, S.O., Corral Quintana, S., Pereira, A.G., De Marchi, B., Peterson, A.C. and Janssen, P.H.M., 2003, Rivm/Mnp Guidance for Uncertainty Assessment and Communication: Detailed Guidance. Rivm/Mnp (Guidance for Uncertainty Assessment and Communication Series, Vol 3). , Report, Utrecht University and RIVM

Van der Sluijs, J.P., 2007, Uncertainty and Precaution in Environmental Management: Insights from the Upem Conference. Environmental Modelling & Software, 22: 590-598.

Van der Sluijs, J.P., Petersen, A.C., Janssen, P.H.M., Risbey, J.S. and Ravetz, J.R., 2008, Exploring the Quality of Evidence for Complex and Contested Policy Decisions. Environmental Research Letters, 3: 024008.

Van der Sluijs, J.P., Craye, M., Funtowicz, S., Kloprogge, P., Ravetz, J. and Risbey, J., 2005, Combining Quantitative and Qualitative Measures of Uncertainty in Model-Based Environmental Assessment: The Nusap System. Risk Analysis, 25: 481-492.

van Herwijnen, M., 1999, Spatiak Decision Support for Environmental Management. Elinkwijk bv

Vanclay, J.K., 1994, Modelling Forest Growth and Yield: Applications to Mixed Tropical Forests. Wallingford (RU). CAB International

Vidale, P.L., Lüthi, D., Frei, C., Seneviratne, S. and Schär, C., 2003, Predictability and Uncertainty in a Regional Climate Model. J. Geophys. Res, 108: 4586.

Voogd, H., 1983, Multicriteria Evaluation for Urban and Regional Planning. Pion, London 367 p.

Walker, W.E., Harremoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P. and von Krauss, M.P.K., 2003, Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support. Integrated Assessment, 4: 5-17.

Wramneby, A., Smith, B., Zaehle, S. and Sykes, M.T., 2008, Parameter Uncertainties in the Modelling of Vegetation Dynamics—Effects on Tree Community Structure and Ecosystem Functioning in European Forest Biomes. Ecological Modelling, 216: 277-290.

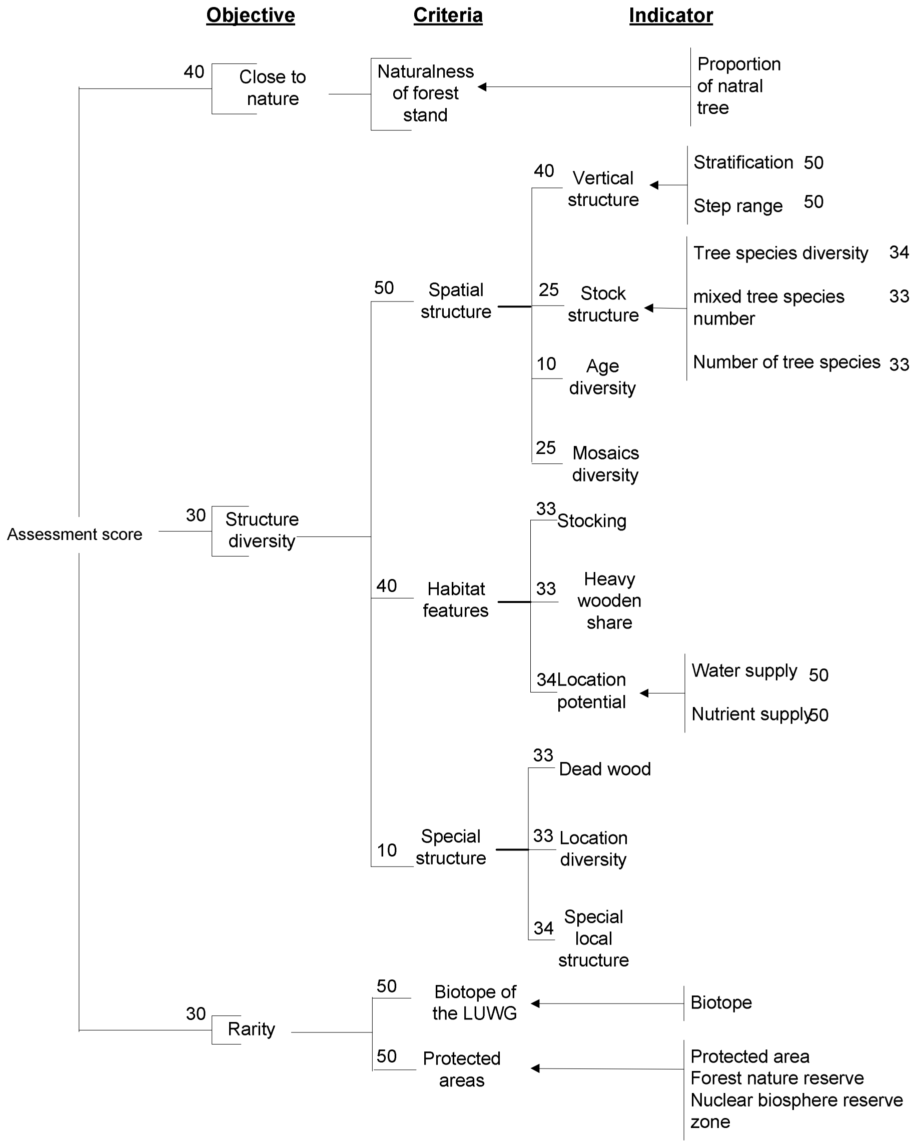
Xenakis, G., Ray, D. and Mencuccini, M., 2008, Sensitivity and Uncertainty Analysis from a Coupled 3-Pg and Soil Organic Matter Decomposition Model. Ecological Modelling, 219: 1-16.

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/OPYC3	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)		(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)		(Castro et al., 1993)

Appendix 2: Criteria tree for habitat evaluation model (source FAWF)



b

Appendix 3: Habitat evaluation model summary (source FAWF)

Objective	Criteria	Indicator	Indicator	Unit
Close to nature - closeness of tree to nature indicated by naturally growth of tree species in that particular soil type and moisture content of the area	**Naturalness of forest stand**	Proportion of natural trees		Percentage of tree species sharing the same soil type and moisture content 1 = < 40% 2 = 40% - 80% 3 = 80%
Structural diversity	**Spatial structure** -horizontal and vertical diversity of forest	**Vertical structure**	**Stratification** number of vertical layers/ stratum	Index ranges from 1(no layer) to 5 (all aged of trees)
			Step range Area within the stand with difference height which is more than 8m	Index ranges from 0 (<20% of the area in the stand have the 8m difference of height) to 3 (>60%)
		Stock structure	**Tree species diversity** proportion of dominant tree species at the upper layer of the stand	Percentage of area covered by dominant tree.
			Mixed tree species number Number of different tree species with area coverage ≥ 5% of the total stand area	< 5% of mixed tree species in the stand do not take into consideration > 5% of tree species
			number of tree species Total number of tree species	The code range from <4 to ≥ 6 trees
		Age diversity	number of different age groups in the stand – covering ≥ 5% of total area	The Code range from <3 ages to >4 ages
		Mosaic diversity	Distribution or composition of tree species	index with values from 1.0 (homogeneous) – 3.0 (clustered)
	Habitat features	**Stocking**	Stand density (the value obtained from university). which depends on intervention and type of tree	1 bad outcome > 1.0 or ≤ 0,3 2 medium Score ≤ 1.0 and ≥ 0.7 3 Good Score ≥ 0.4 and ≤ 0.6
		Heavy wooden share	Based on DBH size. The higher the	Percentage of the share

			value the more the share.	1 badly ≤ 10% 2 medium 11% - 30% 3 Good> 30%
		Location potential	Water supply	Water supply 1 (extremely dry) to 12 (wet)
			Nutrient supply	Nutrient supply 1 to 9
	Special structure	**Dead wood**	Number of dead wood in the stand including standing and lying dead wood	Index ranges from 0 (a lot of dead wood) to 3 (less dead wood) and based on the cubic meter value of dead wood.
		Location diversity	Rare soil type -if it occurs <5% then it is not good. 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 structure	Description of the structure of the landscape such as rock, lake, cave grassland.	Yes or no
Rarity	**Biotopes of the LUWG**	**Biotope**	The area coverage of ecological valuable area such as biotope	The percentage coverage of these areas 1 = bad area ≤ 25% 2 medium surface proportion> 25% and <50% 3 Good surface share ≥ 50%
	Protected areas		The area coverage of nature protected areas, forest nature reserve, nuclear biosphere reserve zone, NWR 100	The percentage coverage of these areas

Appendix 4 Description of Ecological indices

Habitat evaluation criteria	SILVA Matched	Description	SILVA output score	Reference
Stratification	**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.	Denoted as Index A Tree species portions divide in to three height zones:0-50% , 50%-80% and 80%-100%. It defines as	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)	(Pretzsch, 1998; Pommerening, 2002)
Mixed tree species number	**Mingling index** -proportion of the nearest neighbour tree to the reference tree with different species-)	Denoted as M	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	(Pommerening, 2002; Kint et al., 2004)
mosaic diversity	**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.	Denoted as R	Range between 0 (greatest clustering) and 2.1491. <1 – clustering formation or distribution =1 – random distribution >1 – regular distribution	(Pretzsch, 1998; Pommerening, 2002)

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 : ______________________________

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

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

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

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