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Master Thesis

Mapping tree species suitability based on fuzzy set theory

submitted by

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Affidavit

I hereby declare that I am the sole author of this work. No assistance other than that which is permitted has been used. Ideas and quotes taken directly or indirectly from other sources are identified as such. This written work has not yet been submitted in any part.

Vienna, April 11, 2022

A handwritten signature in black ink, appearing to read 'T. Thanh' or similar, with a stylized flourish at the end.

Son Tran Thanh

Acknowledgement

I would like to express my gratitude to my supervisor Univ.Prof. Dipl.-Ing. Dr.nat.techn. Manfred J. Lexer and my co-supervisor Ao.Univ.Prof. Dipl.-Ing. Dr.nat.techn. Harald Vacik for mentoring and supporting me in this thesis. Their outstanding knowledge, motivation and patience not only helped me to complete my thesis but also developed my academic skills. Special thanks to Michael Kessler who supported me to prepare data and literature.

From this thesis, I have gained new experience in the field of decision support system. I got to know the ways to develop and evaluate models. I also had a chance to improve my knowledge with MATLAB. These skills will be valuable for my future career. I hope that the results of my thesis will contribute to forest science and support managers in decision making and addressing forest-related issues.

Finally, I would like to thank my family for loving and standing by my side. Without them I wouldn't have been able to pass this challenge.

Summary

Tree species choice plays an important role in sustainable forest management. Several approaches have been studied to match the best tree species with given site conditions. However, the need for the current study has arisen due to the lack of crisp data and the difference in expert perspectives. Fuzzy logic controller is an appropriate solution to address these limitations as it could combine quantitative and qualitative approaches. The system utilizes rules instead of algorithms to model expert knowledge with crisp data.

The objectives of this thesis were (1) Developing the conceptual frame for a Tree Species Suitability model, (2) Implementing the model within the MATLAB environment, and (3) Evaluating the model with data from the federal province of Styria, Austria.

The environmental factors were divided into three groups including temperature regime, nutrient supply and water supply. Each group was modeled by Mamdani fuzzy logic controllers to formulate Temperature Suitability Index, Nutrient Suitability Index and Water Suitability Index. Eventually, these indices were aggregated and compared by two methods, namely Gamma operator and Minimum operator. For the model evaluation, 30 sites along different ecological gradients were selected in Styria, Austria (FORSITE project) to analyze model behavior for *Picea abies*, *Abies alba*, *Fagus sylvatica* and *Quercus robur*.

Overall, the species suitability model behavior met the expectations regarding the estimated suitability indices for individual species along the gradients as well as regards the relative performance of the analyzed tree species. However, model outputs along the input gradients were partly found to be inconsistent with the given input data because of (1) the Center of Gravity defuzzification method, (2) the overlap of the output fuzzy sets, (3) the Maximum aggregation method of the output fuzzy sets, and (4) the rule base. Gamma operator produced smoother output data than Minimum operator. Results of the model showed that *Picea abies* and *Abies alba* are suitable to grow from high to medium elevations while *Fagus sylvatica* and *Quercus robur* are appropriate to plant in medium and low altitudes. The Tree Species Suitability model is a promising tool to support managers in tree species selection.

Kurzfassung

Die Baumartenwahl ist eine der langfristig wirkenden Entscheidungen im Rahmen nachhaltiger Waldbewirtschaftung. Unterschiedliche Ansätze wurden vorgeschlagen bzw. sind in Verwendung, um die Eignung einer Baumart für einen bestimmten Standort zu beurteilen. Die gegenständliche Arbeit fokussiert auf das weitgehende Fehlen von quantitativen Daten und die unscharfe und zum Teil unterschiedliche Meinung von Experten. Fuzzy Logic Ansätze werden in diesem Kontext als ein möglicher methodischer Ansatz gesehen. Die Ziele der vorliegenden Arbeit sind: (i) die Entwicklung des konzeptionellen Rahmens für ein Baumarteneignungsmodell, (ii) die Implementierung des Modells mit MATLAB, und (iii) Die vorläufige Evaluierung des Modells mit Daten aus dem FORSITE Projekt aus der Steiermark, Österreich.

Standortsmerkmale wurden in das Temperaturregime, die Nährstoff- und die Wasserversorgung strukturiert. Jede Merkmalsgruppe wurde als Mamdani Kontrolleinheit modelliert. Als Ergebnis jeder Einheit ergibt sich jeweils ein Eignungsindex, die drei Indices werden dann in einem weiteren Schritt zu einer Gesamteignung aggregiert. Für die Aggregation wurden sowohl ein Gamma-Operator als auch ein Minimum-Operator verwendet.

Das Modellverhalten wurde anhand von 30 Standorten in der Steiermark aus dem FORSITE Projekt evaluiert. Dazu wurden Eignungswerte für *Picea abies*, *Abies alba*, *Fagus sylvatica* und *Quercus robur* berechnet und vergleichend analysiert. Insgesamt entsprach das Modellverhalten entlang der ökologischen Gradienten den Erwartungen, sowohl absolut als auch in Bezug auf das relative Verhalten der Baumarteneignungswerte. Es wurde allerdings festgestellt, dass teilweise die Relationen von Input zu Output nicht konsistent waren. Gründe waren (i) die Center of Gravity Defuzzifizierungsmethode (COG), (ii) die Überlappungsbereiche von Fuzzy Sets, (iii) die Maximum-Aggregierungsmethode für Output-Fuzzy Sets, und (iv) die Regelbasis. Der Gamma-Operator produzierte gleichmäßigere Outputs im Vergleich zum Minimum-Operator. Die Resultate zeigten, dass *Picea abies* und *Abies alba* von Hochlagenstandorten bis in mittlere Höhenlagen sehr gut geeignet sind, während *Fagus sylvatica* und *Quercus robur* in mittleren und tiefer gelegenen Höhenlagen gute Eignungswerte aufwiesen. Das vorgestellte Baumarteneignungsmodell erwies sich als vielversprechendes Tool um die Baumartenwahl zu unterstützen.

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Abbreviations

GDD: Growing Degree Days

WF: Winter Frost

LVP: Length of Vegetation Period

LF: Last Frost

SD: Soil Depth

ST: Soil Type

BSP: Base Saturation Percentage

CF: Coarse Fraction

SMI: Soil Moisture Index

GW: Ground Water

ZAMG: Zentralanstalt für Meteorologie und Geodynamik

FAO: Food and Agriculture Organization of the United Nations

SAM: Soil Adsorption Matrix

TSI: Temperature Suitability Index

NSI: Nutrient Suitability Index

WSI: Water Suitability Index

TSSI: Tree Species Suitability Index

OL: Overlap percentage

1 Introduction

Forests play a vital role in providing long-term ecosystem services, combating rural poverty, and ensuring food security. Due to human overpopulation and increasing demand for foods and lands, forests have been extremely degraded for decades (FAO, 2015). Annually, 13 million hectares are deforested which devastatingly affects the world's biodiversity (Bremer et al., 2010). Land use and land use change activities cause soil compaction, forest fragmentation, loss of endemic species and their habitat, among others (Noss and Copperrider, 1994). To address these issues, sustainable use, management, and restoration of forest ecosystems have been considered as priorities of the Sustainable Development Goals (FAO, 2018).

The suitable choice of tree species is a key element in sustainable forest management and forest restoration due to its positive effects on productivity, ecosystem services, tree survival rate and investment costs. Climate change has added to the complexity of decisions about tree species composition in forest management. Several approaches have been studied about tree species selection. Garcia et al. (2013) conducted simulations that included climate change scenarios to assess the survival capacity of tree species. Rollan et al. (2018) devised a planning tool that combines tree species selection with the plantation schedule, while considering the maximization of carbon sequestration and income generation. Conway and Vander Vecht (2015) employed surveys and interviews to explore tree selection criteria of actors who plant and supply urban trees. Villacís et al. (2016) generated a list of recommended tree species by evaluating the performance of saplings, such as sapling survival, causes of mortality, increment of sapling height and diameter, and effects of plants on soil properties. Another approach basing on species distribution was developed to assess tree species suitability. It assumes the absolute frequency of species presence as a direct indicator of habitat suitability (Braunisch et al., 2008). Based on this theory, Gastón et al. (2014) evaluated the species suitability through species distribution model and compared results with expert experience.

In general, these previous approaches could be classified into two categories including qualitative and quantitative. The qualitative approach mainly focuses on empirical analysis and expert recommendation method. This could lead to subjectivity and ambiguity in decision making due to the differences of expert perspectives and experience. The uncertainty factors are not thoroughly weighed and criteria for tree suitability are not unified

(Xu et al., 2018). For example, a bias may be introduced by human promotion of certain tree species because of their economic superiority. The conceptual inconsistency may increase if such models are extrapolated into novel climatic conditions. By contrast, quantitative approach considers the collection and analysis of data. Numerous experiments have been conducted to study the growth and habit of the tree species (Xu et al., 2018). However, these experiments require more time, manpower, materials, and financial resources. Thus, the insufficiency of data is conspicuously a limitation in this approach. Besides, the changing of environment due to climate change led to the uncertainty of these previous methods. For instance, the scarcity of optimal habitat forces most of the individuals to live in suboptimal conditions, increasing uncertainty to select relevant tree species based on species distribution (Braunisch et al., 2008).

Another approach in tree species selection has been studied, namely the fundamental niche approach. The fundamental niche is considered as a set of environmental conditions and resources that allow a given species to survive and reproduce without being affected by biotic factors (Varghese et al., 2010). In other words, the fundamental niche of a species is specified by its physiological range of tolerance to environmental factors (Kearney, 2004). The fundamental niche is a relevant approach in tree species selection because it allows managers to define the best species for current site conditions and climate change scenario. To employ this approach, forest managers usually try to match physiological requirements of tree species with suitable bioclimatic and chemo-physical site conditions (Lexer et al., 2000). However, as discussed above, there are two main problems involved in solving this task including knowledge uncertainty and data uncertainty. Site related information in the literature is primarily based on the experts' own experiences and qualitative knowledge (Sjöman et al., 2018), which is always subject to uncertainty (Niamir et al., 2019). Furthermore, a lack of quantitative data on site parameters leads to ambiguity of selecting suitable tree species (Lexer et al., 2000). An inability to apply fundamental niche knowledge on species selection could limit the scenario analysis application in tree species selection.

The development of fuzzy logic theory offers a potential solution to address the limitation of qualitative and quantitative manners as it is a combination of these two approaches. Fuzzy logic has emerged since Lofti Zadeh published the paper "Fuzzy Sets" in 1965. A fuzzy set expresses the relationship between an uncertain quantity x and a membership function μ , which belongs to interval $[0,1]$ (Nasr, 2012). It is employed to handle the concept of partial truth, where the true value may range between "completely true" and "completely false". In

contrast to classical sets, fuzzy sets thus provide a convenient way of defining memberships more general than a simple Boolean true or false approach. Fuzzy logic is much closer in spirit to human thinking and natural language comparing to the traditional logical systems (Lee, 1990). The advantage of this approach is to mathematically represent uncertainty and vagueness and to provide formalized tools for dealing with the imprecision intrinsic to many problems. Fuzzy logic is powerful due to the ability of transferring into algorithm a completely unstructured set of heuristics expressed by linguistic variables (Mamdani, 1999). Fuzzy logic has been applied to develop fuzzy inference systems, which formalize the mapping from given inputs to outputs. Several types of fuzzy inference system (FIS) have been proposed by researchers (Nasr et al., 2012). Two most common used inference systems are Mamdani fuzzy control (Mamdani and Assilian, 1975) and Takagi–Sugeno fuzzy control (Takagi and Sugeno, 1985).

During the past years, fuzzy inference systems have found numerous applications in the forestry sector. Toledo-Castro et al. (2018) developed a forest fire controller based on fuzzy logic which analyses environmental information to estimate the existence of forest fire risks, and to detect the occurrence of fire outbreaks over different forest areas. A fuzzy inference model was developed by Wu et al. (2019) to assess soil quality and map land use types with appropriate soil quality grades. Mendoza and Prabhu (2004) defined criteria and indicators as instrument to assess sustainable forest management based on fuzzy logic methods. Riedler et al. (2002) integrated soil and site variables into a fuzzy logic-based model and proposed a set of rules to predict forest soil degradation. In Lexer and Hönninger (2001), fuzzy inference was used to model the effect of site nutrient status on tree growth in a hybrid forest dynamics model. Joss et al. (2008) applied a fuzzy inference modeling approach to evaluate land suitability for afforestation of hybrid poplar (*Populus* spp.) across the Prairie Provinces of Canada. These previous studies are premise for the application of fuzzy logic in fundamental niche of the tree species.

2 Objectives

The main aim of this study is to develop a Tree Species Suitability model based on fuzzy set theory. The model approach will be demonstrated by example of four selected European tree species. To achieve this overall aim, several technical objectives must be accomplished:

- (i) Developing the conceptual frame for a Tree Species Suitability model.
- (ii) Implementing the model within the MATLAB environment.
- (iii) Evaluating the model with data from the federal province of Styria, Austria.

3 Materials and methods

3.1 Mamdani fuzzy control approach

According to Keshwani et al. (2008), the Mamdani scheme is a type of fuzzy relational model which is based on if-then rules. It is also called a linguistic model because both the antecedent and the consequent are fuzzy propositions (Babuska, 1998). Mamdani fuzzy model is the most applied fuzzy methodology due to its popularity and easy application (Nasr, 2012). Mamdani systems are suitable to expert system applications where the rules are developed from human expert knowledge because they have more intuitive and easier to understand rule bases. Due to these advantages, the Mamdani fuzzy inference system has been selected in this study.

In general, the Mamdani fuzzy inference system contains of four parts: fuzzification, fuzzy rule base (knowledge base), fuzzy inference engine and defuzzification (see Figure 1).

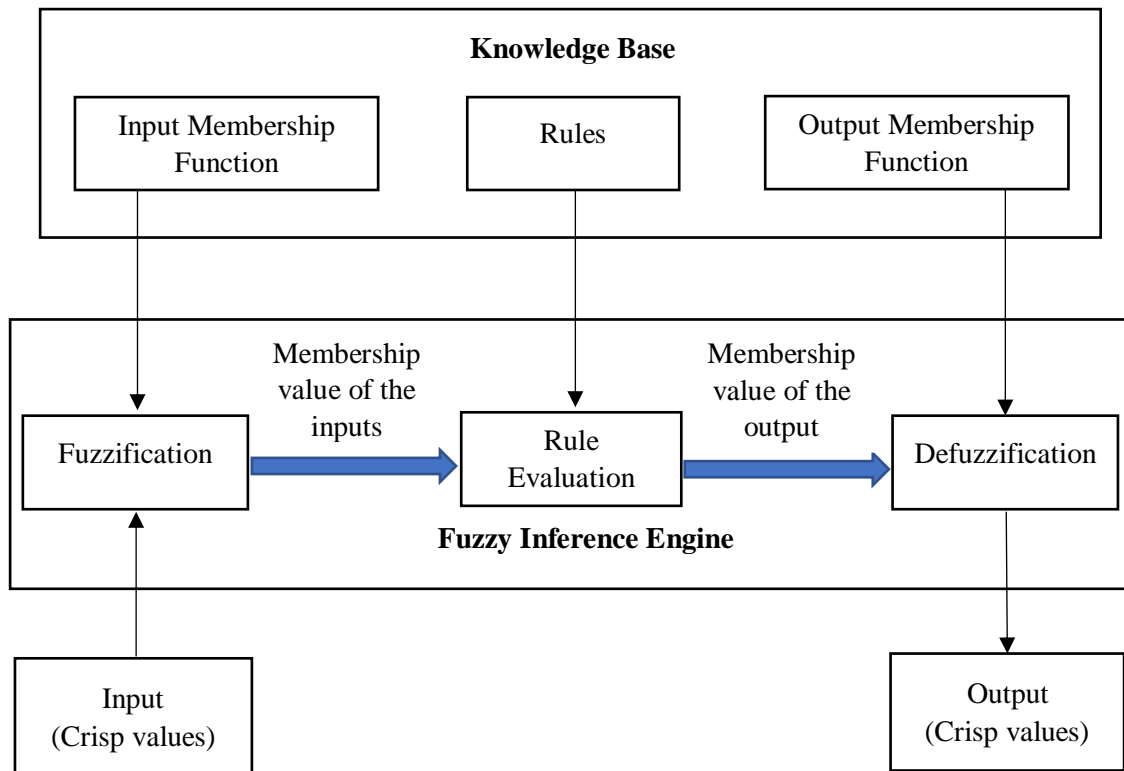


Figure 1: Mamdani Inference System

3.1.1 Fuzzification

Fuzzification is the process of transforming a crisp expression into fuzzy sets using membership functions (see Figure 2). A fuzzy set maps a natural base variable into a term

of a linguistic variable via a membership function and admits the possibility of partial membership in it. Linguistic variables were defined as variables whose values are words or sentences. For instance, temperature can be a linguistic variable if its values are linguistic rather than numerical, i.e., hot, warm, cool, cold instead of 30, 20, 10, 0 degree Celsius. Mathematically, the fuzzy set A can be represented as a set of ordered pairs (Ocampo-Duque et al., 2006) (Eq. 1)

$$A = \{x, \mu_A(x) \mid x \in U\} \quad (1)$$

Where $\mu_A(x)$ is the membership function of x in A and U is a universe of discourse. If $\mu_A(x) = 1$, x is totally in A. If $\mu_A(x) = 0$, x is not in A. If $0 < \mu_A(x) < 1$, x is partly in A.

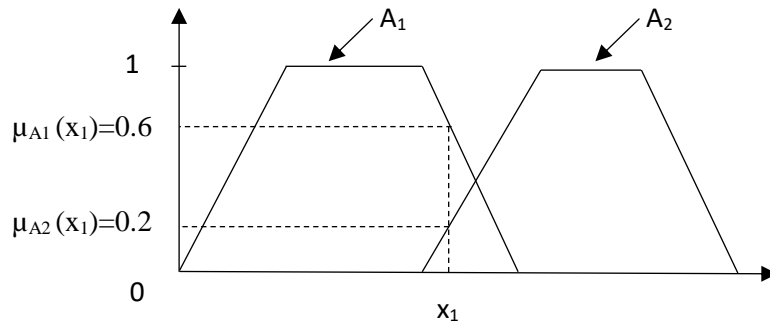


Figure 2: Fuzzification method

The shape of a membership function can vary depending on the application. There are some common types of membership functions such as Triangle, Trapezoidal, Sigmoidal, Generalized bell and Gaussian. Trapezoidal membership function (see Figure 3) is frequently suggested for an efficient computation (Zimmermann, 1996). Mathematically, fuzzy membership values are computed through following equation (2):

$$\mu_{A(x)} = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \quad (2)$$

Where the parameters are defined by a lower limit a, an upper limit d, a lower support limit b, and an upper support limit c, and $a < b < c < d$. Trapezoidal membership function was selected in this study.

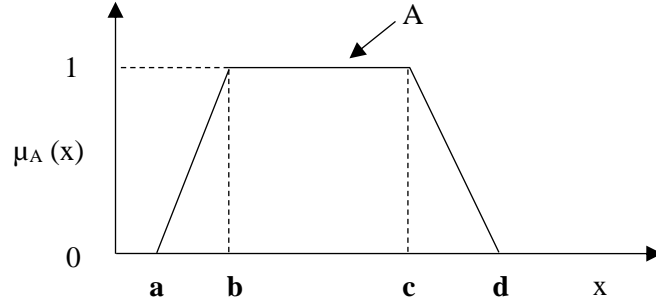


Figure 3: Trapezoidal membership function

3.1.2 Fuzzy rule base

In knowledge-based systems, fuzzy rules with the form of If-Then (conditional propositional forms) are utilized to illustrate the relation between input and output linguistic variables (Nasr, 2012). A single fuzzy if-then rule is formed by If x is A , then y is B , where A and B are linguistic variables determined by fuzzy sets on the ranges (universes of discourse) X and Y , respectively. The If-part of the rule " x is A " is the antecedent or premise, while the Then-part of the rule " y is B " is the consequent or conclusion. Fuzzy set theory contains a group of mathematical set operations, including union (OR) and intersection (AND) (Mamdani, 1975) for combining factors in a multicriteria evaluation (Reynolds et al., 2000). Components of the antecedent part are aggregated by fuzzy operators to compute the rule strength which represents the antecedent. If two fuzzy sets A and A_1 are defined on the universe X , for a given element x belonging to X , the following operations can be carried out:

$$\text{Intersection (AND): } \mu_{A \cap A_1}(x) = \min(\mu_A(x), \mu_{A_1}(x)) \quad (3)$$

$$\text{Union (OR): } \mu_{A \cup A_1}(x) = \max(\mu_A(x), \mu_{A_1}(x)) \quad (4)$$

Where $\mu_{A \cap A_1}$ is aggregation of the antecedent; μ_A and μ_{A_1} are monocausal factors. An example of the fuzzy rule is given below:

- *If Growing Degree Day is Very low AND Winter Frost is Very cold AND Length of Vegetation Period is Very short AND Last Frost is Very early then Temperature Suitability is Unsuitable*

In which, Growing Degree Day, Winter Frost, Length of Vegetation Period and Last Frost are input variables. Temperature Suitability is the output variable. Very low, Very cold, Very short, Very early and Unsuitable are terms of linguistic variables. AND is the fuzzy operator.

3.1.3 Fuzzy inference engine

A fuzzy inference engine combines fuzzy if-then rules, using fuzzy reasoning methods to link inputs and outputs (Eyoh et al., 2013). There are many methods for the fuzzy inference engine in which the max–min and max–product methods are the two most used techniques (Akgun et al., 2012). Max-min method was selected for this study and implemented as follows (see Figure 4):

- Step 1: Input membership values are aggregated using fuzzy operators to compute a rule strength. The rule strength is a single membership value which represents the antecedent. A common operator is the minimum operator.
- Step 2: The implication method is applied for all rules to find the relation between the antecedent and the consequent. The consequent as fuzzy sets are truncated to the degree specified by the antecedent following the minimum operator (Izquierdo et al., 2017):

$$\mu_{Ri}(y) = \min[\mu_{Ai}(x), \mu_{Bi}(y)], i=1,2,...,n \quad (5)$$

Where $\mu_{Ri}(y)$ is the relation's membership degree of rule "i" according to "x" and "y" inputs, $\mu_{Ai}(x)$ and $\mu_{Bi}(y)$ are the membership degrees of "x" and "y" inputs respectively, "n" is the number of rules.

- Step 3: Aggregation method is implemented to combine all truncated output fuzzy sets into a final fuzzy set using the following maximum operator (Izquierdo et al., 2017):

$$\mu_{\bar{B}}(y) = \max[\mu_{Ri}(y)], i=1,2,...,n \quad (6)$$

Where $\mu_{\bar{B}}(y)$ is the aggregated fuzzy set of the consequent, $\mu_{Ri}(y)$ is the membership degree of rule "i", "n" is the number of rules.

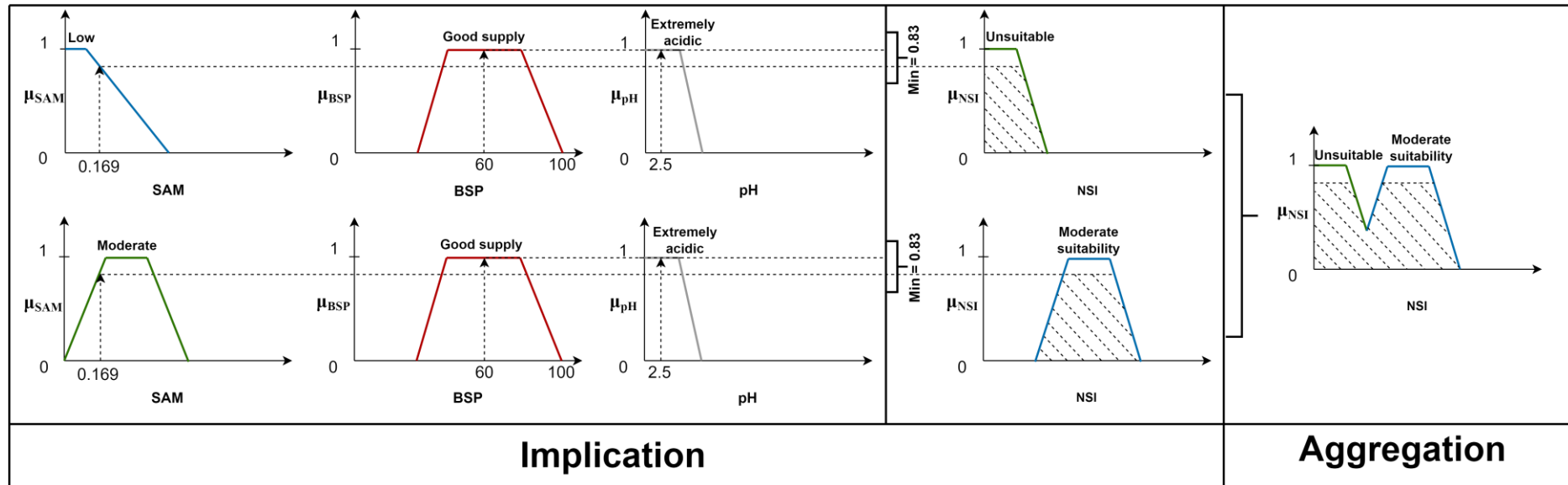


Figure 4: Implication and aggregation in Mamdani fuzzy control (SAM: Soil Adsorption Matrix, BSP: Base Saturation Percentage, NSI: Nutrient Suitability Index), two rule bases are processed: “IF SAM is Low AND BSP is Good supply AND pH is Extremely acidic THEN NSI is Unsuitable” and “IF SAM is Moderate AND BSP is Good supply AND pH is Extremely acidic THEN NSI is Moderate suitability”

3.1.4 Defuzzification

Defuzzification is the process of mapping from a space of inferred fuzzy control actions to a space of non-fuzzy control actions. The purpose of defuzzification is producing a crisp value that best represent for the possibility distribution of the inferred fuzzy control action (Lee, 1990). There are some common defuzzification methods including Mean of Maximum, Center of Gravity, Bisector, Middle of Maximum, Smallest of Maximum and Largest of Maximum. Center of Gravity method was selected for defuzzification process due to its higher consistency compared to other methods (Husain et al., 2017). A crisp value is computed depending on the center of gravity of the overall output fuzzy set (see Figure 5), which is mathematically represented by the following equation:

$$x^* = \frac{\sum_{i=1}^n x_i \cdot \mu(x_i)}{\sum_{i=1}^n \mu(x_i)} \quad (7)$$

Where $\mu(x_i)$ is the membership value for point x_i in the universe of discourse, n represents the number of elements in the fuzzy set.

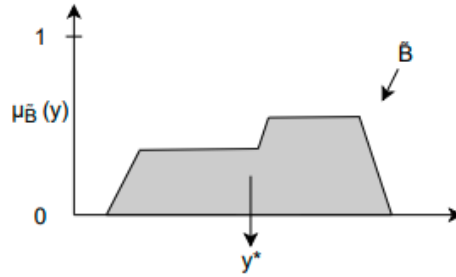


Figure 5: Center of Gravity defuzzification method

3.2 Structure of the Tree Species Suitability model

The Tree Species Suitability model was built for four species (*Picea abies*, *Abies alba*, *Fagus sylvatica*, *Quercus robur*) based on the Mamdani fuzzy control approach (see Figure 6).

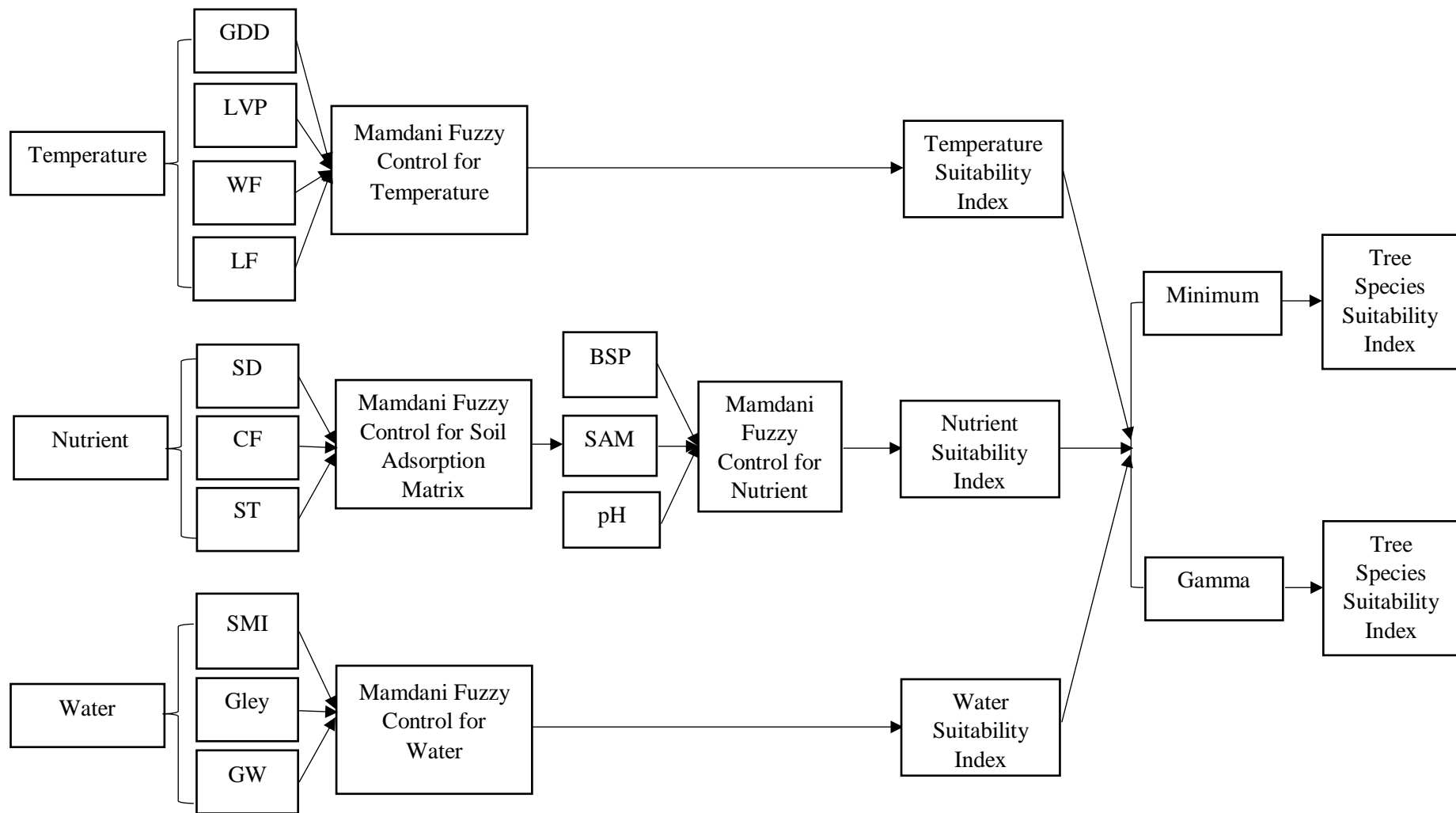


Figure 6: Tree Species Suitability model

To model the eco-physiological suitability of tree species, the site parameters were structured into three factor groups: temperature regime, nutrient supply, and water supply. The fuzzy sets and rule base were constructed based on (1) data of the FORSITE project and (2) expert knowledge.

The temperature part consisted of four variables including Growing Degree Days (GDD), Winter Frost (WF), Length of Vegetation Period (LVP) and Last Frost (LF). These parameters were modelled in a Mamdani Fuzzy Control unit to generate the Temperature Suitability Index.

To reduce the complexity of nutrient part which contained five variables, a hierarchical approach was employed. First, Soil Depth (SD), Coarse Fraction (CF) and Soil Type (ST) were processed in a Mamdani Fuzzy Control unit to define the Soil Adsorption Matrix (SAM). The variable SAM was then combined with Base Saturation Percentage (BSP) and pH in a second Mamdani Fuzzy Control unit to determine the final Nutrient Suitability Index.

The water group contained three variables including Soil Moisture Index (SMI), Gley and Ground Water (GW), which were performed in a Mamdani Fuzzy Control unit to formulate the Water Suitability Index.

Finally, two approaches were implemented to model the combined effect of temperature regime, nutrient supply, and water supply on tree species, namely the Gamma operator and Minimum operator. The Gamma operator is an algebraic product of the two fuzzy operators (fuzzy Sum and fuzzy Product), which are both raised to the power of gamma. The generalized function is as follows (Giesecke et al., 2009):

$$\mu_{A\gamma B\gamma C} = (\mu_A \cdot \mu_B \cdot \mu_C)^{(1-\gamma)} \cdot (1 - (1 - \mu_A) \cdot (1 - \mu_B) \cdot (1 - \mu_C))^\gamma, \gamma \in [0,1] \quad (8)$$

Where $\mu_{A\gamma B\gamma C}$ is the aggregate environmental response; μ_A , μ_B and μ_C are monocausal responses. According to Lexer and Hönninger (2001), this is a flexible operator which can handle compensating effects depending on the value of the gamma coefficient. When the specific γ is 1, no compensation is expected between the input variables and if γ is 0, full compensation is provided. Values in between permit combination of these two extremes.

The second method is Minimum operator, which was utilized, for instance, by Botkin et al. (1972) and Kienast (1987) based on the Liebig's law of the minimum to aggregate the environmental response from various monocausal responses:

$$\mu_{A \cap B \cap C} = \min(\mu_A, \mu_B, \mu_C) \quad (9)$$

Where $\mu_{A \cap B \cap C}$ is the aggregate environmental response; μ_A, μ_B and μ_C are monocausal responses.

3.2.1 Temperature Suitability Index

Growing Degree Days (GDD) is an indicator for estimating the growth and development of plants during the growing season. GDD is based on the concept that development only occurs if the temperature exceeds minimum development thresholds or base temperature. According to McMaster et al. (1997), the formula to calculate GDD is:

$$GDD = \frac{T_{Max} + T_{Min}}{2} - T_{Base} \quad (10)$$

Where T_{Max} is the daily maximum air temperature, T_{Min} is the daily minimum air temperature, and T_{Base} is the temperature below which plant growth is zero. T_{Base} differs among tree species, growth stage and possibly cultivars (Wang, 1960). Here T_{Base} was fixed at 5°C.

Winter Frost (WF) is considered as a major environmental factor which limits the productivity and distribution of plants (Larcher et al., 1981). Subsequent cell damages to species could be occurred if temperatures fall below WF's threshold (Larcher, 1995). Species are most vulnerable to frost and mortality during the regeneration stage (Murray et al., 1994). Frost in growing season can destroy buds, terminal twigs, or the entire plant (Nitschke et al., 2008). Net photosynthesis and stomatal conductance rates are decreased by frost (Rahimi et al., 2007). The most affected organelle during frost-days is chloroplast

(Kratsch and Wise, 2000). During freezing, cells are dehydrated, and the membrane is destabilized, which are the key processes leading to frost damage (Pearce, 2001). In addition, frost-damaged trees are more susceptible to disease and insects (Dale et al., 2001; Murray et al., 1994). Frost events are assumed to occur when temperatures fall below 0 °C. Minimum temperature thresholds are utilized to determine the appearance of winter frosts (Lexer et al., 2000).

Length of Vegetation Period (LVP) is usually defined as the part of the year where the daily average temperature exceeds a certain limit. It is the rhythmically repeating part of the year in which a plant actively grows and develops. The temperature limit is commonly between +3°C and +5°C depending on the type of plant. LVP is determined by calculating the number of days between the first 5-day period with average temperatures above 5°C (leaf-on date) and the first 5-day period with temperatures below 5°C (leaf-off date) (Buitenwerf et al., 2015). LVP is an important determinant of plant growth and distribution. Changes in the LVP might have both positive and negative effects on the yield of the forest. In principle, longer vegetation period could indicate increased productivity and new planting opportunities in forest setting. However, a longer vegetation period could also disrupt the function and structure of a region's ecosystems and encourage invasive species or weed growth.

Last Frost (LF) refers to the average final spring frost in a specific growing location. This date and temperature vary between locations and elevations. The last spring frost occurs at the beginning of the growing season, which damages seedlings, young plants, and flowering-stage trees (Vestal, 1971). LF in the spring causes variety of damages to fruits, depending on its growing stage (Tait and Zheng, 2003). Understanding LF date would support managers to select suitable time and species for plantation.

3.2.2 Nutrient Suitability Index

Soil Depth (SD) refers to the thickness of the soil materials. It determines rooting, moisture and nutrient storage, mineral reserves, anchorage, and a variety of factors that influence plant growth or land suitability for any intended usage (Yost et al., 2020). Although most plant roots are in the upper one meter of soil, certain plants may reach depths of up to 18 m (Nepstad et al., 1994), which are important for soil water extraction, reducing nutrient loss, and soil carbon sequestration (Maeght et al., 2013). Deeper soils supply more nutrients and

water for plants than shallower soils in general (Rajakaruna et al., 2019). Soil depth also affects soil processes, soil properties, and microbial communities (Goebes et al., 2019).

Coarse Fraction (CF) refers to fraction of the solid particle in soil with grain size larger than 2 mm. According to Donald (2007), Coarse Fraction is an important site factor to be considered due to its large occupation of space in soil with less contribution of porosity (water and/or air storage) and chemical reactivity (sorption and/or nutrient storage). As a result, coarse fraction limits the available soil volume to hold water and the capacity of a given volume of soil to retain nutrients.

Soil Type is a significant abiotic factor which would affect growth of the plants by changing the function of plant roots and soil borne microbes (Sripontan et al., 2014). According to Dan et al. (2017), the relative growth rate, the elongation rate, leaf production rate and the root to shoot ratio were impacted by soil type and water level.

Base Saturation Percentage (BSP) illustrates the proportion of the Cation-Exchange Capacity (CEC) occupied by the basic cations Calcium, Magnesium and Potassium and Sodium (Havlin, 2005). It is also considered as a dynamic soil feature influenced by climatic, geochemical, and environmental conditions (Osman, 2012). BSP plays an important role in soil taxonomic classification, soil fertility (Rawal et al., 2019) and was included as an indication of soil quality among numerous soil chemical properties (Soil Survey Staff, 2004). Increase in BSP could enhance the availability of Ca^{2+} , Mg^{2+} , and K^{+} for plants (Havlin, 2005). Conversely, low base saturation is an ordinary cause of nutrient deficiencies, soil acidification, alterations in soil biota, and general degradation of soil health (Ouimet et al., 1996). Suitable measurement and consideration of the BSP could prevent nutrient deficiencies in plants (Rawal et al., 2019).

The soil pH value is a measure of soil acidity or alkalinity, which ranges from 0 to 14. Neutral soils have pH a of 6.5-7.5, acid soils have a $\text{pH} \leq 6.5$ and basic soils have a $\text{pH} \geq 7.5$. Soil pH is described as a key variable due to its significant influences on soil biological, chemical, and physical properties and processes affecting plant growth as well as biomass yield (Minasny et al., 2016; Gentili et al., 2018). For instance, most micronutrients are more accessible to tree species in acid soils than in neutral-alkaline soils, promoting plant development (Lončarić et al., 2008). However, if the concentration is excessively high, some of these micronutrients have contribution to generating reactive oxygen species, causing substantial cellular damage (Morgan et al., 2013). Contrariwise, despite macronutrients is

increased in alkaline soils, the availability of phosphorus and micronutrient is decreased which could negatively affect plant growth (Gentili et al., 2018). Soils with high concentrations of available nutrients commonly have a pH of 6.0-7.0 (Williston and LaFayette, 1978).

3.2.3 Water Suitability Index

Soil Moisture Index (SMI) is defined as the percentage of actual (AET) to potential evapotranspiration (PET) at a site (Lexer et al., 2000). According to Steiner (1998), SMI could be utilized to determine the drought tolerance of a species because the higher the species demands, the higher its sensitivity to water deficit.

$$SMI = 1 - \left(\frac{AET}{PET} \right) \quad (11)$$

Gley (or gleyed) soils are soils developed under conditions of poor drainage, resulting in a typical grey/blue soil colouring and in reduction of iron and other elements. Two main types of gley soil were considered as environmental factors for this study including (1) Surface water gleys (Gley) where water saturating the soil comes from surface drainage and (2) Ground water gleys (GW) where saturation is due to fluctuating groundwater levels. Surface water gleys and ground water gleys could limit the root penetration of the tree in soil, which leads to poor nutrients absorption. Besides, these soils are aerated and therefore the respiration of the tree roots is reduced due to a limited access to oxygen. Consequently, the roots may die under such conditions or tolerate to a certain degree.

3.3 Model evaluation

3.3.1 Site and climate data

Climate data

Climate refers to temperature, humidity, daylight, and wind conditions of a specific region. Climate variables have a significant impact on all stages and processes of the plant growth.

Therefore, collecting and evaluating climate data could provide significant information for tree species selection, which reduces time, efforts and finance.

For evaluation of the Tree Species Suitability model, climate data was taken from a network of weather stations from the Central Institute of Meteorology and Geodynamic in Vienna (ZAMG). The climate data for all the necessary climate variables for the analyses were taken from the climate data records a 30-year period from 1989 to 2018. These variables include information of Growing Degree Days, Winter Frost, Length of Vegetation Period and Last Frost.

Site data

According to Leitgeb and Reiter (2009), beside of climatic conditions determined largely by precipitation and temperature, the physical and chemical soil conditions also play a critical role for tree species suitability. In this analysis of limiting factors of tree species, data on nutrient and water groups were collected from FORSITE project. FORSITE is a forestry project leaded by the Institute of Silviculture – University of Natural Resources and Life Sciences under the sponsorship of Office of the Styrian Provincial Government. The aim of the FORSITE project is to generate comprehensive data on geology, soil, water, heat, and nutrient balance of forest locations for the entire forest area in Styria, Austria.

Data were collected and analyzed in the soil laboratories of the Austrian Research Centre for Forests (BWF) regarding soil physical and chemical parameters. Additional analyzes of soil hydrological parameters were carried out to estimate water storage capacity of the soils.

3.3.2 Evaluation experiments

3.3.2.1 The maximum and minimum values of output variables in Tree Species Suitability model

The maximum and minimum values of Tree Species Suitability represent for the best and the worst scenarios of site condition for tree species. In Tree Species Suitability model, the range of output variables (Soil Adsorption Matrix, Temperature Suitability Index, Nutrient Suitability Index, Water Suitability Index and Tree Species Suitability Index) were designed from 0 to 1. Thus, the lowest value and highest value of these outputs were expected to be 0 and 1, respectively. If the actual maximum and minimum Suitability values that the model can produce are different from 0 and 1, then the model has inconsistent behavior. In this

section, an experiment was conducted to calculate the actual maximum and minimum Suitability values of the Tree Species Suitability model. Results were compared with the maximum and minimum values of initial design. From that, sources of inconsistency and model behavior were described.

To define the maximum value which the model can produce, optimum values of environmental variables were selected to present the best site conditions for tree species. On the contrary, poorest values were utilized to calculate the minimum Tree Species Suitability Index. Detail about the input data could be found in Table 1.

Table 1: The environmental factors of European tree species in best and worst scenarios

| Scenario | Species | GDD | WF | LVP | LF | SD | CF | ST | BSP | pH | SMI | Gley | GW |
|-----------------|-----------------|------------|-----------|------------|-----------|-----------|-----------|-----------|------------|-----------|------------|-------------|-----------|
| Best | Picea abies | 800 | -20 | 250 | 100 | 100 | 5 | 3 | 50 | 5 | 0 | 0 | 0 |
| | Abies alba | 1900 | 2 | 250 | 100 | 100 | 5 | 3 | 50 | 5 | 0 | 0 | 0 |
| | Fagus sylvatica | 1900 | 2 | 250 | 100 | 100 | 5 | 3 | 50 | 5 | 0 | 0 | 0 |
| | Quercus robur | 1900 | 2 | 250 | 100 | 100 | 5 | 3 | 50 | 6 | 0 | 0 | 0 |
| Worst | Picea abies | 0 | -20 | 100 | 100 | 5 | 5 | 1 | 100 | 2.5 | 0 | 2 | 0 |
| | Abies alba | 0 | -20 | 100 | 100 | 5 | 5 | 1 | 100 | 2.5 | 0.4 | 0 | 0 |
| | Fagus sylvatica | 0 | -20 | 100 | 100 | 5 | 5 | 1 | 4 | 2.5 | 0 | 2 | 1 |
| | Quercus robur | 0 | -20 | 100 | 100 | 5 | 5 | 1 | 4 | 2.5 | 0.4 | 0 | 0 |

3.3.2.2 The effects of overlap of input fuzzy sets on Tree Species Suitability Index

The overlap of fuzzy sets is a characteristic of fuzzy logic model. Overlap denotes uncertainty in participation of members of one set to other set. It is fundamental that an element of a fuzzy set is also an element of some other fuzzy sets with some degree of membership. When the membership functions of a fuzzy controller have overlap, the system obtains a smooth and continuous control signal near the boundaries of the membership functions. However, it is necessary to understand how different overlap percentages of input fuzzy sets affects model results. For this purpose, an experiment was employed in the Nutrient Suitability model of *Picea abies*. The “Moderate” and “Good” fuzzy sets of Soil Adsorption Matrix variable (SAM) were selected for the analysis. Given A_1, A_2, A_3, A_4 and B_1, B_2, B_3, B_4 as parameters to define “Moderate” and “Good” fuzzy sets, respectively (see Figure 7).

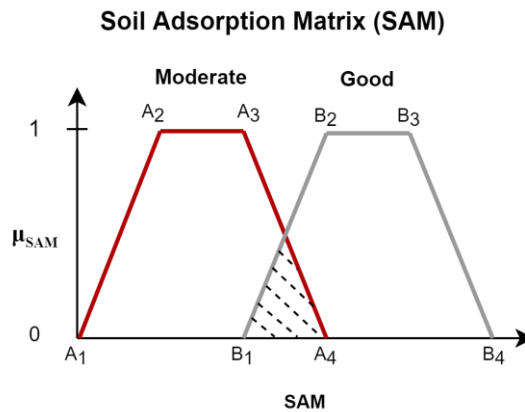


Figure 7: The overlap of input fuzzy sets in Soil Adsorption Matrix

The overlap percentage is calculated as follows:

$$OL (\%) = \frac{B_1A_4}{A_1B_4} \cdot 100 \quad (12)$$

Where B_1A_4 is length of overlapping area, A_1B_4 is total length of two fuzzy sets. The experiment was conducted in the following way: the overlap percentage (OL) was varied in

5 levels (10%, 20%, 30%, 40% and 50%) while keeping SAM constant at 0.45, 0.5 and 0.55 (middle and two border points of the overlapping area). BSP and pH were remained unchanged at optimum value (BSP = 60, pH = 2.5) to prevent their influence on Nutrient Suitability Index (NSI). The aggregation method of consequence part and defuzzification method were constant as initial design. This allowed analyzing how changing in OL could affect NSI. Data of membership functions for different OL were summarized in Table 2.

Table 2: The membership functions of Soil Adsorption Matrix at different overlap percentages

| OL (%) | B_1A_4 | A_1 | A_2 | A_3 | A_4 | B_1 | B_2 | B_3 | B_4 |
|--------|----------|-------|-------|-------|-------|-------|-------|-------|-------|
| 10 | 0.1 | 0 | 0.2 | 0.4 | 0.55 | 0.45 | 0.6 | 0.8 | 1 |
| 20 | 0.2 | 0 | 0.2 | 0.4 | 0.6 | 0.4 | 0.6 | 0.8 | 1 |
| 30 | 0.3 | 0 | 0.2 | 0.4 | 0.65 | 0.35 | 0.6 | 0.8 | 1 |
| 40 | 0.4 | 0 | 0.2 | 0.4 | 0.7 | 0.3 | 0.6 | 0.8 | 1 |
| 50 | 0.5 | 0 | 0.2 | 0.4 | 0.75 | 0.25 | 0.6 | 0.8 | 1 |

3.3.2.3 The effects of overlap of output fuzzy sets on Tree Species Suitability Index

Similar to input variables of the Tree Species Suitability model, the output variables were designed with overlapping areas between fuzzy sets. It is assumed that the overlap of output fuzzy sets leads to inconsistent result of Tree Species Suitability Index because the lower membership values of the overlapping area are ignored in aggregation step. This could lead to the case that different rule bases produce the same output value. To test this assumption, an experiment was employed with Nutrient Suitability models of *Picea abies* and *Abies alba*. Three overlapping output fuzzy sets were analyzed including “Moderate suitability”, “Good suitability” and “Very good suitability”. Data for input variables (SAM, BSP and pH) was selected to match the chosen output fuzzy sets. Given A_1 , A_2 , A_3 , A_4 ; B_1 , B_2 , B_3 , B_4 and C_1 , C_2 , C_3 , C_4 as parameters to define “Moderate suitability”, “Good suitability” and “Very good suitability” output fuzzy sets (see Figure 8).

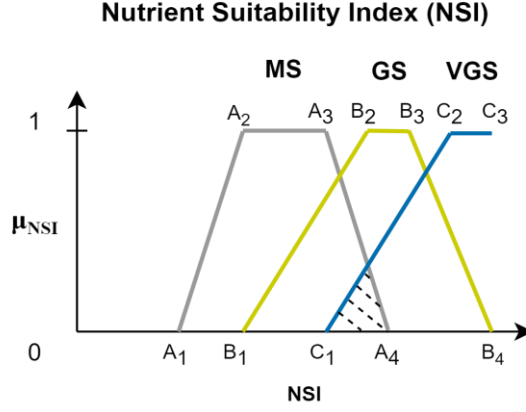


Figure 8: The overlap of fuzzy sets in Nutrient Suitability Index (MS: Moderate Suitability, GS: Good Suitability, VGS: Very Good Suitability)

The overlapping area between three fuzzy sets is calculated as follows:

$$OL (\%) = \frac{C_1A_4}{A_1B_4} \cdot 100 \quad (13)$$

Where C_1A_4 is length of overlapping area and A_1B_4 is total length of three fuzzy sets. The experiment was conducted as follows: the overlapping area were varied in 3 levels (0%, 20%, and 40%) while keeping all input variables constant (SAM = 0.831, BSP = 95, pH = 3.5). With these given inputs, *Picea abies* and *Abies alba* produced different rule bases. Thus, the output values (NSI) for two species were expected to be different. By comparing NSI of two species, the assumption would be explained. The membership functions of fuzzy sets were summarized in Table 3.

Table 3: Membership functions of analyzed fuzzy sets in different overlap percentages

| OL (%) | C_1A_4 | A_1 | A_2 | A_3 | A_4 | B_1 | B_2 | B_3 | B_4 | C_1 | C_2 | C_3 | C_4 |
|--------|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 0 | 0 | 0.25 | 0.4 | 0.6 | 0.7 | 0.4 | 0.7 | 0.8 | 1 | 0.7 | 0.9 | 1 | Inf |
| 20 | 0.15 | 0.25 | 0.4 | 0.6 | 0.775 | 0.4 | 0.7 | 0.8 | 1 | 0.625 | 0.9 | 1 | Inf |
| 40 | 0.3 | 0.25 | 0.4 | 0.6 | 0.85 | 0.4 | 0.7 | 0.8 | 1 | 0.55 | 0.9 | 1 | Inf |

3.3.2.4 The effects of aggregation method of output fuzzy sets on Tree Species Suitability Index

As described in section 3.1, output fuzzy sets of all single rule bases will be aggregated by Maximum operator into a final fuzzy set before defuzzification. This aggregation method was assumed to cause inconsistency behavior for Tree Species Suitability model because it only considers highest membership values in the overlapping area. As a result, the contribution of lower membership values is ignored, and the output will be inconsistent with the inputs. To test this hypothesis, an experiment was conducted with Nutrient Suitability models of *Picea abies* and *Abies alba*. The input variables were remained unchanged (SAM = 0.831, BSP = 95, pH = 3.5) while varying two aggregation methods (Maximum and Bounded sum). Defuzzification method was constant with Center of Gravity. According to Mizumoto et al. (1981), the Bounded sum of fuzzy set R1 and fuzzy set R2 is defined as:

$$\mu_{R1} \oplus \mu_{R2} = \min(\mu_{R1} + \mu_{R2}, 1) \quad (14)$$

Where μ_{R1} and μ_{R2} are the membership values of fuzzy sets R1 and R2, respectively. With given input variables, rule bases for *Picea abies* and *Abies alba* were different. Thus, it is expected that the Nutrient Suitability Index of these two species will be different. If two species have the same outcome, the model will be inconsistent, and the hypothesis will be proven.

3.3.2.5 The discontinuous response of the Tree Species Suitability model

The discontinuous response of Tree Species Suitability model is assumed to occur when two different input fuzzy sets of a variable produce the same output fuzzy set. It leads to the inconsistent behavior of the Tree Species Suitability model. To test this hypothesis, an experiment was employed with Soil Adsorption Matrix model. Soil Depth and Soil Type were remained unchanged at 100 cm and clay soils, respectively while varying Coarse Fraction (CF) from 10% to 20%. By this way, two different rules were processed as:

- Rule 80: *IF SD is very deep AND CF is very low AND ST is clay soils then SAM is very good.*

- Rule 85: *IF SD is very deep AND CF is low AND ST is clay soils then SAM is very good.*

Two input fuzzy sets of CF (Very low and Low) produced the same output fuzzy set (Very good). By analyzing the outcome of SAM, the hypothesis would be tested.

3.3.2.6 Species suitability response along gradients

The aim of this section is to analyze how Tree Species Suitability Index of European tree species responds along different gradients. 30 sample plots were selected for 10 different altitudes in Styria, Austria. The environmental variables were extracted for calculating Tree Species Suitability Index of four European tree species (see Table 4). Results of the Maximum and Gamma functions were compared to define a better method.

Table 4: Environmental factors of the sample plots in Styria

| Plot | Elevation (m) | GDD | WF | LVP | LF | SD | CF | ST | BSP | pH | SMI | GW | Gley |
|------|---------------|------|------|-----|-----|-----|------|-----|------|-----|-----|----|------|
| 1 | 1880 | 636 | -7.7 | 125 | 162 | 50 | 77.6 | 2.0 | 55.6 | 4.7 | 0.0 | 0 | 0 |
| 2 | 1880 | 636 | -7.7 | 125 | 162 | 50 | 78.0 | 2.0 | 5.0 | 3.5 | 0.2 | 0 | 0 |
| 3 | 1880 | 636 | -7.7 | 125 | 162 | 100 | 10.0 | 2.0 | 55.0 | 4.7 | 0.0 | 0 | 0 |
| 4 | 1750 | 753 | -7.3 | 142 | 151 | 80 | 65.3 | 4.0 | 4.8 | 3.8 | 0.0 | 0 | 0 |
| 5 | 1750 | 753 | -7.3 | 142 | 151 | 100 | 10.0 | 2.0 | 55.6 | 4.7 | 0.0 | 0 | 0 |
| 6 | 1750 | 753 | -7.3 | 142 | 151 | 80 | 65.0 | 4.0 | 4.8 | 3.7 | 0.2 | 0 | 0 |
| 7 | 1580 | 897 | -7.2 | 156 | 142 | 80 | 69.2 | 2.0 | 6.3 | 3.7 | 0.0 | 0 | 0 |
| 8 | 1580 | 897 | -7.2 | 156 | 142 | 100 | 10.0 | 2.0 | 55.6 | 4.7 | 0.0 | 0 | 0 |
| 9 | 1580 | 897 | -7.2 | 156 | 142 | 80 | 69.2 | 2.0 | 6.3 | 3.7 | 0.2 | 0 | 0 |
| 10 | 1402 | 1083 | -5.2 | 172 | 135 | 70 | 70.2 | 3.0 | 98.7 | 6.6 | 0.0 | 0 | 0 |
| 11 | 1402 | 1083 | -5.2 | 172 | 135 | 100 | 10.0 | 3.0 | 55.0 | 4.5 | 0.0 | 0 | 0 |
| 12 | 1402 | 1083 | -5.2 | 172 | 135 | 70 | 70.2 | 3.0 | 5.0 | 3.5 | 0.2 | 0 | 0 |
| 13 | 1165 | 1259 | -6.4 | 185 | 122 | 80 | 32.8 | 3.0 | 93.8 | 6.0 | 0.1 | 0 | 0 |
| 14 | 1165 | 1259 | -6.4 | 185 | 122 | 100 | 10.0 | 3.0 | 55.0 | 4.5 | 0.1 | 0 | 0 |
| 15 | 1165 | 1259 | -6.4 | 185 | 122 | 80 | 33.0 | 3.0 | 5.0 | 3.5 | 0.2 | 0 | 0 |
| 16 | 895 | 1460 | -5.9 | 193 | 123 | 80 | 27.5 | 3.0 | 12.0 | 3.9 | 0.0 | 0 | 0 |
| 17 | 895 | 1460 | -5.9 | 193 | 123 | 100 | 10.0 | 3.0 | 55.0 | 4.5 | 0.0 | 0 | 0 |
| 18 | 895 | 1460 | -5.9 | 193 | 123 | 80 | 27.5 | 3.0 | 12.0 | 3.9 | 0.2 | 0 | 0 |
| 19 | 880 | 1655 | -4.7 | 203 | 108 | 100 | 24.0 | 2.0 | 42.3 | 4.2 | 0.0 | 0 | 0 |
| 20 | 880 | 1655 | -4.7 | 203 | 108 | 50 | 60.0 | 2.0 | 5.0 | 3.5 | 0.0 | 0 | 0 |
| 21 | 880 | 1655 | -4.7 | 203 | 108 | 50 | 60.0 | 2.0 | 42.3 | 4.2 | 0.2 | 0 | 0 |
| 22 | 680 | 1886 | -5.8 | 217 | 115 | 80 | 25.7 | 2.0 | 38.8 | 4.2 | 0.1 | 0 | 0 |
| 23 | 680 | 1886 | -5.8 | 217 | 115 | 50 | 70.0 | 2.0 | 5.0 | 3.5 | 0.1 | 0 | 0 |
| 24 | 680 | 1886 | -5.8 | 217 | 115 | 50 | 70.0 | 2.0 | 38.8 | 4.2 | 0.2 | 0 | 0 |
| 25 | 520 | 2152 | -3.7 | 229 | 100 | 100 | 10.5 | 1.0 | 14.3 | 3.7 | 0.1 | 0 | 1 |
| 26 | 520 | 2152 | -3.7 | 229 | 100 | 100 | 10.5 | 1.0 | 55.0 | 4.5 | 0.1 | 0 | 1 |
| 27 | 520 | 2152 | -3.7 | 229 | 100 | 50 | 60.0 | 1.0 | 14.3 | 3.7 | 0.2 | 0 | 1 |
| 28 | 310 | 2351 | -4.0 | 238 | 102 | 100 | 0.0 | 4.0 | 89.0 | 5.2 | 0.1 | 0 | 1 |
| 29 | 310 | 2351 | -4.0 | 238 | 102 | 100 | 0.0 | 4.0 | 5.0 | 3.5 | 0.1 | 0 | 1 |
| 30 | 310 | 2351 | -4.0 | 238 | 102 | 50 | 50.0 | 4.0 | 89.0 | 5.2 | 0.2 | 0 | 1 |

4 Results

4.1 The Tree Species Suitability model

4.1.1 Membership functions and linguistic terms of the Tree Species Suitability model

Temperature

The linguistic terms and membership functions were defined for each of temperature's variables depended on expert knowledge, and available data from FORSITE project. The number of linguistic terms is corresponded to the number of membership functions. Growing Degree Days was described by five linguistic terms including Very low, Low, Moderate, High, and Very high in the range from 0 to 3000. Four linguistic terms particularly Very cold, Cold, Cool and Mild were selected to illustrate Winter Frost within interval $[-20, 0]$ C°. Similarly, Length of Vegetable Period were varied from 100 to 250 days with six linguistics terms (Very short, Short, Moderately short, Moderately long, Long, and Very long). Five terms were employed for Last Frost (Very early, Early, Moderately late, Late and Very late). The Temperature Suitability Index consisted of five terms namely Unsuitable, Low suitability, Moderate suitability, Good suitability, and Very good suitability, ranging from 0 to 1. The details about linguistic terms and membership functions of the temperature variables can be found in Table 5 and Figure 9.

Table 5: Membership functions and linguistic terms of the Temperature Suitability model

| | Variables | Linguistic Term | Lower limit a (0) | Lower support limit b (1) | Upper support limit c (1) | Upper limit d (0) |
|--------|-------------------------------------|------------------------|----------------------------------|--|--|----------------------------------|
| Input | Growing Degree Days | Very low | Inf | Inf | 200 | 500 |
| | | Low | 0 | 400 | 600 | 800 |
| | | Moderate | 500 | 800 | 1200 | 1800 |
| | | High | 800 | 1600 | 2000 | 2500 |
| | | Very high | 2000 | 2500 | 3000 | Inf |
| | Winter Frost | Very cold | Inf | -20 | -15 | -7 |
| | | Cold | -20 | -12 | -10 | -2 |
| | | Cool | -10 | -7 | -5 | 0 |
| | | Mild | -7 | -2 | 0 | Inf |
| | Length of Vegetation Period | Very short | Inf | 100 | 120 | 140 |
| | | Short | 100 | 130 | 150 | 170 |
| | | Moderately short | 120 | 160 | 170 | 200 |
| | | Moderately long | 140 | 180 | 190 | 220 |
| | | Long | 160 | 200 | 220 | 250 |
| | | Very long | 180 | 230 | 250 | Inf |
| | Last Frost | Very early | Inf | 100 | 110 | 140 |
| | | Early | 100 | 120 | 140 | 160 |
| | | Moderately late | 120 | 150 | 160 | 180 |
| | | Late | 140 | 170 | 180 | 200 |
| | | Very late | 160 | 190 | 200 | Inf |
| Output | Temperature Suitability Index | Unsuitable | Inf | 0 | 0.15 | 0.3 |
| | | Low suitability | 0 | 0.2 | 0.3 | 0.5 |
| | | Moderate suitability | 0.25 | 0.4 | 0.6 | 0.75 |
| | | Good suitability | 0.4 | 0.7 | 0.8 | 1 |
| | | Very good suitability | 0.6 | 0.9 | 1 | Inf |

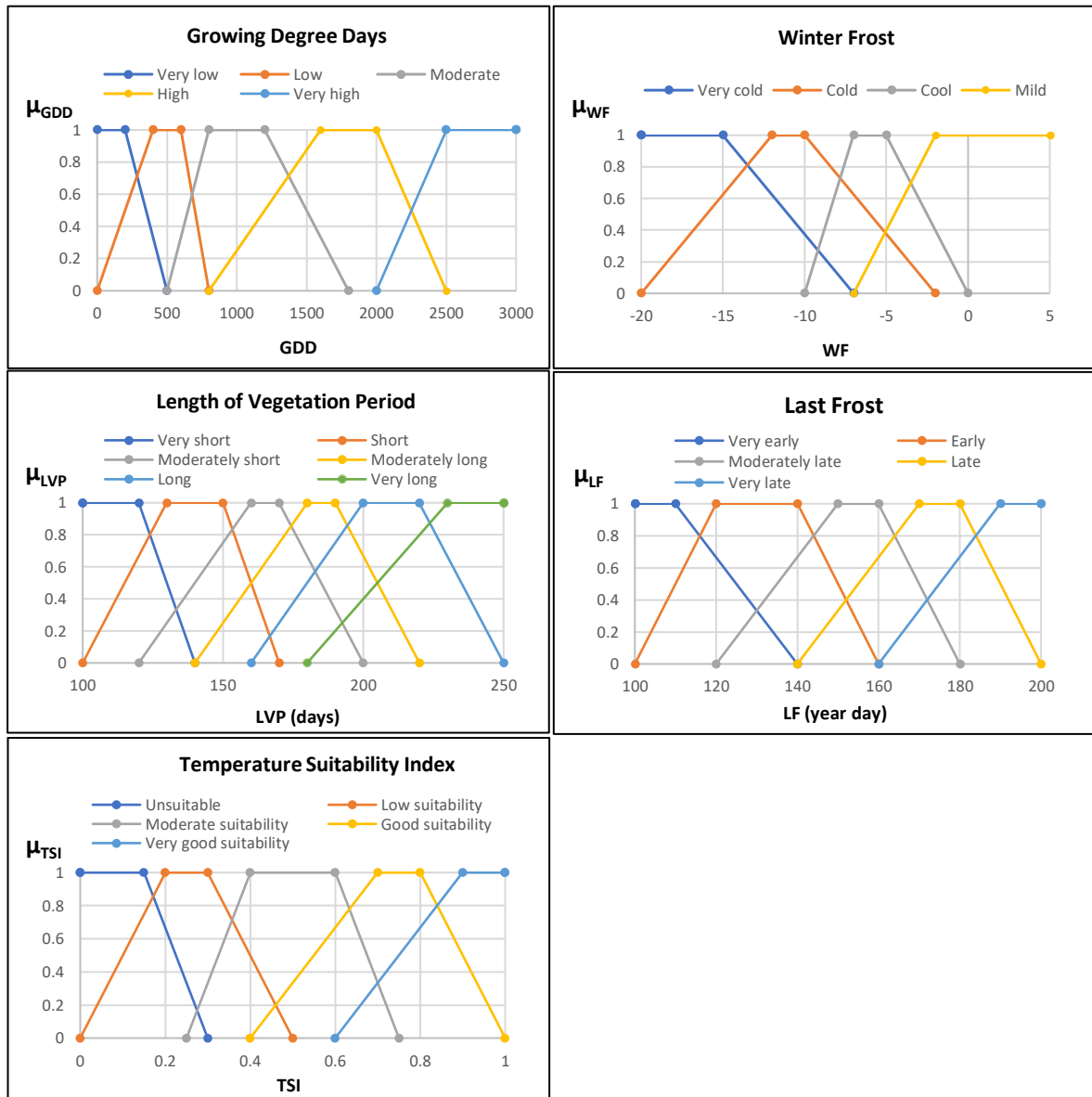


Figure 9: Membership functions of the Temperature Suitability model

Nutrients

The linguistic terms and parameters to build membership functions of the Soil Adsorption Matrix model are presented in Table 6, and Figure 10. Five linguistic terms namely Very shallow, Shallow, Moderately deep, Deep, and Very deep were defined for Soil Depth from 10 to 100 cm. Coarse Fraction contained five terms including Very low, Low, Moderately high, High and Very high, corresponding to the range of 0-100 %. Soil Type consisted of four terms (Sandy soils, Loamy sand, Loamy soils, Clay soils), and were defined as singleton

fuzzy sets. Soil Adsorption Matrix (SAM) was described by four terms (Low, Moderate, Good, Very good) in the range between 0 and 1.

Table 6: Membership functions and linguistic terms of the Soil Adsorption Matrix

| Variables | | Linguistic Term | Lower limit a (0) | Lower support limit b (1) | Upper support limit c (1) | Upper limit d (0) |
|-----------|------------------------|-----------------|-------------------------|------------------------------------|------------------------------------|-------------------------|
| Input | Soil Depth | Very shallow | Inf | Inf | 10 | 30 |
| | | Shallow | 15 | 20 | 30 | 50 |
| | | Moderately deep | 30 | 40 | 60 | 80 |
| | | Deep | 60 | 70 | 80 | 100 |
| | | Very deep | 80 | 90 | 100 | Inf |
| | Coarse Fraction | Very low | Inf | 0 | 10 | 30 |
| | | Low | 10 | 20 | 30 | 50 |
| | | Moderately high | 30 | 40 | 50 | 70 |
| | | High | 50 | 60 | 70 | 90 |
| | | Very high | 70 | 80 | 100 | Inf |
| | Soil Type | Sandy soils | 1 | 1 | 1 | 1 |
| | | Loamy sands | 2 | 2 | 2 | 2 |
| | | Loamy soils | 3 | 3 | 3 | 3 |
| | | Clay soils | 4 | 4 | 4 | 4 |
| Output | Soil Adsorption Matrix | Low | Inf | 0 | 0.1 | 0.5 |
| | | Moderate | 0 | 0.2 | 0.4 | 0.6 |
| | | Good | 0.4 | 0.6 | 0.8 | 1 |
| | | Very good | 0.5 | 0.9 | 1 | Inf |

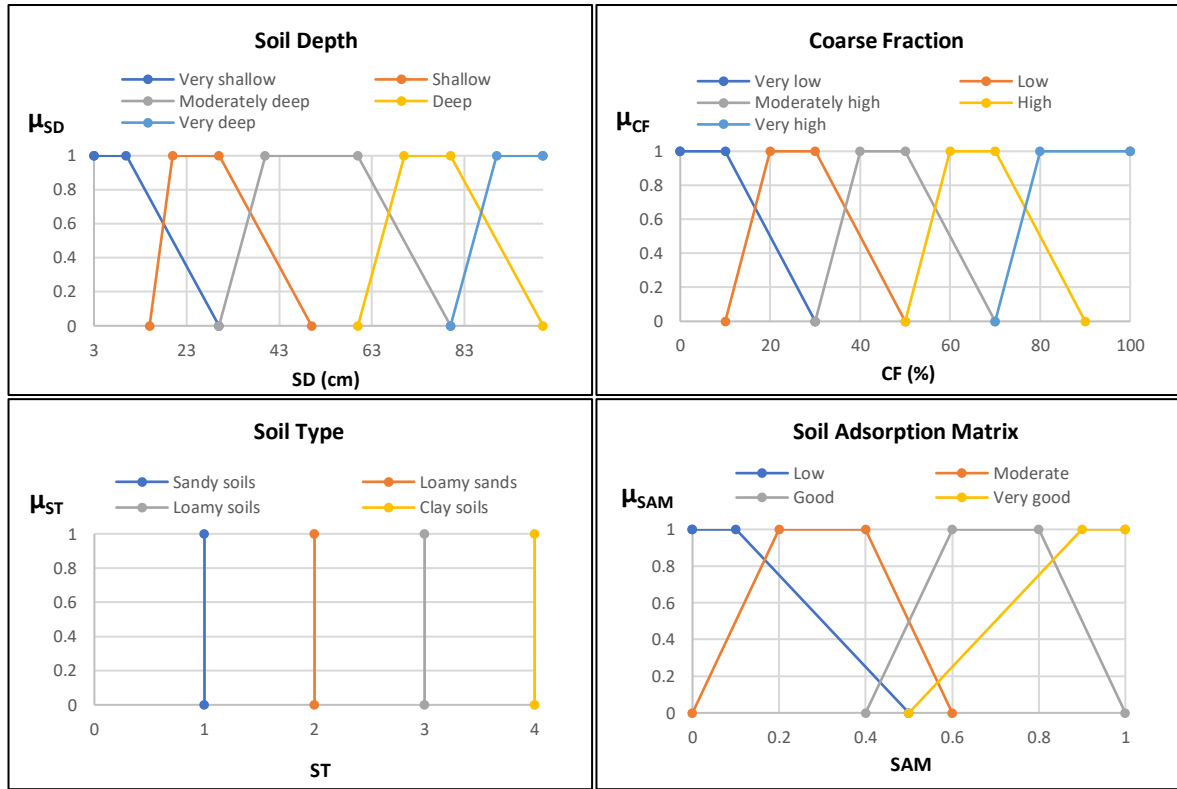


Figure 10: Membership functions of the Soil Adsorption Matrix

SAM was combined with Base Saturation Percentage (BSP) and pH in the Nutrient Suitability model. The linguistic terms and parameters to construct the model are summarized in Table 7 and Figure 11. BPS contains four terms including Low & unbalanced, Good supply, Moderately good supply, and Low supply. pH was described by four terms, namely Extremely acidic, Very acidic, Moderately acidic, Weak acidic/Weak alkaline, respectively. Finally, Nutrient Suitability Index was ranked from 0 to 1 with five terms (Unsuitable, Low suitability, Moderate suitability, Good suitability, Very good suitability).

Table 7: Membership functions and linguistic terms of the Nutrient Suitability model

| | Variables | Linguistic Term | Lower limit a (0) | Lower support limit b (1) | Upper support limit c (1) | Upper limit d (0) |
|--------|----------------------------|---------------------------|-------------------|---------------------------|---------------------------|-------------------|
| Input | Soil Adsorption Matrix | Low | Inf | 0 | 0.1 | 0.5 |
| | | Moderate | 0 | 0.2 | 0.4 | 0.6 |
| | | Good | 0.4 | 0.6 | 0.8 | 1 |
| | | Very good | 0.5 | 0.9 | 1 | Inf |
| | Base Saturation Percentage | Low & unbalanced | 80 | 90 | 100 | Inf |
| | | Good supply | 30 | 45 | 80 | 100 |
| | | Moderately good supply | 5 | 15 | 35 | 50 |
| | | Low supply | Inf | 0 | 5 | 15 |
| | pH | Extremely acidic | Inf | Inf | 3,0 | 3,5 |
| | | Very acidic | 3,0 | 3,5 | 4,0 | 4,5 |
| | | Moderately acidic | 3,5 | 4,5 | 5,0 | 5,5 |
| | | Weak acidic/weak alkaline | 5,0 | 6,0 | Inf | Inf |
| Output | Nutrient Suitability Index | Unsuitable | Inf | 0 | 0.15 | 0.3 |
| | | Low suitability | 0 | 0.2 | 0.3 | 0.5 |
| | | Moderate suitability | 0.25 | 0.4 | 0.6 | 0.75 |
| | | Good suitability | 0.4 | 0.7 | 0.8 | 1 |
| | | Very good suitability | 0.6 | 0.9 | 1 | Inf |

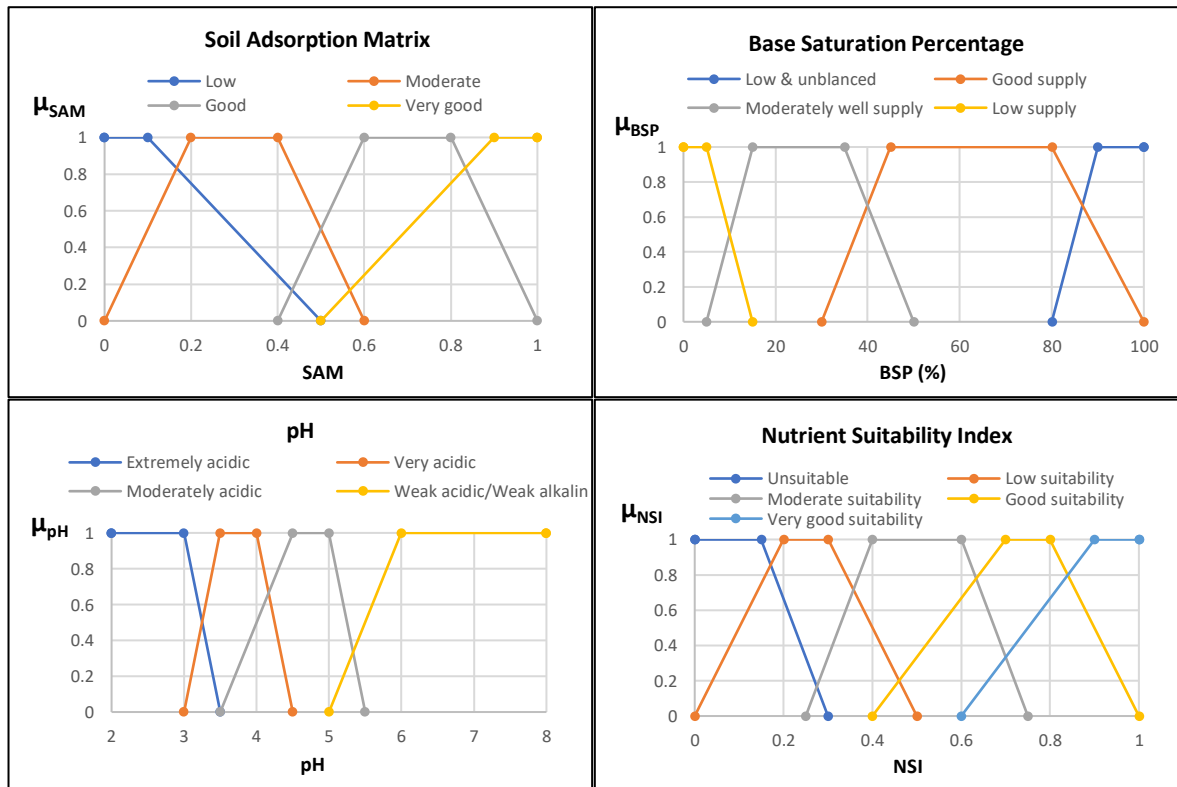


Figure 11: Membership functions of the Nutrient Suitability model

Water

The membership functions and linguistic terms of the Water Suitability model were presented in Table 8 and Figure 12. The crisp value's range of Soil Moisture Index was defined from 0 to 1 with four linguistic terms (Good water supply, Moderate water supply, Limited water supply and Very limited water supply). Gley was described by three terms including No gley, Weak gley soil and Strong gley soil. Similarly, three linguistic terms were developed for Ground water (GW) namely No ground water, Ground water weak and Ground water strong. Gley and GW were illustrated by singleton fuzzy sets. Eventually, the linguistic terms of the Water Suitability Index were Unsuitable, Low suitability, Moderate suitability, Good suitability, and Very good suitability, ranking from 0 to 1.

Table 8: Membership functions and linguistic terms of the Water Suitability model

| | Variables | Linguistic Term | Lower limit a (0) | Lower support limit b (1) | Upper support limit c (1) | Upper limit d (0) |
|--------|-------------------------------|---------------------------|-------------------------|------------------------------------|------------------------------------|-------------------------|
| Input | Soil Moisture Index | Good water supply | Inf | Inf | 0.05 | 0.15 |
| | | Moderate water supply | 0 | 0.1 | 0.15 | 0.2 |
| | | Limited water supply | 0.15 | 0.25 | 0.3 | 0.4 |
| | | Very limited water supply | 0.25 | 0.35 | Inf | Inf |
| | Gley | No gley | 1 | 1 | 1 | 1 |
| | | Weak gley soil | 2 | 2 | 2 | 2 |
| | | Strong gley soil | 3 | 3 | 3 | 3 |
| | Ground Water | No ground water | 1 | 1 | 1 | 1 |
| | | Ground water weak | 2 | 2 | 2 | 2 |
| | | Ground water strong | 3 | 3 | 3 | 3 |
| Output | Water Suitability Index | Unsuitable | Inf | 0 | 0.15 | 0.3 |
| | | Low suitability | 0 | 0.2 | 0.3 | 0.5 |
| | | Moderate suitability | 0.25 | 0.4 | 0.6 | 0.75 |
| | | Good suitability | 0.4 | 0.7 | 0.8 | 1 |
| | | Very good suitability | 0.6 | 0.9 | 1 | Inf |

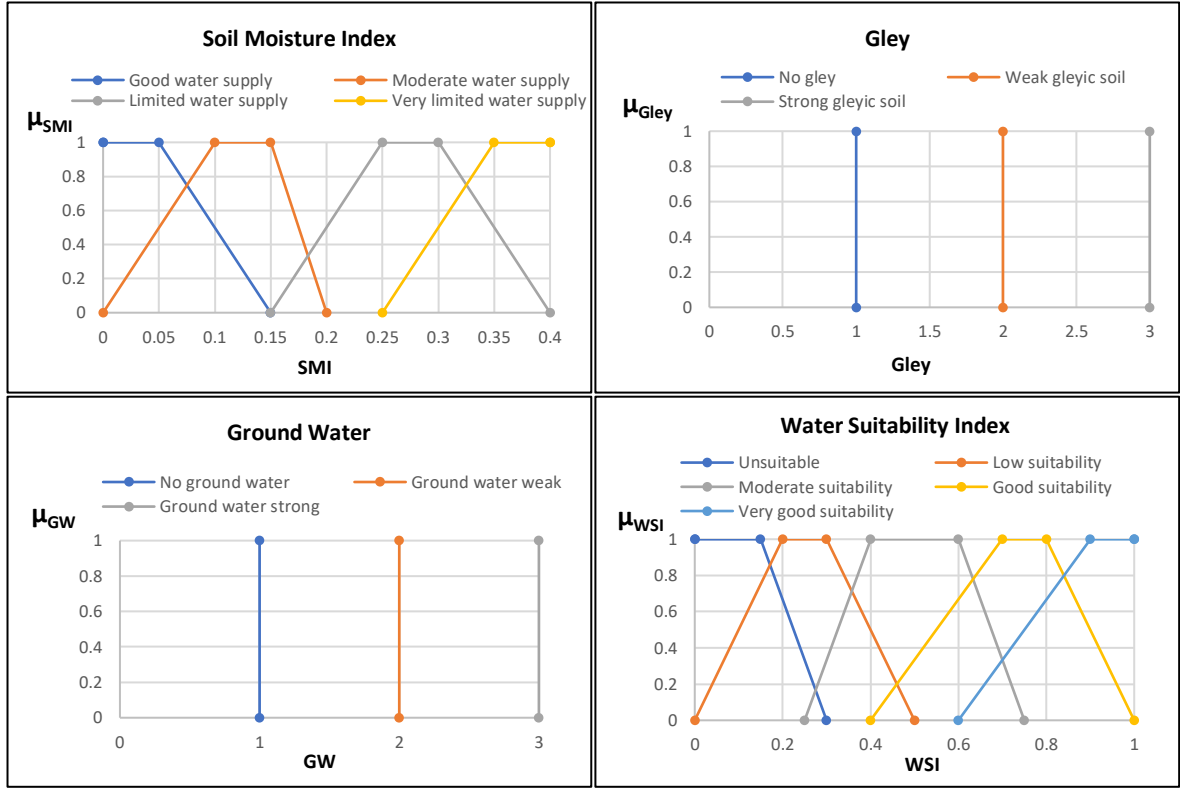


Figure 12: Membership functions of the Water Suitability model

4.1.2 Rules of the Tree Species Suitability model

For the construction of the Tree Species Suitability model, total 800 rules were developed for each tree species on the basic of available datasets and expert knowledges. In this model, the number of rules depend on the number of input variables and membership functions (MFs). If the number of MFs for each input variable is k and the number of input variables is n , then the total rule of the model is defined as:

$$R(\text{rule}) = k(x_1)k(x_2)\dots k(x_n) \quad (15)$$

Therefore, since the Temperature Suitability model consisted of 4 input variables in which each variable contained from 4 to 6 MFs, the implemented rules for this model equal 600 ($5 \times 4 \times 6 \times 5$). The number of MFs for Temperature Suitability Index (output variable) was 5. It should be noticed that if the input variable has more MFs than output variable, then two different rules can produce the same output fuzzy set. Thus, two different fuzzy sets of

Length of Vegetation Period can produce the same fuzzy set of Temperature Suitability Index. An example rule of the Temperature Suitability model is:

- If GDD is Very low AND WF is Very cold AND LVP is Very short AND LF is Very early then SUI is Unsuitable.

The Soil Adsorption Matrix (SAM) model consisted of three input variables in which Soil Depth and Soil Type contained 5 MFs, and Coarse Fraction had 4 MFs. SAM (output variable) was constructed with 4 MFs. Thus, 100 rules (5x5x4) were produced for the SAM model. Nutrient Suitability model had 3 input variables in which each variable included 4 MFs. The Nutrient Suitability Index (output variable) contained 4 MFs. As a result, 64 rules (4x4x4) were employed for this model. Examples of rules for Soil Adsorption Matrix and Nutrient Suitability models are given below:

- If SD is Very shallow AND CF is Very low AND ST is Sandy soils then SAM is Low.

- If SAM is Very good AND BSP is Moderately good supply AND pH is Moderately acidic then SUI is Very good.

Water Suitability model consisted of 4 MFs in Soil Moisture Index, 3 MFs in Ground Water and 3 MFs in Gley. The Water Suitability Index (output variable) contained 4 MFs. Therefore, 36 rules (4x3x3) were developed. An example of rule for this model is presented below:

- If SMI is Good water supply AND GW is No ground water AND Gley is No gley then SUI is Very good suitability.

The entire rules of the Tree Species Suitability model were detailed in annex.

4.2 Model evaluation

4.2.1 The maximum and minimum values of output variables in Tree Species Suitability model

Table 9 illustrates the minimum and maximum values of four output variables including Temperature Suitability Index (TSI), Soil Adsorption Matrix (SAM), Nutrient Suitability Index (NSI) and Water Suitability Index (WSI). Results shows that the highest and lowest results of SAM were 0.831 and 0.169, respectively. Maximum and minimum values of TSI were even for four European tree species (0.863 and 0.114). The minimum NSI of *Picea*

abies was higher comparing to other species (0.25 vs 0.119) while the maximum value was even (0.863). The minimum WSI of *Quercus robur* was larger than that of remained species (0.25 vs 0.114). There was no difference in maximum WSI among species.

Table 9: The minimum and maximum values of output variables in Tree Species Suitability model

| Value | Species | SAM | TSI | NSI | WSI |
|-------|------------------------|-------|-------|-------|-------|
| Max | <i>Picea abies</i> | 0.831 | 0.863 | 0.863 | 0.863 |
| | <i>Abies alba</i> | 0.831 | 0.863 | 0.863 | 0.863 |
| | <i>Fagus sylvatica</i> | 0.831 | 0.863 | 0.863 | 0.863 |
| | <i>Quercus robur</i> | 0.831 | 0.863 | 0.863 | 0.863 |
| Min | <i>Picea abies</i> | 0.169 | 0.114 | 0.25 | 0.114 |
| | <i>Abies alba</i> | 0.169 | 0.114 | 0.119 | 0.114 |
| | <i>Fagus sylvatica</i> | 0.169 | 0.114 | 0.119 | 0.114 |
| | <i>Quercus robur</i> | 0.169 | 0.114 | 0.119 | 0.25 |

The minimum NSI of *Picea abies* and the minimum WSI of *Quercus robur* were higher than results of other species due to the difference in rule base. In the “worst” scenario, *Picea abies* produced “Low suitability” fuzzy set while *Abies alba*, *Fagus sylvatica* and *Quercus robur* had “Unsuitable suitability” fuzzy set. Similarly, the poorest fuzzy set for *Quercus robur* was “Low suitability”, which is slightly higher than “Unsuitable suitability” fuzzy set of other species.

All Mamdani fuzzy controls of the Tree Species Suitability model could not produce optimum output values (0 and 1) as initial design. The reason for this problem was Center of Gravity (COG) defuzzification method (see Figure 13). The COG method calculated a crisp value corresponding to a center point of the output fuzzy set. Consequently, the actual maximum Suitability Index was always lower than the desired maximum value of the fuzzy set (underestimated). By contrast, the actual minimum Suitability Index was higher than the desired minimum value of the fuzzy set (overestimated).

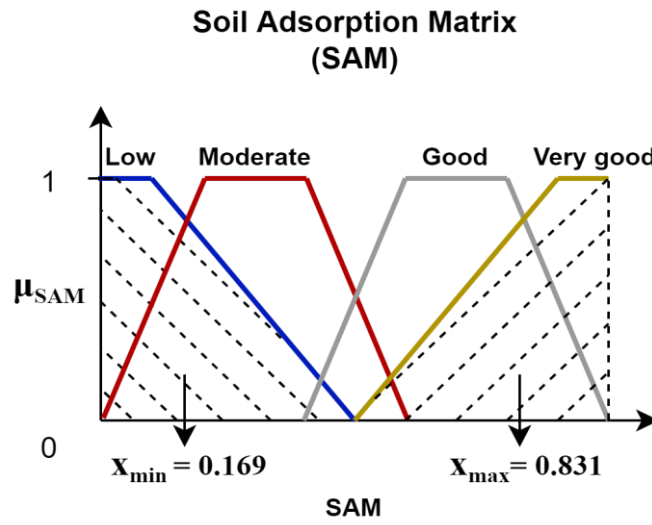


Figure 13: Effect of Center of Gravity defuzzification method on output value

The minimum NSI of all species were higher than minimum TSI and minimum WSI. The reason for this difference was illustrated in Figure 14 with result of minimum NSI for *Abies alba*.

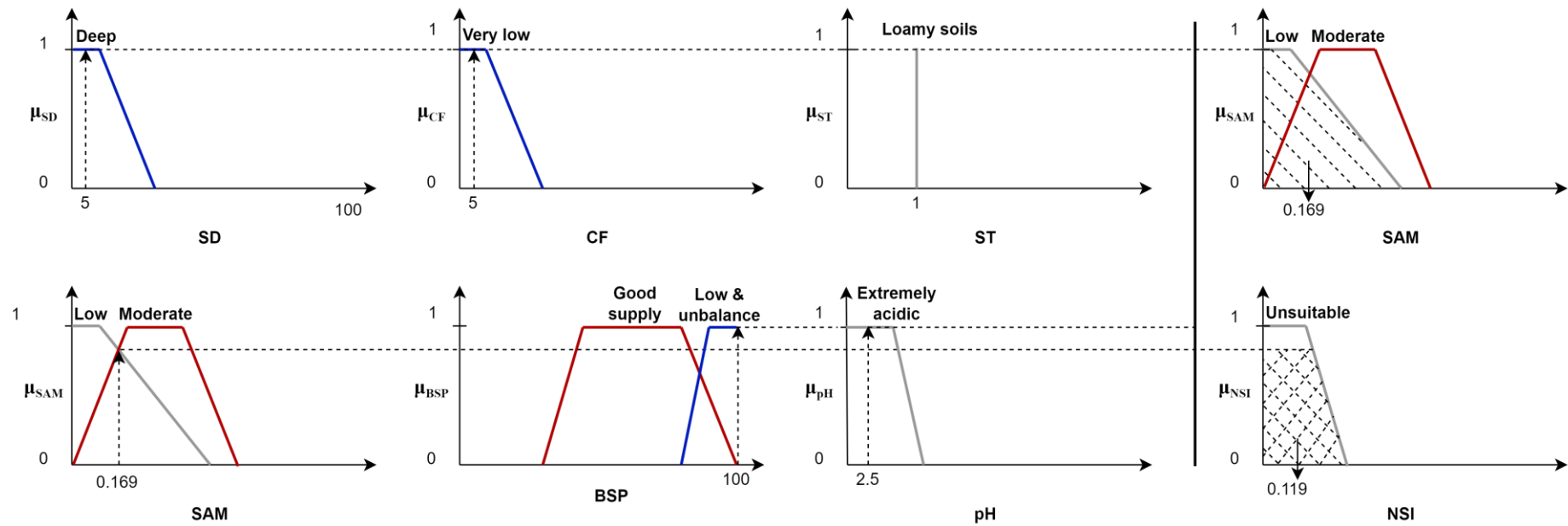


Figure 14: The impact of Center of Gravity defuzzification method on Nutrient Suitability model

With given input data, the model produced following rule bases:

- (1) If *SD is very shallow* AND *CF is very low* AND *ST is sandy soils* then *SAM is low* (Rule 1 of SAM model).
- (2) If *SAM is low* AND *BSP is low & unbalanced* AND *pH is extremely acidic* then *NSI is unsuitable* (Rule 1 of NSI model).
- (3) If *SAM is moderate* AND *BSP is low & unbalanced* AND *pH is extremely acidic* then *NSI is unsuitable* (Rule 17 of NSI model).

It is conspicuous that the Soil Adsorption Matrix model only produced a “Low” output fuzzy set, which resulted in SAM of 0.169. However, when the same value of SAM was utilized as an input for Nutrient Suitability model, it was belonged to two input fuzzy sets (Low and Moderate). This difference was consequence of the Center of Gravity defuzzification method. COG tended to find a line which divides the aggregated fuzzy set into two equal masses. Therefore, SAM could not reach extreme value (0) of the output range even with the “worst” site condition. The overestimate of SAM led to its additional input fuzzy set in Nutrient Suitability model (Moderate), resulting in two “Unsuitable” output fuzzy sets (two sets were overlapped in black checkered area). Consequently, NSI was overestimated (0.119).

The type of membership function is an important factor which affects the crisp value. Different shape of fuzzy sets led to the difference in maximum and minimum values of SAM comparing to TSI, NSI and WSI. The maximum and minimum values of 1 and 0 can only be obtained if the output fuzzy set is singleton.

4.2.2 The effects of overlap of input fuzzy sets on Tree Species Suitability Index

The results of Nutrient Suitability Index (NSI) at different overlap percentages (OL) are illustrated in Table 10 and Figure 15. As OL increased, NSI increased gradually from 0.462 to 0.568 at Soil Adsorption Matrix (SAM) of 0.45. Contrariwise, decrease trends of NSI were occurred at SAM of 0.5 and 0.55 (from 0.621 to 0.616 and from 0.69 to 0.637, correspondingly).

Table 10: Nutrient Suitability Index of *Picea abies* at different overlap percentages of input fuzzy sets

| SAM | OL (%) | NSI |
|------|--------|-------|
| 0.45 | 10 | 0.462 |
| | 20 | 0.527 |
| | 30 | 0.550 |
| | 40 | 0.561 |
| | 50 | 0.568 |
| 0.5 | 10 | 0.621 |
| | 20 | 0.619 |
| | 30 | 0.618 |
| | 40 | 0.617 |
| | 50 | 0.616 |
| 0.55 | 10 | 0.690 |
| | 20 | 0.673 |
| | 30 | 0.653 |
| | 40 | 0.643 |
| | 50 | 0.637 |

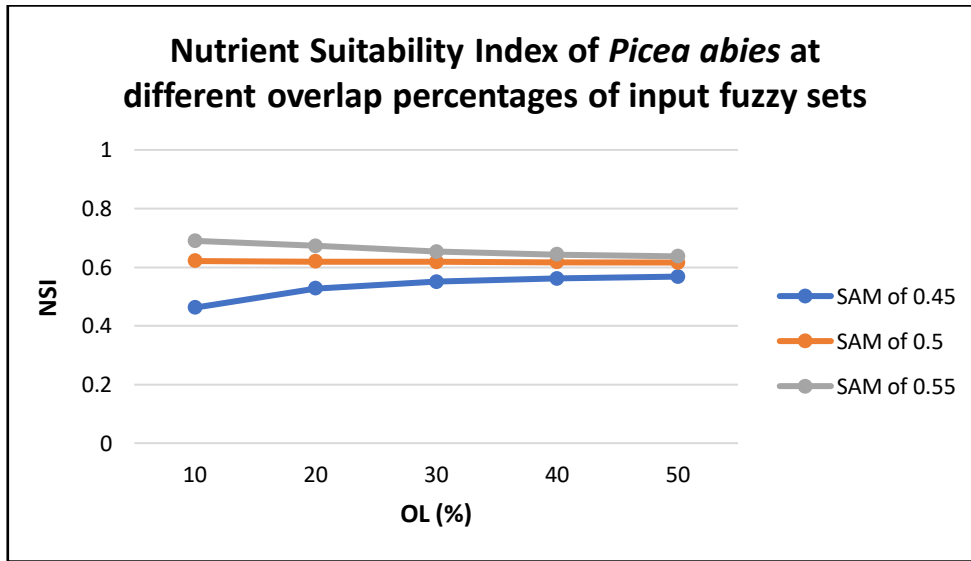


Figure 15: Nutrient Suitability Index of *Picea abies* at different overlap percentages of input fuzzy sets

It is obvious that the increment of OL increased membership function value of SAM (μ_{SAM}) in both “Moderate” and “Good” fuzzy sets (see Figure 16). This led to the rise in output fuzzy sets of NSI. However, since the rise of output fuzzy set both increased and decreased NSI (increased at SAM of 0.45 while decreased at SAM of 0.5 and 0.55), it is necessary to evaluate other factors which affect the final output value.

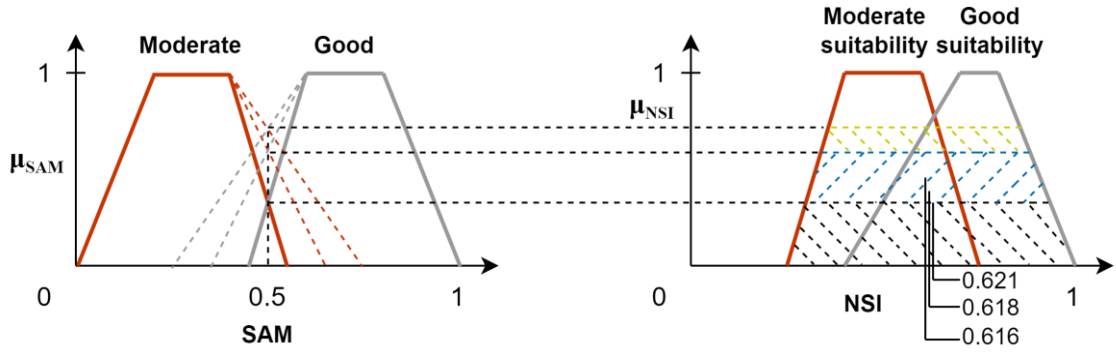


Figure 16: Nutrient Suitability Index of *Picea abies* at different overlap percentages (OL = 10%, 30%, 50%; SAM = 0.5). OL at 20% and 40% were ignored for better visualization

The shape of the output fuzzy set affected NSI (see Figure 16). In this case, “Moderate suitability” and “Good suitability” output fuzzy sets had different shape. Since defuzzification value always stays in the line that divides aggregated output fuzzy set into two equal masses, it will behave depending on the shape of the fuzzy set. Thus, as OL increased, NSI can either increased or decreased or stable. The stable case will occur if “Moderate suitability” and “Good suitability” output fuzzy sets are symmetric, and their membership values are equal.

The position of input value in overlapping area also affected NSI (see Figure 17). Three different input values of SAM (0.45, 0.5, 0.55) led to three different aggregated output fuzzy sets. As OL increased, NSI behaved differently for each case.

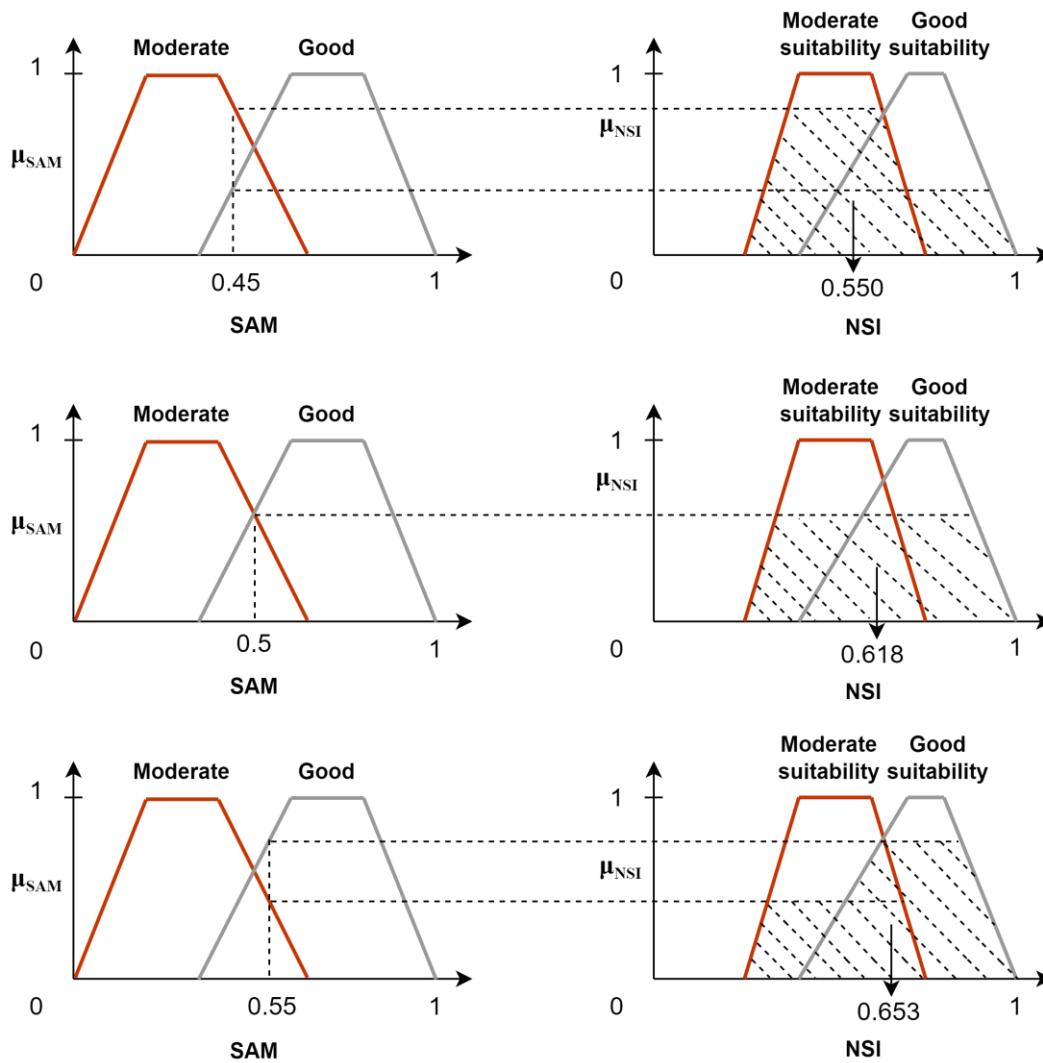


Figure 17: Nutrient Suitability Index of different Soil Adsorption Matrix at 30% of overlap

4.2.3 The effects of overlap of the output fuzzy sets to Tree Species Suitability Index

The Nutrient Suitability Index (NSI) of *Picea abies* and *Abies alba* at different overlap percentages (OL) of output fuzzy sets were presented in Table 11. Two species had even NSI at 20% and 40% OL while the difference occurred at 0% OL.

Table 11: Nutrient Suitability Index of *Picea abies* and *Abies alba* at different overlap percentages

| OL (%) | NSI | |
|--------|--------------------|-------------------|
| | <i>Picea abies</i> | <i>Abies alba</i> |
| 0 | 0.562 | 0.558 |
| 20 | 0.568 | 0.568 |
| 40 | 0.575 | 0.575 |

For given input data, four rules were processed including rule 34, rule 46, rule 50 and rule 62 (Annex). The output fuzzy set for each rule and their aggregation could be observed through an example of 20% OL (see Figure 18).

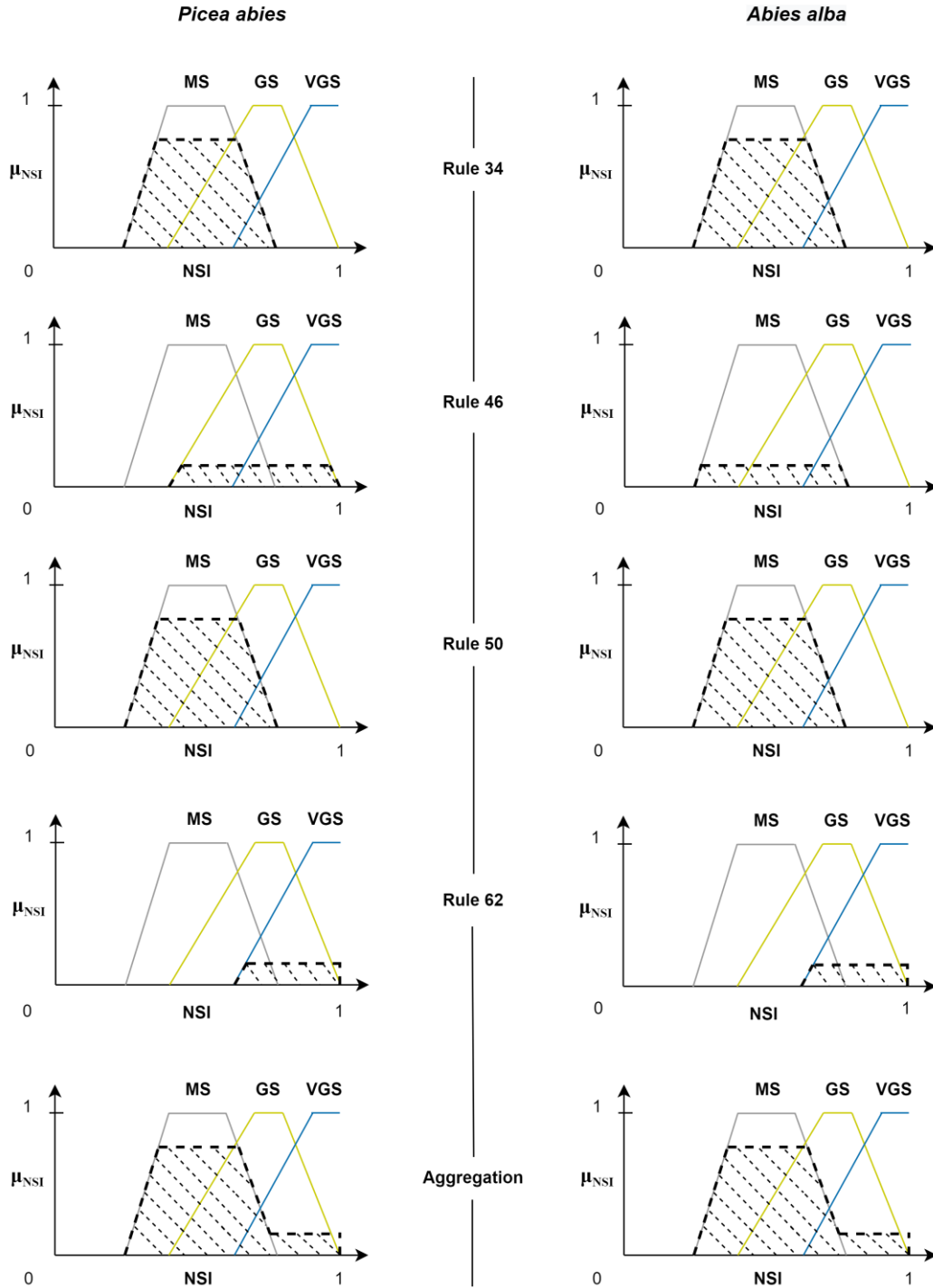


Figure 18: Output fuzzy sets of *Picea abies* and *Abies alba* at 20% overlap

In this case, two species had the same output fuzzy sets for rule 34, rule 50 and rule 62. The difference occurred in rule 46. *Picea abies* had “Good suitability” set while result for *Abies*

alba was “Moderate suitability” set. In spite of this difference, the final aggregated output fuzzy sets of two species was even. The reason for this phenomenon was the overlap between three output fuzzy sets, in which the “Good suitability” set was occupied by “Moderate suitability” set and “Very good suitability” set. Consequently, a half fuzzy area of “Good suitability” set of *Picea abies* in rule 46 was overlapped by “Moderate suitability” sets in rule 34 and rule 50 while the other half was overlap by “Very good suitability” set of rule 62. Similarly, the “Moderate suitability” set of *Abies alba* in rule 46 was overlapped by “Moderate suitability” sets in rule 34 and rule 50. Since the model used Maximum aggregation method, the fuzzy sets of two species in rule 46 were removed, resulting in the same final aggregated fuzzy sets.

The effect of overlap in output fuzzy sets on NSI could be further explained through Figure 19. As a consequence of overlap, *Picea abies* and *Abies alba* also had the same NSI at 40% OL. Conversely, without overlap (0% OL), two species had difference in the red area of the “Good suitability” set, resulting in different NSI.

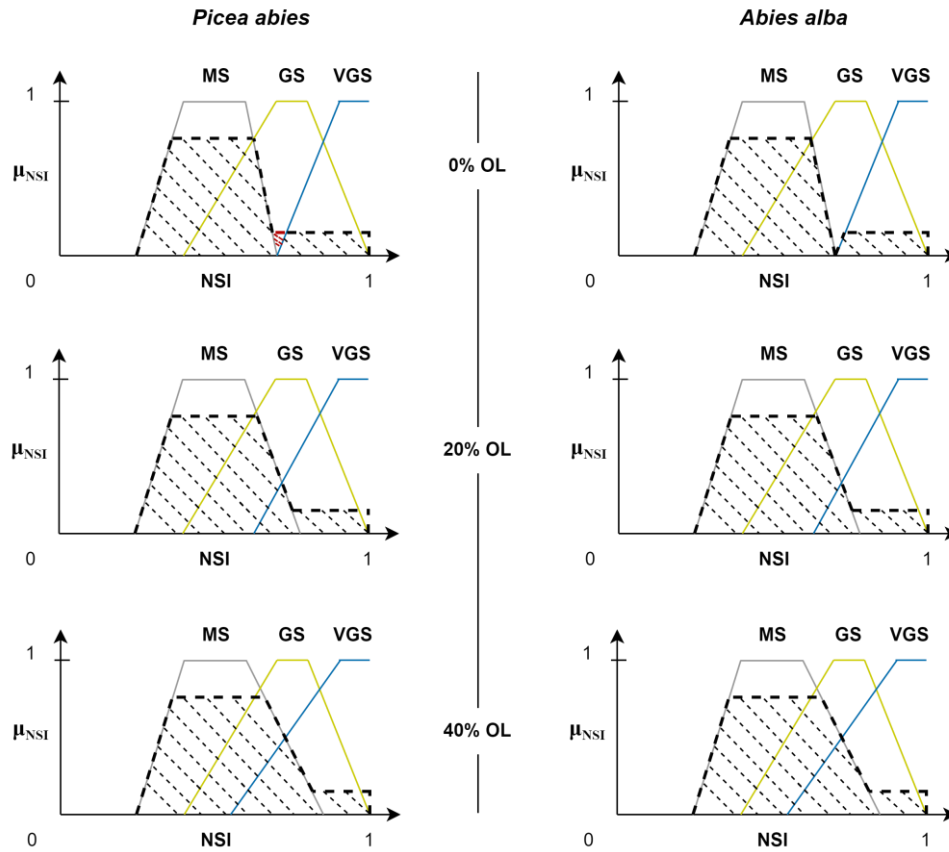


Figure 19: Aggregated output fuzzy set of *Picea abies* and *Abies alba* at different overlap percentages

4.2.4 The effects of aggregation method of output fuzzy sets on the Tree Species Suitability Index

As shown in Table 12, the Nutrient Suitability Index of *Picea abies* and *Abies alba* were even (0.566) with the Maximum aggregation method. There was a difference in the results of two species with Bounded sum approach, in which the NSI of *Picea abies* was slightly higher than that of *Abies alba* (0.567 and 0.535).

Table 12: The Nutrient Suitability Index of *Picea abies* and *Abies alba* in different aggregation methods

| Aggregation method | NSI | |
|--------------------|--------------------|-------------------|
| | <i>Picea abies</i> | <i>Abies alba</i> |
| Maximum | 0.566 | 0.566 |
| Bounded sum | 0.567 | 0.535 |

The performance of Nutrient Suitability model with Maximum aggregation method is presented in Figure 20. Four rules were processed, including rule 34, rule 46, rule 50 and rule 62 (see annex). Two species had the same output fuzzy sets in rule 34, rule 50 and rule 62. The difference occurred in rule 46, in which *Picea abies* had “Good suitability” set and *Abies alba* had “Moderate suitability” set. However, fuzzy set of rule 46 in both species were overlapped by fuzzy set of other rules. Since Maximum aggregation method only considers highest value, all membership values in rule 46 was ignored in both species. This led to the equal NSI for *Picea abies* and *Abies alba*.

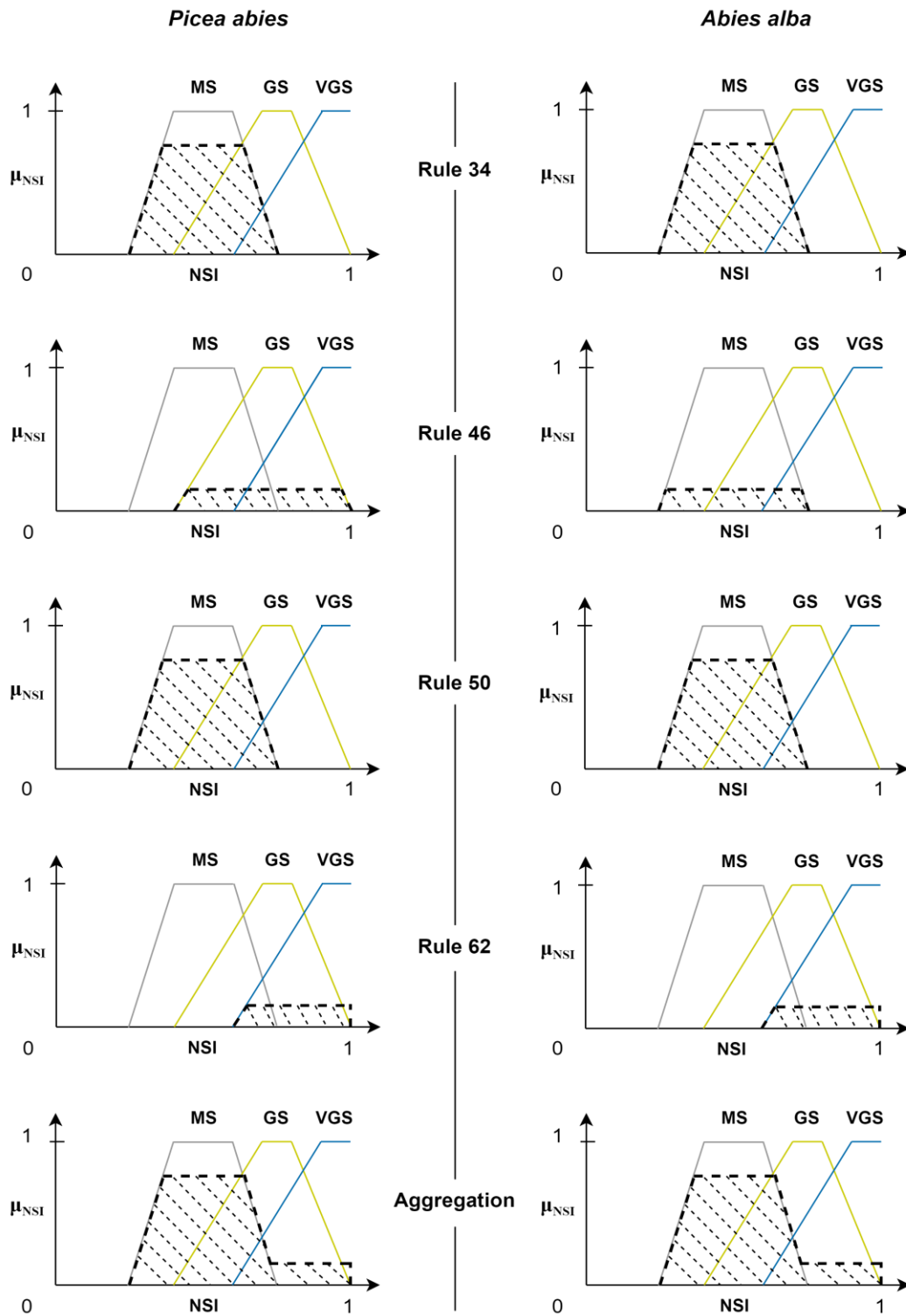


Figure 20: The performance of Maximum aggregation method

Figure 21 illustrated the performance of Nutrient Suitability model with Bounded sum aggregation method. As discussed above, the difference of *Picea abies* and *Abies alba* occurred in rule 46. However, as Bounded sum calculates the sum of membership values, it

considers the contribution of lower values in the overlapping area. This led to the difference in final aggregated fuzzy sets between two species. As a result, NSI of *Picea abies* and *Abies alba* were different.

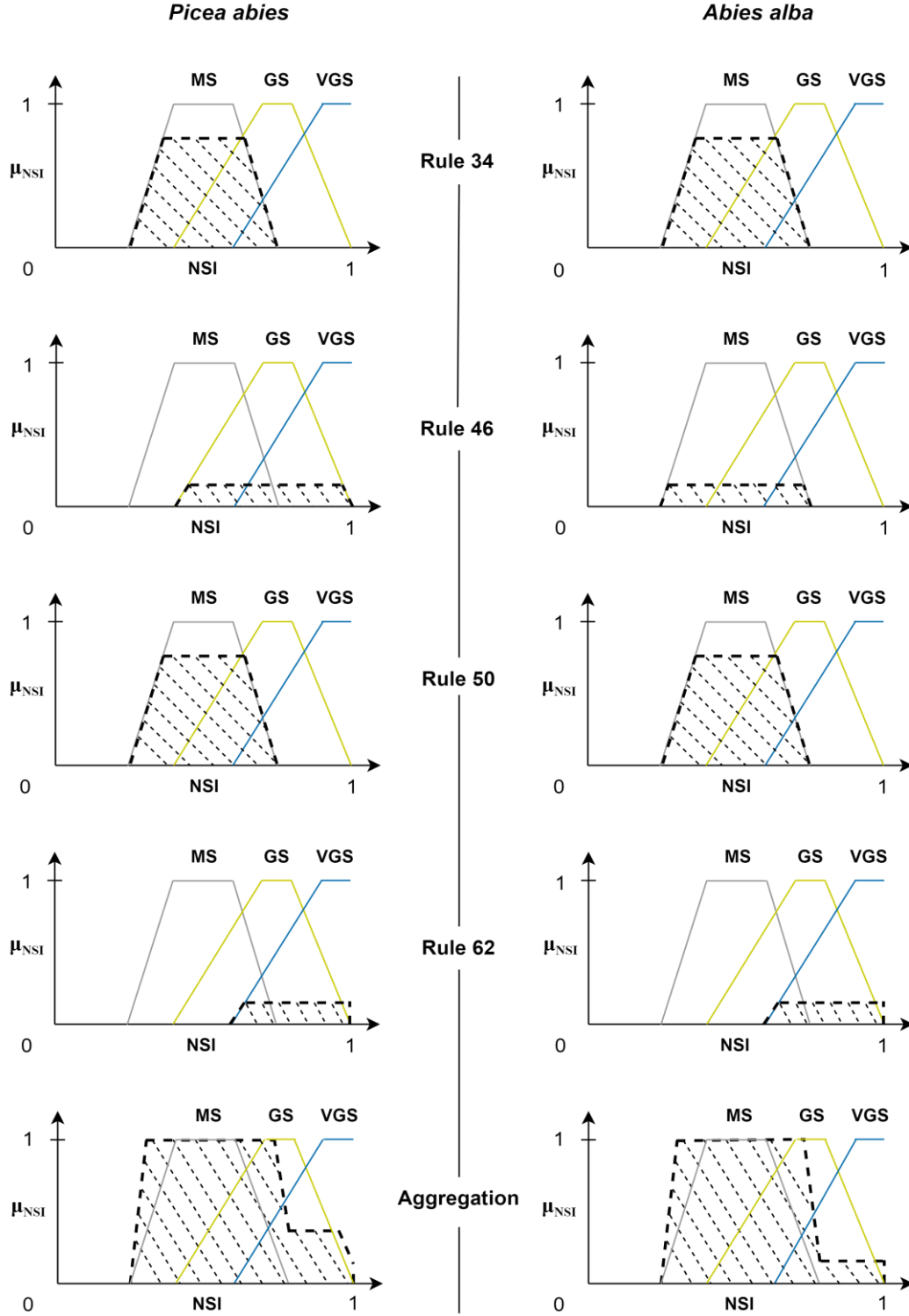


Figure 21: The performance of Bounded sum method

4.2.5 The discontinuous response of Tree Species Suitability model

The results of Soil Adsorption Matrix (SAM) are presented in Table 13 and Figure 22. SAM got the maximum value (0.831) at Coarse Fraction (CF) of 10%. The output values decreased gradually from CF of 11% to 16% and started to increase again until it reached optimum result at CF of 20%. This is an obvious discontinuous response of the model because SAM is expected to decrease following the increment of CF.

Table 13: Soil Adsorption Matrix at different Coarse Fractions

| No. | CF (%) | SAM |
|-----|--------|-------|
| 1 | 10 | 0.831 |
| 2 | 11 | 0.828 |
| 3 | 12 | 0.826 |
| 4 | 13 | 0.823 |
| 5 | 14 | 0.820 |
| 6 | 15 | 0.817 |
| 7 | 16 | 0.814 |
| 8 | 17 | 0.815 |
| 9 | 18 | 0.820 |
| 10 | 19 | 0.826 |
| 11 | 20 | 0.831 |

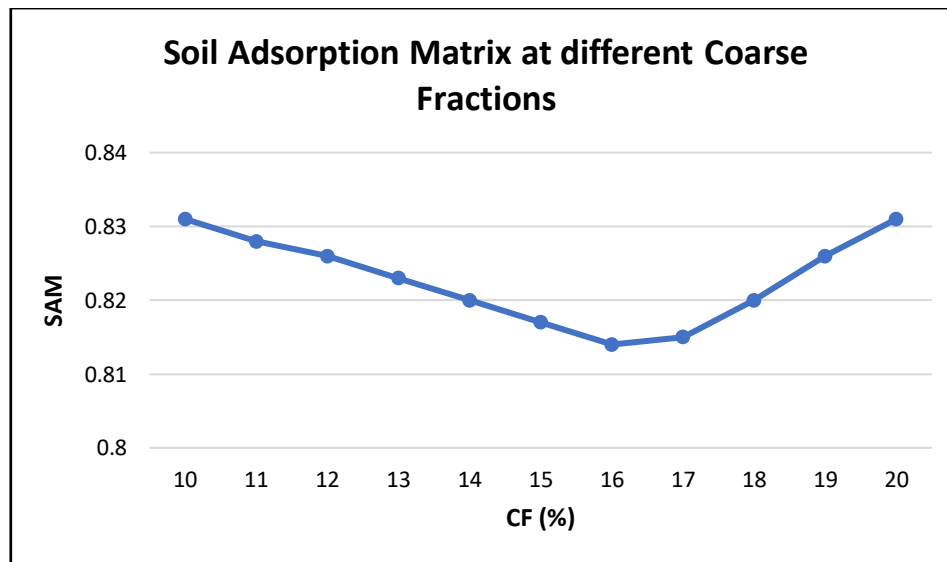


Figure 22: Soil Adsorption Matrix at different Coarse Fractions

The reason for this discontinuous response could be observed through Figure 23. At 12% CF, the model produced two “Very good” output fuzzy sets, which were overlapped (black checkered area). Similarly, at 19% CF, two “Very good” output fuzzy sets were processed

and overlapped. As discussed in section 4.2.4, the Maximum aggregation method removes the lower values in the overlapping area. This led to the equal aggregated fuzzy set of SAM at 12% CF and 19% CF regardless their different CF values. Therefore, the discontinuous response of SAM was occurred.

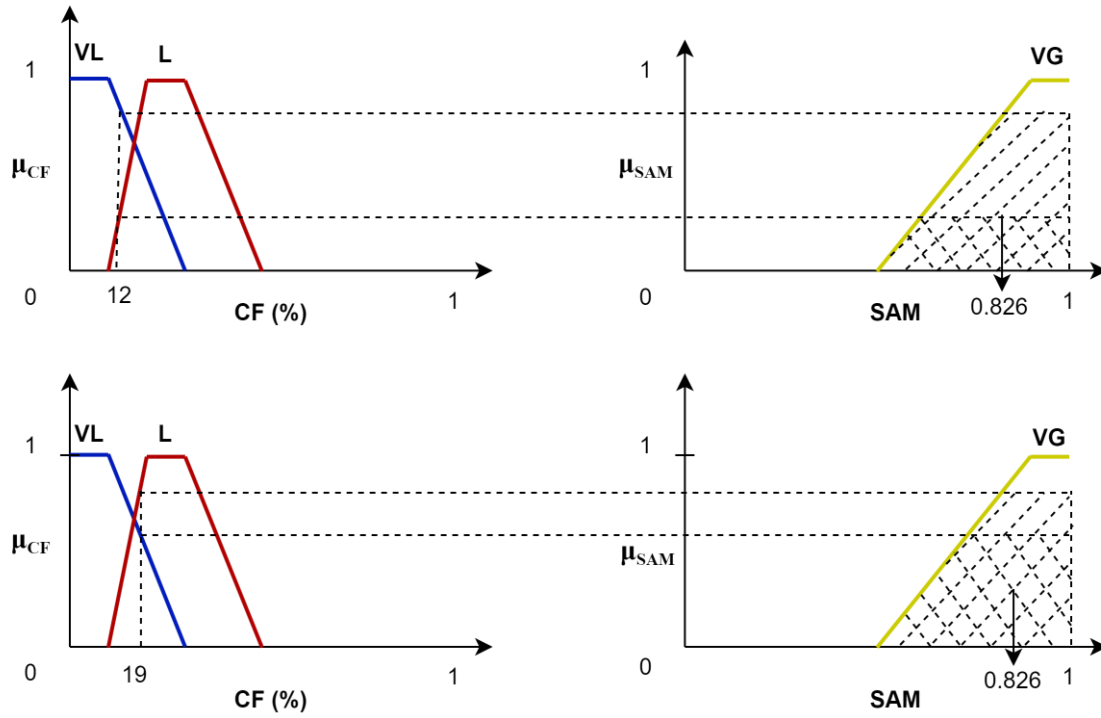


Figure 23: The discontinuous response of Soil Adsorption Matrix (VL: Very low, L: Low, VG: Very good)

4.2.6 Species suitability response along gradients

Figure 24 illustrates the Tree Species Suitability Index (TSSI) of *Picea abies* along different gradients. In general, Minimum approach produced lower TSSI than Gamma approach. Both methods showed quite similar trend of TSSI along different elevations.

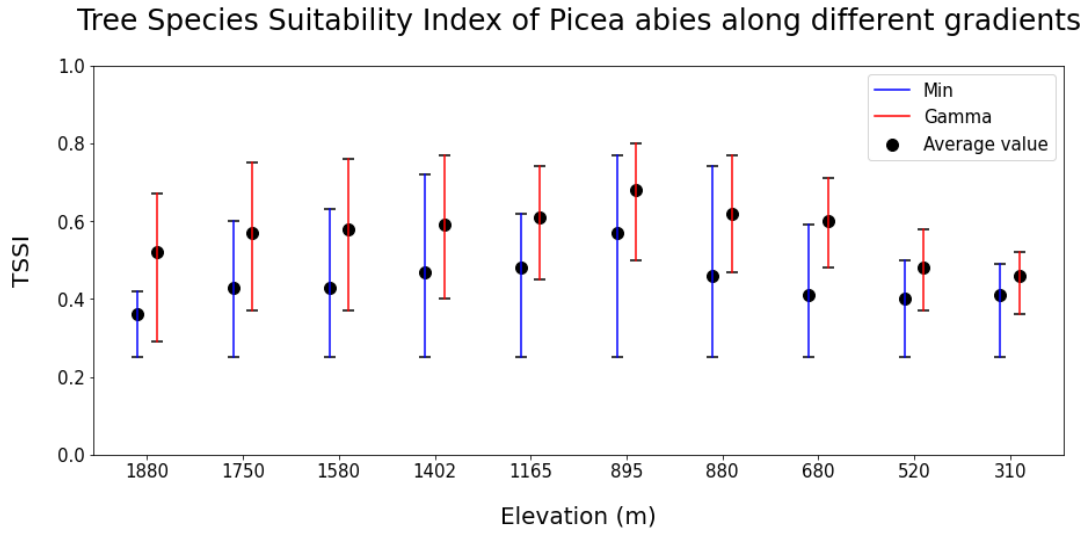


Figure 24: The Tree Species Suitability Index of *Picea abies* along different gradients

The Tree Species Suitability Index (TSSI) of *Abies alba* along different gradients is illustrated in Figure 25. Results indicate that output values of Minimum approach were lower than Gamma approach. Both methods showed similar response curve of TSSI, in which the value reached a peak at elevation of 895 m. The TSSI of different plots at 310 m were the same with Minimum method despite having different soil conditions.

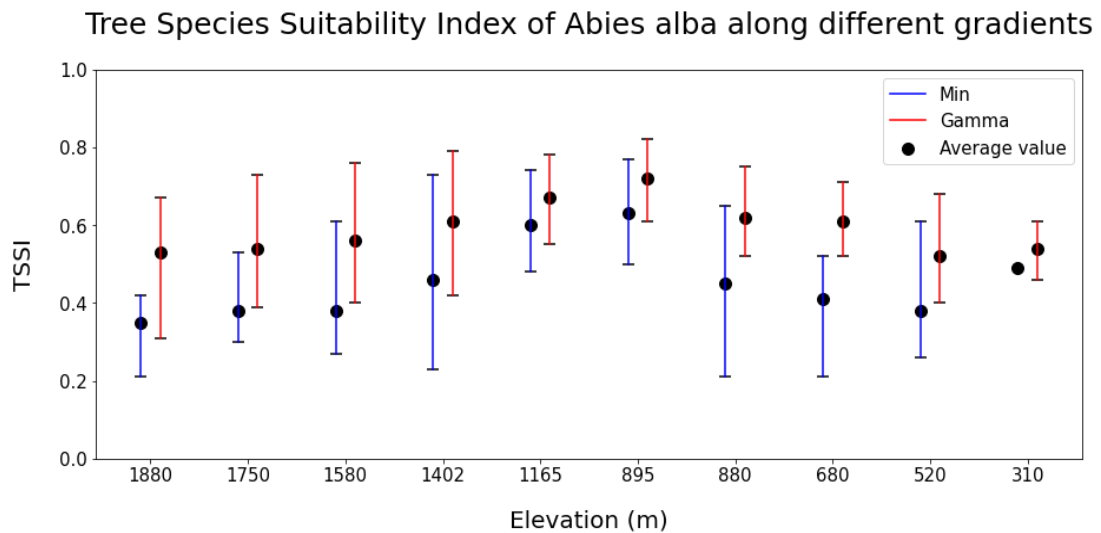


Figure 25: The Tree Species Suitability Index of *Abies alba* along different gradients

Figure 26 presents the Tree Species Suitability Index of *Fagus sylvatica* along different gradients. In general, Gamma method produced higher TSSI than Minimum method. Both approaches showed a similar response curve of TSSI along different gradients. At elevation

of 1880 m, there was no variation in TSSI between different plots with Minimum method despite having different soil conditions.

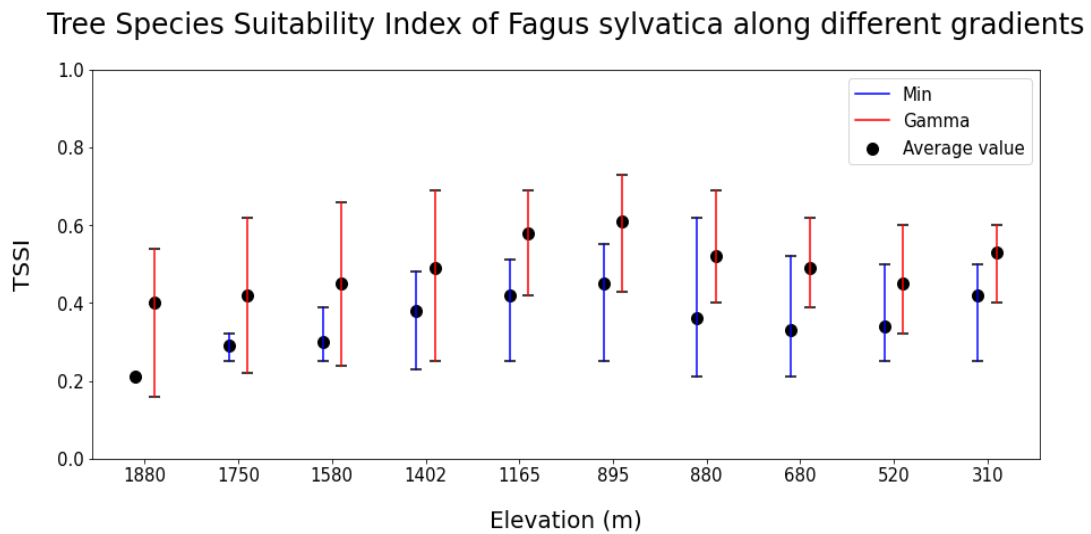


Figure 26: The Tree Species Suitability Index of *Fagus sylvatica* along different gradients

The Tree Species Suitability Index of *Quercus robur* is described in Figure 27. In general, the TSSI of Minimum method is lower than Gamma method. Both methods showed similar trend of TSSI along elevations. It should be noticed that the variation of TSSI at some specific elevations is insignificant or even zero with Minimum approach (1880 m, 1750 m, 1580 m, 1165 m, and 895 m) despite having different soil properties.

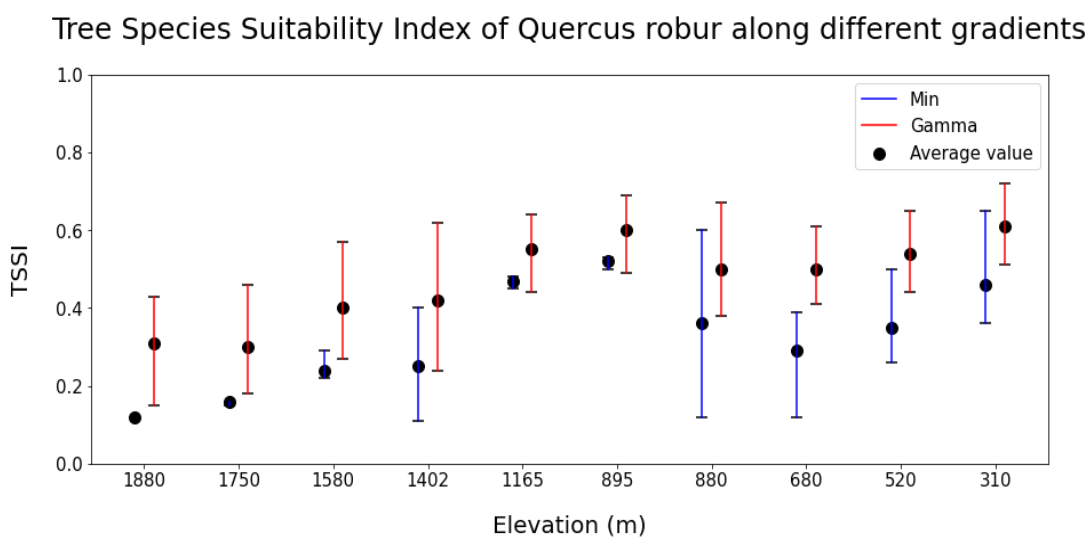


Figure 27: The Tree Species Suitability Index of *Quercus robur* along different gradients

Table 14 presents the maximum difference of Tree Species Suitability Index along altitudes and the maximum difference of Tree Species Suitability Index at the same altitude. Results showed that the variation of TSSI at the same altitude is larger than the variation of TSSI along different altitudes for all species.

Table 14: The maximum difference of Tree Species Suitability Index at the same altitude and along different altitudes

| Method | Species | Maximum difference of TSSI along altitudes | Maximum difference of TSSI at the same altitude |
|--------|------------------------|--|---|
| Gamma | <i>Picea abies</i> | 0.22 | 0.39 |
| | <i>Abies alba</i> | 0.19 | 0.37 |
| | <i>Fagus sylvatica</i> | 0.21 | 0.44 |
| | <i>Quercus robur</i> | 0.31 | 0.38 |
| Min | <i>Picea abies</i> | 0.21 | 0.52 |
| | <i>Abies alba</i> | 0.28 | 0.5 |
| | <i>Fagus sylvatica</i> | 0.24 | 0.41 |
| | <i>Quercus robur</i> | 0.4 | 0.48 |

The Tree Species Suitability Index of four European species with Gamma method is presented in Figure 28. In general, *Picea abies* and *Abies alba* had higher TSSI than *Fagus sylvatica* and *Quercus robur*. The TSSI of *Picea abies* and *Abies alba* were higher in the high and medium elevations (1880 m – 895 m). *Fagus sylvatica* and *Quercus robur* had higher TSSI in medium and low elevations (895 m – 310 m). All species reached a peak at medium altitude (895 m).

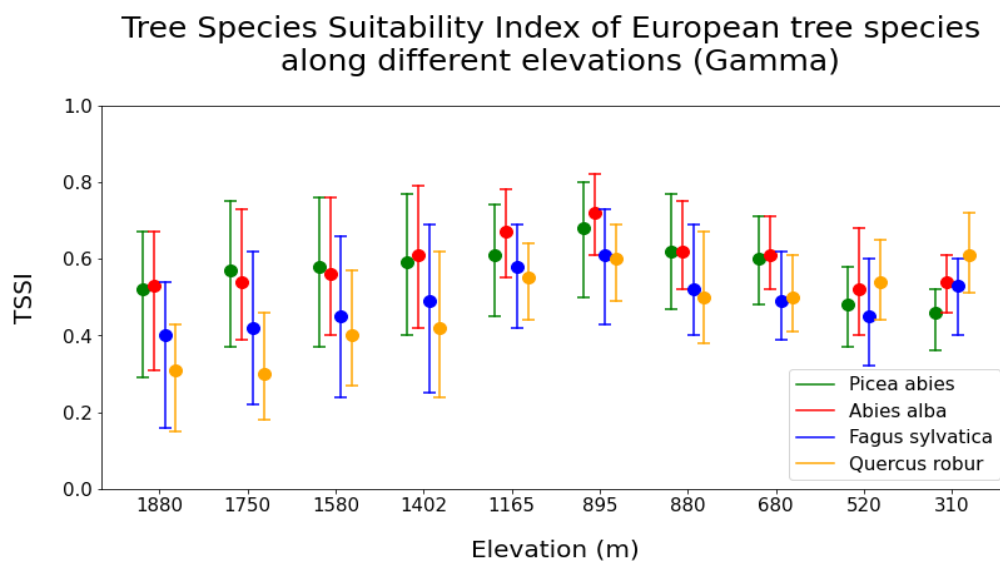


Figure 28: The Tree Species Suitability Index of European tree species along different elevations with Gamma method (the dots represent for the average value)

5 Discussions and conclusion

Proceeding from the consideration that there are limitations in both qualitative and quantitative approaches of tree species selection, the thesis aims to develop a Tree Species Suitability model based on fuzzy-logic theory. Mamdani fuzzy inference systems were applied to link environmental factors with Tree Species Suitability Index. The model consisted of four sub-models including Temperature Suitability, Soil Adsorption Matrix, Nutrient Suitability and Water Suitability. The input variables were processed to generate Temperature Suitability Index, Nutrient Suitability Index and Water Suitability Index. Finally, these indices were aggregated by Minimum and Gamma operators to produce Tree Species Suitability Index.

Here some selected but crucial methodological assumptions are scrutinized.

First, the study revealed the inconsistent behavior of Tree Species Suitability model to the input variables. The factors that caused this problem were Center of gravity defuzzification method, overlap of output fuzzy sets, Maximum aggregation method, and the rule base. Center of Gravity defuzzification method causes the inconsistent response of the Tree Species Suitability model for the outermost output fuzzy sets. The actual maximum and minimum values which Tree Species Suitability model can produce are in fact the centroid points of the extreme output fuzzy sets. It means two bands of values at the top and the bottom of the output range cannot reach as optimum as initial design unless the output fuzzy sets are singleton. The output value is not guaranteed to fulfil the consequence of an IF-THEN rule to at least the same extent that the input fulfil the antecedent (Izquierdo et al., 2017). This inconsistent behavior is more significant in the hierarchical system which an underestimated/overestimated output of a Mamdani Fuzzy Control unit is utilized as an input for other Mamdani Fuzzy Control unit. An adhoc improvement of the COG method might be accomplished by reducing the width of the extreme output fuzzy sets to bring actual output values closer to the limits of the output range. However, further studies are recommended to evaluate the effects of this approach on the smoothness of the output data.

The overlap and the Maximum aggregation method of the output fuzzy sets causes inconsistency between the rule base and the Tree Species Suitability Index. As an impact of the Max operator, output fuzzy sets of IF-THEN rules are not guaranteed to be simultaneously satisfied (Izquierdo et al., 2017). Specifically, this method considers just elements of highest membership degrees and ignores lower membership values in the

overlapping area. Consequently, a worst-case scenario may happen in which the same Tree Species Suitability indices are obtained despite having different rule bases. This certainly generates uncertainty while attempting to interpret the set of rules or combine expert knowledge in Mamdani fuzzy logic system. To overcome this issue, it is recommended to avoid the overlap of over two output fuzzy sets in the same area. Another solution could be considered is changing aggregation method of the output fuzzy sets to Bounded sum. This approach considers the contribution of the smaller fuzzy set in the overlapping area. Therefore, it provides a fairer treatment for overlapping problem. Further work should be directed at studying the effect of Bounded sum aggregation method on the smoothness of output values.

The rule base is also a cause of the inconsistent behavior in the Tree Species Suitability model. If two different rules are designed to produce the same output fuzzy set, then a discontinuity of the Tree Species Suitability Index will occur. This could lead to the worst situation in which the model produces lower Tree Species Suitability Index despite having better site conditions. To obtain a continuous response curve of the outputs, each input fuzzy set should be linked to a different output fuzzy set. This means that the number of input fuzzy sets and output fuzzy sets should be equal.

The overlap percentage of input fuzzy set and the output fuzzy area has a positive correlation. As the overlap percentage increases, the output value corresponding to each specific input value may increase, decrease, or remain constant, depending on the shape of output fuzzy set and the position of input value in the overlapping area.

Gamma function provides a smoother response curve of the Tree Species Suitability Index than Minimum function. Minimum function only considers the lowest value and ignore the contribution of other variables. Consequently, the final output is only increased if the lowest value is improved. This reduces the smoothness of the output response curve. By contract, Gamma function provides a better compensation among Temperature Suitability Index, Nutrient Suitability Index and Water Suitability Index, and thus generates smoother outputs.

The variation of Tree Species Suitability Index at the same altitude is higher than the one varies along different altitudes. It means that tree species is affected more by soil properties in the small scale than being affected by temperature regime in the large scale. *Picea abies* and *Abies alba* are suitable to live from high to medium elevations. *Fagus sylvatica* and *Quercus robur* are appropriate to grow in medium and low altitudes.

The membership functions and rule bases of the Tree Species Suitability model were built based on expert knowledge, and data of FORSITE project. This could be a source of uncertainty for the model. Due to the limitation of time, the study has not evaluated several potential factors which could influence model performance including type of membership functions and intervals of membership functions. The number of input variables and membership functions could significantly affect computational efficiency of the model in MATLAB environment.

The Tree Species Suitability model was constructed following the fundamental niche approach. Thus, the model ignores other factors which could affect tree species including species competition and presence of insects. Due to the limitation on time and data, the model was only developed for four European tree species. It is recommended to produce Tree Species Suitability model for other valuable species as well.

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Annex

1. Rule bases of the Temperature Suitability model

1.1. *Picea abies*

| No. | IF | AND | AND | AND | THEN |
|-----|----------|-----------|------------------|-----------------|----------|
| | GDD | WF | LVP | LF | SUI |
| 1 | moderate | mild | very short | very early | low |
| 2 | moderate | mild | very short | early | low |
| 3 | moderate | mild | very short | moderately late | low |
| 4 | moderate | mild | very short | late | low |
| 5 | moderate | mild | very short | very late | low |
| 6 | moderate | very cold | short | very early | moderate |
| 7 | moderate | very cold | short | early | moderate |
| 8 | moderate | very cold | short | moderately late | moderate |
| 9 | moderate | very cold | short | late | moderate |
| 10 | moderate | very cold | short | very late | moderate |
| 11 | moderate | cold | short | very early | moderate |
| 12 | moderate | cold | short | early | moderate |
| 13 | moderate | cold | short | moderately late | moderate |
| 14 | moderate | cold | short | late | moderate |
| 15 | moderate | cold | short | very late | moderate |
| 16 | moderate | cool | short | very early | moderate |
| 17 | moderate | cool | short | early | moderate |
| 18 | moderate | cool | short | moderately late | moderate |
| 19 | moderate | cool | short | late | moderate |
| 20 | moderate | cool | short | very late | moderate |
| 21 | moderate | mild | short | very early | moderate |
| 22 | moderate | mild | short | early | moderate |
| 23 | moderate | mild | short | moderately late | moderate |
| 24 | moderate | mild | short | late | moderate |
| 25 | moderate | mild | short | very late | moderate |
| 26 | moderate | very cold | moderately short | very early | moderate |
| 27 | moderate | very cold | moderately short | early | moderate |
| 28 | moderate | very cold | moderately short | moderately late | moderate |
| 29 | moderate | very cold | moderately short | late | moderate |
| 30 | moderate | very cold | moderately short | very late | moderate |
| 31 | moderate | cold | moderately short | very early | good |
| 32 | moderate | cold | moderately short | early | good |
| 33 | moderate | cold | moderately short | moderately late | good |
| 34 | moderate | cold | moderately short | late | good |
| 35 | moderate | cold | moderately short | very late | good |
| 36 | moderate | cool | moderately short | very early | good |
| 37 | moderate | cool | moderately short | early | good |

| | | | | | |
|----|----------|-----------|------------------|-----------------|------|
| 38 | moderate | cool | moderately short | moderately late | good |
| 39 | moderate | cool | moderately short | late | good |
| 40 | moderate | cool | moderately short | very late | good |
| 41 | moderate | mild | moderately short | very early | good |
| 42 | moderate | mild | moderately short | early | good |
| 43 | moderate | mild | moderately short | moderately late | good |
| 44 | moderate | mild | moderately short | late | good |
| 45 | moderate | mild | moderately short | very late | good |
| 46 | moderate | very cold | moderately long | very early | good |
| 47 | moderate | very cold | moderately long | early | good |
| 48 | moderate | very cold | moderately long | moderately late | good |
| 49 | moderate | very cold | moderately long | late | good |
| 50 | moderate | very cold | moderately long | very late | good |
| 51 | moderate | cold | moderately long | very early | good |
| 52 | moderate | cold | moderately long | early | good |
| 53 | moderate | cold | moderately long | moderately late | good |
| 54 | moderate | cold | moderately long | late | good |
| 55 | moderate | cold | moderately long | very late | good |
| 56 | moderate | cool | moderately long | very early | good |
| 57 | moderate | cool | moderately long | early | good |
| 58 | moderate | cool | moderately long | moderately late | good |
| 59 | moderate | cool | moderately long | late | good |
| 60 | moderate | cool | moderately long | very late | good |
| 61 | moderate | mild | moderately long | very early | good |
| 62 | moderate | mild | moderately long | early | good |
| 63 | moderate | mild | moderately long | moderately late | good |
| 64 | moderate | mild | moderately long | late | good |
| 65 | moderate | mild | moderately long | very late | good |
| 66 | moderate | very cold | long | very early | good |
| 67 | moderate | very cold | long | early | good |
| 68 | moderate | very cold | long | moderately late | good |
| 69 | moderate | very cold | long | late | good |
| 70 | moderate | very cold | long | very late | good |
| 71 | moderate | cold | long | very early | good |
| 72 | moderate | cold | long | early | good |
| 73 | moderate | cold | long | moderately late | good |
| 74 | moderate | cold | long | late | good |
| 75 | moderate | cold | long | very late | good |
| 76 | moderate | cool | long | very early | good |
| 77 | moderate | cool | long | early | good |
| 78 | moderate | cool | long | moderately late | good |
| 79 | moderate | cool | long | late | good |
| 80 | moderate | cool | long | very late | good |
| 81 | moderate | mild | long | very early | good |
| 82 | moderate | mild | long | early | good |

| | | | | | |
|-----|----------|-----------|------------|-----------------|-----------|
| 83 | moderate | mild | long | moderately late | good |
| 84 | moderate | mild | long | late | good |
| 85 | moderate | mild | long | very late | good |
| 86 | moderate | very cold | very long | very early | very good |
| 87 | moderate | very cold | very long | early | very good |
| 88 | moderate | very cold | very long | moderately late | very good |
| 89 | moderate | very cold | very long | late | very good |
| 90 | moderate | very cold | very long | very late | very good |
| 91 | moderate | cold | very long | very early | very good |
| 92 | moderate | cold | very long | early | very good |
| 93 | moderate | cold | very long | moderately late | very good |
| 94 | moderate | cold | very long | late | very good |
| 95 | moderate | cold | very long | very late | very good |
| 96 | moderate | cool | very long | very early | very good |
| 97 | moderate | cool | very long | early | very good |
| 98 | moderate | cool | very long | moderately late | very good |
| 99 | moderate | cool | very long | late | very good |
| 100 | moderate | cool | very long | very late | very good |
| 101 | moderate | mild | very long | very early | very good |
| 102 | moderate | mild | very long | early | very good |
| 103 | moderate | mild | very long | moderately late | very good |
| 104 | moderate | mild | very long | late | very good |
| 105 | moderate | mild | very long | very late | very good |
| 106 | high | very cold | very short | very early | moderate |
| 107 | high | very cold | very short | early | moderate |
| 108 | high | very cold | very short | moderately late | moderate |
| 109 | high | very cold | very short | late | moderate |
| 110 | high | very cold | very short | very late | moderate |
| 111 | high | cold | very short | very early | moderate |
| 112 | high | cold | very short | early | moderate |
| 113 | high | cold | very short | moderately late | moderate |
| 114 | high | cold | very short | late | moderate |
| 115 | high | cold | very short | very late | moderate |
| 116 | high | cool | very short | very early | moderate |
| 117 | high | cool | very short | early | moderate |
| 118 | high | cool | very short | moderately late | moderate |
| 119 | high | cool | very short | late | moderate |
| 120 | high | cool | very short | very late | moderate |
| 121 | high | mild | very short | very early | moderate |
| 122 | high | mild | very short | early | moderate |
| 123 | high | mild | very short | moderately late | moderate |
| 124 | high | mild | very short | late | moderate |
| 125 | high | mild | very short | very late | moderate |
| 126 | high | very cold | short | very early | good |
| 127 | high | very cold | short | early | good |

| | | | | | |
|-----|------|-----------|------------------|-----------------|-----------|
| 128 | high | very cold | short | moderately late | good |
| 129 | high | very cold | short | late | good |
| 130 | high | very cold | short | very late | good |
| 131 | high | cold | short | very early | good |
| 132 | high | cold | short | early | good |
| 133 | high | cold | short | moderately late | good |
| 134 | high | cold | short | late | good |
| 135 | high | cold | short | very late | good |
| 136 | high | cool | short | very early | good |
| 137 | high | cool | short | early | good |
| 138 | high | cool | short | moderately late | good |
| 139 | high | cool | short | late | good |
| 140 | high | cool | short | very late | good |
| 141 | high | mild | short | very early | good |
| 142 | high | mild | short | early | good |
| 143 | high | mild | short | moderately late | good |
| 144 | high | mild | short | late | good |
| 145 | high | mild | short | very late | good |
| 146 | high | very cold | moderately short | very early | very good |
| 147 | high | very cold | moderately short | early | very good |
| 148 | high | very cold | moderately short | moderately late | very good |
| 149 | high | very cold | moderately short | late | very good |
| 150 | high | very cold | moderately short | very late | very good |
| 151 | high | cold | moderately short | very early | very good |
| 152 | high | cold | moderately short | early | very good |
| 153 | high | cold | moderately short | moderately late | very good |
| 154 | high | cold | moderately short | late | very good |
| 155 | high | cold | moderately short | very late | very good |
| 156 | high | cool | moderately short | very early | very good |
| 157 | high | cool | moderately short | early | very good |
| 158 | high | cool | moderately short | moderately late | very good |
| 159 | high | cool | moderately short | late | very good |
| 160 | high | cool | moderately short | very late | very good |
| 161 | high | mild | moderately short | very early | very good |
| 162 | high | mild | moderately short | early | very good |
| 163 | high | mild | moderately short | moderately late | very good |
| 164 | high | mild | moderately short | late | very good |
| 165 | high | mild | moderately short | very late | very good |
| 166 | high | very cold | moderately long | very early | very good |
| 167 | high | very cold | moderately long | early | very good |
| 168 | high | very cold | moderately long | moderately late | very good |
| 169 | high | very cold | moderately long | late | very good |
| 170 | high | very cold | moderately long | very late | very good |
| 171 | high | cold | moderately long | very early | very good |
| 172 | high | cold | moderately long | early | very good |

| | | | | | |
|-----|------|-----------|-----------------|-----------------|-----------|
| 173 | high | cold | moderately long | moderately late | very good |
| 174 | high | cold | moderately long | late | very good |
| 175 | high | cold | moderately long | very late | very good |
| 176 | high | cool | moderately long | very early | very good |
| 177 | high | cool | moderately long | early | very good |
| 178 | high | cool | moderately long | moderately late | very good |
| 179 | high | cool | moderately long | late | very good |
| 180 | high | cool | moderately long | very late | very good |
| 181 | high | mild | moderately long | very early | very good |
| 182 | high | mild | moderately long | early | very good |
| 183 | high | mild | moderately long | moderately late | very good |
| 184 | high | mild | moderately long | late | very good |
| 185 | high | mild | moderately long | very late | very good |
| 186 | high | very cold | long | very early | very good |
| 187 | high | very cold | long | early | very good |
| 188 | high | very cold | long | moderately late | very good |
| 189 | high | very cold | long | late | very good |
| 190 | high | very cold | long | very late | very good |
| 191 | high | cold | long | very early | very good |
| 192 | high | cold | long | early | very good |
| 193 | high | cold | long | moderately late | very good |
| 194 | high | cold | long | late | very good |
| 195 | high | cold | long | very late | very good |
| 196 | high | cool | long | very early | very good |
| 197 | high | cool | long | early | very good |
| 198 | high | cool | long | moderately late | very good |
| 199 | high | cool | long | late | very good |
| 200 | high | cool | long | very late | very good |
| 201 | high | mild | long | very early | very good |
| 202 | high | mild | long | early | very good |
| 203 | high | mild | long | moderately late | very good |
| 204 | high | mild | long | late | very good |
| 205 | high | mild | long | very late | very good |
| 206 | high | very cold | very long | very early | very good |
| 207 | high | very cold | very long | early | very good |
| 208 | high | very cold | very long | moderately late | very good |
| 209 | high | very cold | very long | late | very good |
| 210 | high | very cold | very long | very late | very good |
| 211 | high | cold | very long | very early | very good |
| 212 | high | cold | very long | early | very good |
| 213 | high | cold | very long | moderately late | very good |
| 214 | high | cold | very long | late | very good |
| 215 | high | cold | very long | very late | very good |
| 216 | high | cool | very long | very early | very good |
| 217 | high | cool | very long | early | very good |

| | | | | | |
|-----|-----------|-----------|------------|-----------------|-----------|
| 218 | high | cool | very long | moderately late | very good |
| 219 | high | cool | very long | late | very good |
| 220 | high | cool | very long | very late | very good |
| 221 | high | mild | very long | very early | very good |
| 222 | high | mild | very long | early | very good |
| 223 | high | mild | very long | moderately late | very good |
| 224 | high | mild | very long | late | very good |
| 225 | high | mild | very long | very late | very good |
| 226 | very high | very cold | very short | very early | moderate |
| 227 | very high | very cold | very short | early | moderate |
| 228 | very high | very cold | very short | moderately late | moderate |
| 229 | very high | very cold | very short | late | moderate |
| 230 | very high | very cold | very short | very late | moderate |
| 231 | very high | cold | very short | very early | moderate |
| 232 | very high | cold | very short | early | moderate |
| 233 | very high | cold | very short | moderately late | moderate |
| 234 | very high | cold | very short | late | moderate |
| 235 | very high | cold | very short | very late | moderate |
| 236 | very high | cool | very short | very early | moderate |
| 237 | very high | cool | very short | early | moderate |
| 238 | very high | cool | very short | moderately late | moderate |
| 239 | very high | cool | very short | late | moderate |
| 240 | very high | cool | very short | very late | moderate |
| 241 | very high | mild | very short | very early | moderate |
| 242 | very high | mild | very short | early | moderate |
| 243 | very high | mild | very short | moderately late | moderate |
| 244 | very high | mild | very short | late | moderate |
| 245 | very high | mild | very short | very late | moderate |
| 246 | very high | very cold | short | very early | good |
| 247 | very high | very cold | short | early | good |
| 248 | very high | very cold | short | moderately late | good |
| 249 | very high | very cold | short | late | good |
| 250 | very high | very cold | short | very late | good |
| 251 | very high | cold | short | very early | good |
| 252 | very high | cold | short | early | good |
| 253 | very high | cold | short | moderately late | good |
| 254 | very high | cold | short | late | good |
| 255 | very high | cold | short | very late | good |
| 256 | very high | cool | short | very early | good |
| 257 | very high | cool | short | early | good |
| 258 | very high | cool | short | moderately late | good |
| 259 | very high | cool | short | late | good |
| 260 | very high | cool | short | very late | good |
| 261 | very high | mild | short | very early | good |
| 262 | very high | mild | short | early | good |

| | | | | | |
|-----|-----------|-----------|------------------|-----------------|------|
| 263 | very high | mild | short | moderately late | good |
| 264 | very high | mild | short | late | good |
| 265 | very high | mild | short | very late | good |
| 266 | very high | very cold | moderately short | very early | good |
| 267 | very high | very cold | moderately short | early | good |
| 268 | very high | very cold | moderately short | moderately late | good |
| 269 | very high | very cold | moderately short | late | good |
| 270 | very high | very cold | moderately short | very late | good |
| 271 | very high | cold | moderately short | very early | good |
| 272 | very high | cold | moderately short | early | good |
| 273 | very high | cold | moderately short | moderately late | good |
| 274 | very high | cold | moderately short | late | good |
| 275 | very high | cold | moderately short | very late | good |
| 276 | very high | cool | moderately short | very early | good |
| 277 | very high | cool | moderately short | early | good |
| 278 | very high | cool | moderately short | moderately late | good |
| 279 | very high | cool | moderately short | late | good |
| 280 | very high | cool | moderately short | very late | good |
| 281 | very high | mild | moderately short | very early | good |
| 282 | very high | mild | moderately short | early | good |
| 283 | very high | mild | moderately short | moderately late | good |
| 284 | very high | mild | moderately short | late | good |
| 285 | very high | mild | moderately short | very late | good |
| 286 | very high | very cold | moderately long | very early | good |
| 287 | very high | very cold | moderately long | early | good |
| 288 | very high | very cold | moderately long | moderately late | good |
| 289 | very high | very cold | moderately long | late | good |
| 290 | very high | very cold | moderately long | very late | good |
| 291 | very high | cold | moderately long | very early | good |
| 292 | very high | cold | moderately long | early | good |
| 293 | very high | cold | moderately long | moderately late | good |
| 294 | very high | cold | moderately long | late | good |
| 295 | very high | cold | moderately long | very late | good |
| 296 | very high | cool | moderately long | very early | good |
| 297 | very high | cool | moderately long | early | good |
| 298 | very high | cool | moderately long | moderately late | good |
| 299 | very high | cool | moderately long | late | good |
| 300 | very high | cool | moderately long | very late | good |
| 301 | very high | mild | moderately long | very early | good |
| 302 | very high | mild | moderately long | early | good |
| 303 | very high | mild | moderately long | moderately late | good |
| 304 | very high | mild | moderately long | late | good |
| 305 | very high | mild | moderately long | very late | good |
| 306 | very high | very cold | long | very early | good |
| 307 | very high | very cold | long | early | good |

| | | | | | |
|-----|-----------|-----------|------------|-----------------|----------|
| 308 | very high | very cold | long | moderately late | good |
| 309 | very high | very cold | long | late | good |
| 310 | very high | very cold | long | very late | good |
| 311 | very high | cold | long | very early | good |
| 312 | very high | cold | long | early | good |
| 313 | very high | cold | long | moderately late | good |
| 314 | very high | cold | long | late | good |
| 315 | very high | cold | long | very late | good |
| 316 | very high | cool | long | very early | good |
| 317 | very high | cool | long | early | good |
| 318 | very high | cool | long | moderately late | good |
| 319 | very high | cool | long | late | good |
| 320 | very high | cool | long | very late | good |
| 321 | very high | mild | long | very early | good |
| 322 | very high | mild | long | early | good |
| 323 | very high | mild | long | moderately late | good |
| 324 | very high | mild | long | late | good |
| 325 | very high | mild | long | very late | good |
| 326 | very high | very cold | very long | very early | moderate |
| 327 | very high | very cold | very long | early | moderate |
| 328 | very high | very cold | very long | moderately late | moderate |
| 329 | very high | very cold | very long | late | moderate |
| 330 | very high | very cold | very long | very late | moderate |
| 331 | very high | cold | very long | very early | moderate |
| 332 | very high | cold | very long | early | moderate |
| 333 | very high | cold | very long | moderately late | moderate |
| 334 | very high | cold | very long | late | moderate |
| 335 | very high | cold | very long | very late | moderate |
| 336 | very high | cool | very long | very early | moderate |
| 337 | very high | cool | very long | early | moderate |
| 338 | very high | cool | very long | moderately late | moderate |
| 339 | very high | cool | very long | late | moderate |
| 340 | very high | cool | very long | very late | moderate |
| 341 | very high | mild | very long | very early | bad |
| 342 | very high | mild | very long | early | bad |
| 343 | very high | mild | very long | moderately late | bad |
| 344 | very high | mild | very long | late | bad |
| 345 | very high | mild | very long | very late | bad |
| 346 | moderate | mild | very short | very early | low |
| 347 | moderate | mild | very short | early | low |
| 348 | moderate | mild | very short | moderately late | low |
| 349 | moderate | mild | very short | late | low |
| 350 | moderate | mild | very short | very late | low |
| 351 | moderate | very cold | short | very early | moderate |
| 352 | moderate | very cold | short | early | moderate |

| | | | | | |
|-----|----------|-----------|------------------|-----------------|----------|
| 353 | moderate | very cold | short | moderately late | moderate |
| 354 | moderate | very cold | short | late | moderate |
| 355 | moderate | very cold | short | very late | moderate |
| 356 | moderate | cold | short | very early | moderate |
| 357 | moderate | cold | short | early | moderate |
| 358 | moderate | cold | short | moderately late | moderate |
| 359 | moderate | cold | short | late | moderate |
| 360 | moderate | cold | short | very late | moderate |
| 361 | moderate | cool | short | very early | moderate |
| 362 | moderate | cool | short | early | moderate |
| 363 | moderate | cool | short | moderately late | moderate |
| 364 | moderate | cool | short | late | moderate |
| 365 | moderate | cool | short | very late | moderate |
| 366 | moderate | mild | short | very early | moderate |
| 367 | moderate | mild | short | early | moderate |
| 368 | moderate | mild | short | moderately late | moderate |
| 369 | moderate | mild | short | late | moderate |
| 370 | moderate | mild | short | very late | moderate |
| 371 | moderate | very cold | moderately short | very early | moderate |
| 372 | moderate | very cold | moderately short | early | moderate |
| 373 | moderate | very cold | moderately short | moderately late | moderate |
| 374 | moderate | very cold | moderately short | late | moderate |
| 375 | moderate | very cold | moderately short | very late | moderate |
| 376 | moderate | cold | moderately short | very early | good |
| 377 | moderate | cold | moderately short | early | good |
| 378 | moderate | cold | moderately short | moderately late | good |
| 379 | moderate | cold | moderately short | late | good |
| 380 | moderate | cold | moderately short | very late | good |
| 381 | moderate | cool | moderately short | very early | good |
| 382 | moderate | cool | moderately short | early | good |
| 383 | moderate | cool | moderately short | moderately late | good |
| 384 | moderate | cool | moderately short | late | good |
| 385 | moderate | cool | moderately short | very late | good |
| 386 | moderate | mild | moderately short | very early | good |
| 387 | moderate | mild | moderately short | early | good |
| 388 | moderate | mild | moderately short | moderately late | good |
| 389 | moderate | mild | moderately short | late | good |
| 390 | moderate | mild | moderately short | very late | good |
| 391 | moderate | very cold | moderately long | very early | good |
| 392 | moderate | very cold | moderately long | early | good |
| 393 | moderate | very cold | moderately long | moderately late | good |
| 394 | moderate | very cold | moderately long | late | good |
| 395 | moderate | very cold | moderately long | very late | good |
| 396 | moderate | cold | moderately long | very early | good |
| 397 | moderate | cold | moderately long | early | good |

| | | | | | |
|-----|----------|-----------|-----------------|-----------------|-----------|
| 398 | moderate | cold | moderately long | moderately late | good |
| 399 | moderate | cold | moderately long | late | good |
| 400 | moderate | cold | moderately long | very late | good |
| 401 | moderate | cool | moderately long | very early | good |
| 402 | moderate | cool | moderately long | early | good |
| 403 | moderate | cool | moderately long | moderately late | good |
| 404 | moderate | cool | moderately long | late | good |
| 405 | moderate | cool | moderately long | very late | good |
| 406 | moderate | mild | moderately long | very early | good |
| 407 | moderate | mild | moderately long | early | good |
| 408 | moderate | mild | moderately long | moderately late | good |
| 409 | moderate | mild | moderately long | late | good |
| 410 | moderate | mild | moderately long | very late | good |
| 411 | moderate | very cold | long | very early | good |
| 412 | moderate | very cold | long | early | good |
| 413 | moderate | very cold | long | moderately late | good |
| 414 | moderate | very cold | long | late | good |
| 415 | moderate | very cold | long | very late | good |
| 416 | moderate | cold | long | very early | good |
| 417 | moderate | cold | long | early | good |
| 418 | moderate | cold | long | moderately late | good |
| 419 | moderate | cold | long | late | good |
| 420 | moderate | cold | long | very late | good |
| 421 | moderate | cool | long | very early | good |
| 422 | moderate | cool | long | early | good |
| 423 | moderate | cool | long | moderately late | good |
| 424 | moderate | cool | long | late | good |
| 425 | moderate | cool | long | very late | good |
| 426 | moderate | mild | long | very early | good |
| 427 | moderate | mild | long | early | good |
| 428 | moderate | mild | long | moderately late | good |
| 429 | moderate | mild | long | late | good |
| 430 | moderate | mild | long | very late | good |
| 431 | moderate | very cold | very long | very early | very good |
| 432 | moderate | very cold | very long | early | very good |
| 433 | moderate | very cold | very long | moderately late | very good |
| 434 | moderate | very cold | very long | late | very good |
| 435 | moderate | very cold | very long | very late | very good |
| 436 | moderate | cold | very long | very early | very good |
| 437 | moderate | cold | very long | early | very good |
| 438 | moderate | cold | very long | moderately late | very good |
| 439 | moderate | cold | very long | late | very good |
| 440 | moderate | cold | very long | very late | very good |
| 441 | moderate | cool | very long | very early | very good |
| 442 | moderate | cool | very long | early | very good |

| | | | | | |
|-----|----------|-----------|------------|-----------------|-----------|
| 443 | moderate | cool | very long | moderately late | very good |
| 444 | moderate | cool | very long | late | very good |
| 445 | moderate | cool | very long | very late | very good |
| 446 | moderate | mild | very long | very early | very good |
| 447 | moderate | mild | very long | early | very good |
| 448 | moderate | mild | very long | moderately late | very good |
| 449 | moderate | mild | very long | late | very good |
| 450 | moderate | mild | very long | very late | very good |
| 451 | high | very cold | very short | very early | moderate |
| 452 | high | very cold | very short | early | moderate |
| 453 | high | very cold | very short | moderately late | moderate |
| 454 | high | very cold | very short | late | moderate |
| 455 | high | very cold | very short | very late | moderate |
| 456 | high | cold | very short | very early | moderate |
| 457 | high | cold | very short | early | moderate |
| 458 | high | cold | very short | moderately late | moderate |
| 459 | high | cold | very short | late | moderate |
| 460 | high | cold | very short | very late | moderate |
| 461 | high | cool | very short | very early | moderate |
| 462 | high | cool | very short | early | moderate |
| 463 | high | cool | very short | moderately late | moderate |
| 464 | high | cool | very short | late | moderate |
| 465 | high | cool | very short | very late | moderate |
| 466 | high | mild | very short | very early | moderate |
| 467 | high | mild | very short | early | moderate |
| 468 | high | mild | very short | moderately late | moderate |
| 469 | high | mild | very short | late | moderate |
| 470 | high | mild | very short | very late | moderate |
| 471 | high | very cold | short | very early | good |
| 472 | high | very cold | short | early | good |
| 473 | high | very cold | short | moderately late | good |
| 474 | high | very cold | short | late | good |
| 475 | high | very cold | short | very late | good |
| 476 | high | cold | short | very early | good |
| 477 | high | cold | short | early | good |
| 478 | high | cold | short | moderately late | good |
| 479 | high | cold | short | late | good |
| 480 | high | cold | short | very late | good |
| 481 | high | cool | short | very early | good |
| 482 | high | cool | short | early | good |
| 483 | high | cool | short | moderately late | good |
| 484 | high | cool | short | late | good |
| 485 | high | cool | short | very late | good |
| 486 | high | mild | short | very early | good |
| 487 | high | mild | short | early | good |

| | | | | | |
|-----|------|-----------|------------------|-----------------|-----------|
| 488 | high | mild | short | moderately late | good |
| 489 | high | mild | short | late | good |
| 490 | high | mild | short | very late | good |
| 491 | high | very cold | moderately short | very early | very good |
| 492 | high | very cold | moderately short | early | very good |
| 493 | high | very cold | moderately short | moderately late | very good |
| 494 | high | very cold | moderately short | late | very good |
| 495 | high | very cold | moderately short | very late | very good |
| 496 | high | cold | moderately short | very early | very good |
| 497 | high | cold | moderately short | early | very good |
| 498 | high | cold | moderately short | moderately late | very good |
| 499 | high | cold | moderately short | late | very good |
| 500 | high | cold | moderately short | very late | very good |
| 501 | high | cool | moderately short | very early | very good |
| 502 | high | cool | moderately short | early | very good |
| 503 | high | cool | moderately short | moderately late | very good |
| 504 | high | cool | moderately short | late | very good |
| 505 | high | cool | moderately short | very late | very good |
| 506 | high | mild | moderately short | very early | very good |
| 507 | high | mild | moderately short | early | very good |
| 508 | high | mild | moderately short | moderately late | very good |
| 509 | high | mild | moderately short | late | very good |
| 510 | high | mild | moderately short | very late | very good |
| 511 | high | very cold | moderately long | very early | very good |
| 512 | high | very cold | moderately long | early | very good |
| 513 | high | very cold | moderately long | moderately late | very good |
| 514 | high | very cold | moderately long | late | very good |
| 515 | high | very cold | moderately long | very late | very good |
| 516 | high | cold | moderately long | very early | very good |
| 517 | high | cold | moderately long | early | very good |
| 518 | high | cold | moderately long | moderately late | very good |
| 519 | high | cold | moderately long | late | very good |
| 520 | high | cold | moderately long | very late | very good |
| 521 | high | cool | moderately long | very early | very good |
| 522 | high | cool | moderately long | early | very good |
| 523 | high | cool | moderately long | moderately late | very good |
| 524 | high | cool | moderately long | late | very good |
| 525 | high | cool | moderately long | very late | very good |
| 526 | high | mild | moderately long | very early | very good |
| 527 | high | mild | moderately long | early | very good |
| 528 | high | mild | moderately long | moderately late | very good |
| 529 | high | mild | moderately long | late | very good |
| 530 | high | mild | moderately long | very late | very good |
| 531 | high | very cold | long | very early | very good |
| 532 | high | very cold | long | early | very good |

| | | | | | |
|-----|-----------|-----------|------------|-----------------|-----------|
| 533 | high | very cold | long | moderately late | very good |
| 534 | high | very cold | long | late | very good |
| 535 | high | very cold | long | very late | very good |
| 536 | high | cold | long | very early | very good |
| 537 | high | cold | long | early | very good |
| 538 | high | cold | long | moderately late | very good |
| 539 | high | cold | long | late | very good |
| 540 | high | cold | long | very late | very good |
| 541 | high | cool | long | very early | very good |
| 542 | high | cool | long | early | very good |
| 543 | high | cool | long | moderately late | very good |
| 544 | high | cool | long | late | very good |
| 545 | high | cool | long | very late | very good |
| 546 | high | mild | long | very early | very good |
| 547 | high | mild | long | early | very good |
| 548 | high | mild | long | moderately late | very good |
| 549 | high | mild | long | late | very good |
| 550 | high | mild | long | very late | very good |
| 551 | high | very cold | very long | very early | very good |
| 552 | high | very cold | very long | early | very good |
| 553 | high | very cold | very long | moderately late | very good |
| 554 | high | very cold | very long | late | very good |
| 555 | high | very cold | very long | very late | very good |
| 556 | high | cold | very long | very early | very good |
| 557 | high | cold | very long | early | very good |
| 558 | high | cold | very long | moderately late | very good |
| 559 | high | cold | very long | late | very good |
| 560 | high | cold | very long | very late | very good |
| 561 | high | cool | very long | very early | very good |
| 562 | high | cool | very long | early | very good |
| 563 | high | cool | very long | moderately late | very good |
| 564 | high | cool | very long | late | very good |
| 565 | high | cool | very long | very late | very good |
| 566 | high | mild | very long | very early | very good |
| 567 | high | mild | very long | early | very good |
| 568 | high | mild | very long | moderately late | very good |
| 569 | high | mild | very long | late | very good |
| 570 | high | mild | very long | very late | very good |
| 571 | very high | very cold | very short | very early | moderate |
| 572 | very high | very cold | very short | early | moderate |
| 573 | very high | very cold | very short | moderately late | moderate |
| 574 | very high | very cold | very short | late | moderate |
| 575 | very high | very cold | very short | very late | moderate |
| 576 | very high | cold | very short | very early | moderate |
| 577 | very high | cold | very short | early | moderate |

| | | | | | |
|-----|-----------|-----------|------------|-----------------|----------|
| 578 | very high | cold | very short | moderately late | moderate |
| 579 | very high | cold | very short | late | moderate |
| 580 | very high | cold | very short | very late | moderate |
| 581 | very high | cool | very short | very early | moderate |
| 582 | very high | cool | very short | early | moderate |
| 583 | very high | cool | very short | moderately late | moderate |
| 584 | very high | cool | very short | late | moderate |
| 585 | very high | cool | very short | very late | moderate |
| 586 | very high | mild | very short | very early | moderate |
| 587 | very high | mild | very short | early | moderate |
| 588 | very high | mild | very short | moderately late | moderate |
| 589 | very high | mild | very short | late | moderate |
| 590 | very high | mild | very short | very late | moderate |
| 591 | very high | very cold | short | very early | good |
| 592 | very high | very cold | short | early | good |
| 593 | very high | very cold | short | moderately late | good |
| 594 | very high | very cold | short | late | good |
| 595 | very high | very cold | short | very late | good |
| 596 | very high | cold | short | very early | good |
| 597 | very high | cold | short | early | good |
| 598 | very high | cold | short | moderately late | good |
| 599 | very high | cold | short | late | good |
| 600 | very high | cold | short | very late | good |

1.2. *Abies alba*

| No. | IF | AND | AND | AND | THEN |
|-----|----------|-----------|------------|-----------------|----------|
| | GDD | WF | LVP | LF | SUI |
| 1 | very low | very cold | very short | very early | very low |
| 2 | very low | very cold | very short | early | very low |
| 3 | very low | very cold | very short | moderately late | very low |
| 4 | very low | very cold | very short | late | very low |
| 5 | very low | very cold | very short | very late | very low |
| 6 | very low | cold | very short | very early | very low |
| 7 | very low | cold | very short | early | very low |
| 8 | very low | cold | very short | moderately late | very low |
| 9 | very low | cold | very short | late | very low |
| 10 | very low | cold | very short | very late | very low |
| 11 | very low | cool | very short | very early | very low |
| 12 | very low | cool | very short | early | very low |
| 13 | very low | cool | very short | moderately late | very low |
| 14 | very low | cool | very short | late | very low |
| 15 | very low | cool | very short | very late | very low |
| 16 | very low | mild | very short | very early | very low |
| 17 | very low | mild | very short | early | very low |
| 18 | very low | mild | very short | moderately late | very low |
| 19 | very low | mild | very short | late | very low |
| 20 | very low | mild | very short | very late | very low |
| 21 | very low | very cold | short | very early | very low |
| 22 | very low | very cold | short | early | very low |
| 23 | very low | very cold | short | moderately late | very low |
| 24 | very low | very cold | short | late | very low |
| 25 | very low | very cold | short | very late | very low |
| 26 | very low | cold | short | very early | very low |
| 27 | very low | cold | short | early | very low |
| 28 | very low | cold | short | moderately late | very low |
| 29 | very low | cold | short | late | very low |
| 30 | very low | cold | short | very late | very low |
| 31 | very low | cool | short | very early | very low |
| 32 | very low | cool | short | early | very low |
| 33 | very low | cool | short | moderately late | very low |
| 34 | very low | cool | short | late | very low |
| 35 | very low | cool | short | very late | very low |
| 36 | very low | mild | short | very early | very low |
| 37 | very low | mild | short | early | very low |
| 38 | very low | mild | short | moderately late | very low |
| 39 | very low | mild | short | late | very low |
| 40 | very low | mild | short | very late | very low |

| | | | | | |
|----|----------|-----------|------------------|-----------------|----------|
| 41 | very low | very cold | moderately short | very early | low |
| 42 | very low | very cold | moderately short | early | low |
| 43 | very low | very cold | moderately short | moderately late | low |
| 44 | very low | very cold | moderately short | late | low |
| 45 | very low | very cold | moderately short | very late | low |
| 46 | very low | cold | moderately short | very early | low |
| 47 | very low | cold | moderately short | early | low |
| 48 | very low | cold | moderately short | moderately late | low |
| 49 | very low | cold | moderately short | late | low |
| 50 | very low | cold | moderately short | very late | low |
| 51 | very low | cool | moderately short | very early | low |
| 52 | very low | cool | moderately short | early | low |
| 53 | very low | cool | moderately short | moderately late | low |
| 54 | very low | cool | moderately short | late | low |
| 55 | very low | cool | moderately short | very late | low |
| 56 | very low | mild | moderately short | very early | low |
| 57 | very low | mild | moderately short | early | low |
| 58 | very low | mild | moderately short | moderately late | low |
| 59 | very low | mild | moderately short | late | low |
| 60 | very low | mild | moderately short | very late | low |
| 61 | very low | very cold | moderately long | very early | low |
| 62 | very low | very cold | moderately long | early | low |
| 63 | very low | very cold | moderately long | moderately late | low |
| 64 | very low | very cold | moderately long | late | low |
| 65 | very low | very cold | moderately long | very late | low |
| 66 | very low | cold | moderately long | very early | low |
| 67 | very low | cold | moderately long | early | low |
| 68 | very low | cold | moderately long | moderately late | low |
| 69 | very low | cold | moderately long | late | low |
| 70 | very low | cold | moderately long | very late | low |
| 71 | very low | cool | moderately long | very early | low |
| 72 | very low | cool | moderately long | early | low |
| 73 | very low | cool | moderately long | moderately late | low |
| 74 | very low | cool | moderately long | late | low |
| 75 | very low | cool | moderately long | very late | low |
| 76 | very low | mild | moderately long | very early | low |
| 77 | very low | mild | moderately long | early | low |
| 78 | very low | mild | moderately long | moderately late | low |
| 79 | very low | mild | moderately long | late | low |
| 80 | very low | mild | moderately long | very late | low |
| 81 | very low | very cold | long | very early | moderate |
| 82 | very low | very cold | long | early | moderate |
| 83 | very low | very cold | long | moderately late | moderate |
| 84 | very low | very cold | long | late | moderate |
| 85 | very low | very cold | long | very late | low |

| | | | | | |
|-----|----------|-----------|------------|-----------------|----------|
| 86 | very low | cold | long | very early | moderate |
| 87 | very low | cold | long | early | moderate |
| 88 | very low | cold | long | moderately late | moderate |
| 89 | very low | cold | long | late | moderate |
| 90 | very low | cold | long | very late | moderate |
| 91 | very low | cool | long | very early | moderate |
| 92 | very low | cool | long | early | moderate |
| 93 | very low | cool | long | moderately late | moderate |
| 94 | very low | cool | long | late | moderate |
| 95 | very low | cool | long | very late | moderate |
| 96 | very low | mild | long | very early | moderate |
| 97 | very low | mild | long | early | moderate |
| 98 | very low | mild | long | moderately late | moderate |
| 99 | very low | mild | long | late | moderate |
| 100 | very low | mild | long | very late | moderate |
| 101 | very low | very cold | very long | very early | moderate |
| 102 | very low | very cold | very long | early | moderate |
| 103 | very low | very cold | very long | moderately late | moderate |
| 104 | very low | very cold | very long | late | moderate |
| 105 | very low | very cold | very long | very late | moderate |
| 106 | very low | cold | very long | very early | moderate |
| 107 | very low | cold | very long | early | moderate |
| 108 | very low | cold | very long | moderately late | moderate |
| 109 | very low | cold | very long | late | moderate |
| 110 | very low | cold | very long | very late | moderate |
| 111 | very low | cool | very long | very early | moderate |
| 112 | very low | cool | very long | early | moderate |
| 113 | very low | cool | very long | moderately late | moderate |
| 114 | very low | cool | very long | late | moderate |
| 115 | very low | cool | very long | very late | moderate |
| 116 | very low | mild | very long | very early | moderate |
| 117 | very low | mild | very long | early | moderate |
| 118 | very low | mild | very long | moderately late | moderate |
| 119 | very low | mild | very long | late | moderate |
| 120 | very low | mild | very long | very late | moderate |
| 121 | low | very cold | very short | very early | low |
| 122 | low | very cold | very short | early | low |
| 123 | low | very cold | very short | moderately late | low |
| 124 | low | very cold | very short | late | low |
| 125 | low | very cold | very short | very late | low |
| 126 | low | cold | very short | very early | low |
| 127 | low | cold | very short | early | low |
| 128 | low | cold | very short | moderately late | low |
| 129 | low | cold | very short | late | low |
| 130 | low | cold | very short | very late | low |

| | | | | | |
|-----|-----|-----------|------------------|-----------------|----------|
| 131 | low | cool | very short | very early | low |
| 132 | low | cool | very short | early | low |
| 133 | low | cool | very short | moderately late | low |
| 134 | low | cool | very short | late | low |
| 135 | low | cool | very short | very late | low |
| 136 | low | mild | very short | very early | low |
| 137 | low | mild | very short | early | low |
| 138 | low | mild | very short | moderately late | low |
| 139 | low | mild | very short | late | low |
| 140 | low | mild | very short | very late | low |
| 141 | low | very cold | short | very early | moderate |
| 142 | low | very cold | short | early | moderate |
| 143 | low | very cold | short | moderately late | moderate |
| 144 | low | very cold | short | late | moderate |
| 145 | low | very cold | short | very late | moderate |
| 146 | low | cold | short | very early | moderate |
| 147 | low | cold | short | early | moderate |
| 148 | low | cold | short | moderately late | moderate |
| 149 | low | cold | short | late | moderate |
| 150 | low | cold | short | very late | moderate |
| 151 | low | cool | short | very early | moderate |
| 152 | low | cool | short | early | moderate |
| 153 | low | cool | short | moderately late | moderate |
| 154 | low | cool | short | late | moderate |
| 155 | low | cool | short | very late | moderate |
| 156 | low | mild | short | very early | moderate |
| 157 | low | mild | short | early | moderate |
| 158 | low | mild | short | moderately late | moderate |
| 159 | low | mild | short | late | moderate |
| 160 | low | mild | short | very late | moderate |
| 161 | low | very cold | moderately short | very early | moderate |
| 162 | low | very cold | moderately short | early | moderate |
| 163 | low | very cold | moderately short | moderately late | moderate |
| 164 | low | very cold | moderately short | late | moderate |
| 165 | low | very cold | moderately short | very late | moderate |
| 166 | low | cold | moderately short | very early | moderate |
| 167 | low | cold | moderately short | early | moderate |
| 168 | low | cold | moderately short | moderately late | moderate |
| 169 | low | cold | moderately short | late | moderate |
| 170 | low | cold | moderately short | very late | moderate |
| 171 | low | cool | moderately short | very early | moderate |
| 172 | low | cool | moderately short | early | moderate |
| 173 | low | cool | moderately short | moderately late | moderate |
| 174 | low | cool | moderately short | late | moderate |
| 175 | low | cool | moderately short | very late | moderate |

| | | | | | |
|-----|-----|-----------|------------------|-----------------|----------|
| 176 | low | mild | moderately short | very early | moderate |
| 177 | low | mild | moderately short | early | moderate |
| 178 | low | mild | moderately short | moderately late | moderate |
| 179 | low | mild | moderately short | late | moderate |
| 180 | low | mild | moderately short | very late | moderate |
| 181 | low | very cold | moderately long | very early | moderate |
| 182 | low | very cold | moderately long | early | moderate |
| 183 | low | very cold | moderately long | moderately late | moderate |
| 184 | low | very cold | moderately long | late | moderate |
| 185 | low | very cold | moderately long | very late | moderate |
| 186 | low | cold | moderately long | very early | moderate |
| 187 | low | cold | moderately long | early | moderate |
| 188 | low | cold | moderately long | moderately late | moderate |
| 189 | low | cold | moderately long | late | moderate |
| 190 | low | cold | moderately long | very late | moderate |
| 191 | low | cool | moderately long | very early | moderate |
| 192 | low | cool | moderately long | early | moderate |
| 193 | low | cool | moderately long | moderately late | moderate |
| 194 | low | cool | moderately long | late | moderate |
| 195 | low | cool | moderately long | very late | moderate |
| 196 | low | mild | moderately long | very early | moderate |
| 197 | low | mild | moderately long | early | moderate |
| 198 | low | mild | moderately long | moderately late | moderate |
| 199 | low | mild | moderately long | late | moderate |
| 200 | low | mild | moderately long | very late | moderate |
| 201 | low | very cold | long | very early | moderate |
| 202 | low | very cold | long | early | moderate |
| 203 | low | very cold | long | moderately late | moderate |
| 204 | low | very cold | long | late | moderate |
| 205 | low | very cold | long | very late | moderate |
| 206 | low | cold | long | very early | moderate |
| 207 | low | cold | long | early | moderate |
| 208 | low | cold | long | moderately late | moderate |
| 209 | low | cold | long | late | moderate |
| 210 | low | cold | long | very late | moderate |
| 211 | low | cool | long | very early | moderate |
| 212 | low | cool | long | early | moderate |
| 213 | low | cool | long | moderately late | moderate |
| 214 | low | cool | long | late | moderate |
| 215 | low | cool | long | very late | moderate |
| 216 | low | mild | long | very early | moderate |
| 217 | low | mild | long | early | moderate |
| 218 | low | mild | long | moderately late | moderate |
| 219 | low | mild | long | late | moderate |
| 220 | low | mild | long | very late | moderate |

| | | | | | |
|-----|----------|-----------|------------|-----------------|----------|
| 221 | low | very cold | very long | very early | good |
| 222 | low | very cold | very long | early | good |
| 223 | low | very cold | very long | moderately late | good |
| 224 | low | very cold | very long | late | moderate |
| 225 | low | very cold | very long | very late | moderate |
| 226 | low | cold | very long | very early | good |
| 227 | low | cold | very long | early | good |
| 228 | low | cold | very long | moderately late | good |
| 229 | low | cold | very long | late | moderate |
| 230 | low | cold | very long | very late | moderate |
| 231 | low | cool | very long | very early | good |
| 232 | low | cool | very long | early | good |
| 233 | low | cool | very long | moderately late | good |
| 234 | low | cool | very long | late | moderate |
| 235 | low | cool | very long | very late | moderate |
| 236 | low | mild | very long | very early | good |
| 237 | low | mild | very long | early | good |
| 238 | low | mild | very long | moderately late | good |
| 239 | low | mild | very long | late | moderate |
| 240 | low | mild | very long | very late | moderate |
| 241 | moderate | very cold | very short | very early | low |
| 242 | moderate | very cold | very short | early | low |
| 243 | moderate | very cold | very short | moderately late | low |
| 244 | moderate | very cold | very short | late | low |
| 245 | moderate | very cold | very short | very late | low |
| 246 | moderate | cold | very short | very early | low |
| 247 | moderate | cold | very short | early | low |
| 248 | moderate | cold | very short | moderately late | low |
| 249 | moderate | cold | very short | late | low |
| 250 | moderate | cold | very short | very late | low |
| 251 | moderate | cool | very short | very early | low |
| 252 | moderate | cool | very short | early | low |
| 253 | moderate | cool | very short | moderately late | low |
| 254 | moderate | cool | very short | late | low |
| 255 | moderate | cool | very short | very late | low |
| 256 | moderate | mild | very short | very early | low |
| 257 | moderate | mild | very short | early | low |
| 258 | moderate | mild | very short | moderately late | low |
| 259 | moderate | mild | very short | late | low |
| 260 | moderate | mild | very short | very late | low |
| 261 | moderate | very cold | short | very early | moderate |
| 262 | moderate | very cold | short | early | moderate |
| 263 | moderate | very cold | short | moderately late | moderate |
| 264 | moderate | very cold | short | late | low |
| 265 | moderate | very cold | short | very late | low |

| | | | | | |
|-----|----------|-----------|------------------|-----------------|----------|
| 266 | moderate | cold | short | very early | moderate |
| 267 | moderate | cold | short | early | moderate |
| 268 | moderate | cold | short | moderately late | moderate |
| 269 | moderate | cold | short | late | low |
| 270 | moderate | cold | short | very late | low |
| 271 | moderate | cool | short | very early | moderate |
| 272 | moderate | cool | short | early | moderate |
| 273 | moderate | cool | short | moderately late | moderate |
| 274 | moderate | cool | short | late | low |
| 275 | moderate | cool | short | very late | low |
| 276 | moderate | mild | short | very early | moderate |
| 277 | moderate | mild | short | early | moderate |
| 278 | moderate | mild | short | moderately late | moderate |
| 279 | moderate | mild | short | late | low |
| 280 | moderate | mild | short | very late | low |
| 281 | moderate | very cold | moderately short | very early | moderate |
| 282 | moderate | very cold | moderately short | early | moderate |
| 283 | moderate | very cold | moderately short | moderately late | moderate |
| 284 | moderate | very cold | moderately short | late | low |
| 285 | moderate | very cold | moderately short | very late | low |
| 286 | moderate | cold | moderately short | very early | good |
| 287 | moderate | cold | moderately short | early | good |
| 288 | moderate | cold | moderately short | moderately late | good |
| 289 | moderate | cold | moderately short | late | moderate |
| 290 | moderate | cold | moderately short | very late | moderate |
| 291 | moderate | cool | moderately short | very early | good |
| 292 | moderate | cool | moderately short | early | good |
| 293 | moderate | cool | moderately short | moderately late | good |
| 294 | moderate | cool | moderately short | late | moderate |
| 295 | moderate | cool | moderately short | very late | moderate |
| 296 | moderate | mild | moderately short | very early | good |
| 297 | moderate | mild | moderately short | early | good |
| 298 | moderate | mild | moderately short | moderately late | good |
| 299 | moderate | mild | moderately short | late | moderate |
| 300 | moderate | mild | moderately short | very late | moderate |
| 301 | moderate | very cold | moderately long | very early | good |
| 302 | moderate | very cold | moderately long | early | good |
| 303 | moderate | very cold | moderately long | moderately late | good |
| 304 | moderate | very cold | moderately long | late | moderate |
| 305 | moderate | very cold | moderately long | very late | moderate |
| 306 | moderate | cold | moderately long | very early | good |
| 307 | moderate | cold | moderately long | early | good |
| 308 | moderate | cold | moderately long | moderately late | good |
| 309 | moderate | cold | moderately long | late | moderate |
| 310 | moderate | cold | moderately long | very late | moderate |

| | | | | | |
|-----|----------|-----------|-----------------|-----------------|-----------|
| 311 | moderate | cool | moderately long | very early | good |
| 312 | moderate | cool | moderately long | early | good |
| 313 | moderate | cool | moderately long | moderately late | good |
| 314 | moderate | cool | moderately long | late | moderate |
| 315 | moderate | cool | moderately long | very late | moderate |
| 316 | moderate | mild | moderately long | very early | good |
| 317 | moderate | mild | moderately long | early | good |
| 318 | moderate | mild | moderately long | moderately late | good |
| 319 | moderate | mild | moderately long | late | moderate |
| 320 | moderate | mild | moderately long | very late | moderate |
| 321 | moderate | very cold | long | very early | good |
| 322 | moderate | very cold | long | early | good |
| 323 | moderate | very cold | long | moderately late | good |
| 324 | moderate | very cold | long | late | moderate |
| 325 | moderate | very cold | long | very late | moderate |
| 326 | moderate | cold | long | very early | good |
| 327 | moderate | cold | long | early | good |
| 328 | moderate | cold | long | moderately late | good |
| 329 | moderate | cold | long | late | moderate |
| 330 | moderate | cold | long | very late | moderate |
| 331 | moderate | cool | long | very early | good |
| 332 | moderate | cool | long | early | good |
| 333 | moderate | cool | long | moderately late | good |
| 334 | moderate | cool | long | late | moderate |
| 335 | moderate | cool | long | very late | moderate |
| 336 | moderate | mild | long | very early | good |
| 337 | moderate | mild | long | early | good |
| 338 | moderate | mild | long | moderately late | good |
| 339 | moderate | mild | long | late | moderate |
| 340 | moderate | mild | long | very late | moderate |
| 341 | moderate | very cold | very long | very early | good |
| 342 | moderate | very cold | very long | early | good |
| 343 | moderate | very cold | very long | moderately late | good |
| 344 | moderate | very cold | very long | late | moderate |
| 345 | moderate | very cold | very long | very late | moderate |
| 346 | moderate | cold | very long | very early | very good |
| 347 | moderate | cold | very long | early | very good |
| 348 | moderate | cold | very long | moderately late | very good |
| 349 | moderate | cold | very long | late | good |
| 350 | moderate | cold | very long | very late | good |
| 351 | moderate | cool | very long | very early | very good |
| 352 | moderate | cool | very long | early | very good |
| 353 | moderate | cool | very long | moderately late | very good |
| 354 | moderate | cool | very long | late | good |
| 355 | moderate | cool | very long | very late | good |

| | | | | | |
|-----|----------|-----------|------------|-----------------|-----------|
| 356 | moderate | mild | very long | very early | very good |
| 357 | moderate | mild | very long | early | very good |
| 358 | moderate | mild | very long | moderately late | very good |
| 359 | moderate | mild | very long | late | good |
| 360 | moderate | mild | very long | very late | good |
| 361 | high | very cold | very short | very early | low |
| 362 | high | very cold | very short | early | low |
| 363 | high | very cold | very short | moderately late | low |
| 364 | high | very cold | very short | late | low |
| 365 | high | very cold | very short | very late | low |
| 366 | high | cold | very short | very early | low |
| 367 | high | cold | very short | early | low |
| 368 | high | cold | very short | moderately late | low |
| 369 | high | cold | very short | late | low |
| 370 | high | cold | very short | very late | low |
| 371 | high | cool | very short | very early | low |
| 372 | high | cool | very short | early | low |
| 373 | high | cool | very short | moderately late | low |
| 374 | high | cool | very short | late | low |
| 375 | high | cool | very short | very late | low |
| 376 | high | mild | very short | very early | low |
| 377 | high | mild | very short | early | low |
| 378 | high | mild | very short | moderately late | low |
| 379 | high | mild | very short | late | low |
| 380 | high | mild | very short | very late | low |
| 381 | high | very cold | short | very early | moderate |
| 382 | high | very cold | short | early | moderate |
| 383 | high | very cold | short | moderately late | moderate |
| 384 | high | very cold | short | late | low |
| 385 | high | very cold | short | very late | low |
| 386 | high | cold | short | very early | moderate |
| 387 | high | cold | short | early | moderate |
| 388 | high | cold | short | moderately late | moderate |
| 389 | high | cold | short | late | low |
| 390 | high | cold | short | very late | low |
| 391 | high | cool | short | very early | moderate |
| 392 | high | cool | short | early | moderate |
| 393 | high | cool | short | moderately late | moderate |
| 394 | high | cool | short | late | low |
| 395 | high | cool | short | very late | low |
| 396 | high | mild | short | very early | moderate |
| 397 | high | mild | short | early | moderate |
| 398 | high | mild | short | moderately late | moderate |
| 399 | high | mild | short | late | low |
| 400 | high | mild | short | very late | low |

| | | | | | |
|-----|------|-----------|------------------|-----------------|-----------|
| 401 | high | very cold | moderately short | very early | good |
| 402 | high | very cold | moderately short | early | good |
| 403 | high | very cold | moderately short | moderately late | good |
| 404 | high | very cold | moderately short | late | moderate |
| 405 | high | very cold | moderately short | very late | moderate |
| 406 | high | cold | moderately short | very early | good |
| 407 | high | cold | moderately short | early | good |
| 408 | high | cold | moderately short | moderately late | good |
| 409 | high | cold | moderately short | late | moderate |
| 410 | high | cold | moderately short | very late | moderate |
| 411 | high | cool | moderately short | very early | good |
| 412 | high | cool | moderately short | early | good |
| 413 | high | cool | moderately short | moderately late | good |
| 414 | high | cool | moderately short | late | moderate |
| 415 | high | cool | moderately short | very late | moderate |
| 416 | high | mild | moderately short | very early | good |
| 417 | high | mild | moderately short | early | good |
| 418 | high | mild | moderately short | moderately late | good |
| 419 | high | mild | moderately short | late | moderate |
| 420 | high | mild | moderately short | very late | moderate |
| 421 | high | very cold | moderately long | very early | very good |
| 422 | high | very cold | moderately long | early | very good |
| 423 | high | very cold | moderately long | moderately late | very good |
| 424 | high | very cold | moderately long | late | good |
| 425 | high | very cold | moderately long | very late | good |
| 426 | high | cold | moderately long | very early | very good |
| 427 | high | cold | moderately long | early | very good |
| 428 | high | cold | moderately long | moderately late | very good |
| 429 | high | cold | moderately long | late | good |
| 430 | high | cold | moderately long | very late | good |
| 431 | high | cool | moderately long | very early | very good |
| 432 | high | cool | moderately long | early | very good |
| 433 | high | cool | moderately long | moderately late | very good |
| 434 | high | cool | moderately long | late | good |
| 435 | high | cool | moderately long | very late | good |
| 436 | high | mild | moderately long | very early | very good |
| 437 | high | mild | moderately long | early | very good |
| 438 | high | mild | moderately long | moderately late | very good |
| 439 | high | mild | moderately long | late | good |
| 440 | high | mild | moderately long | very late | good |
| 441 | high | very cold | long | very early | very good |
| 442 | high | very cold | long | early | very good |
| 443 | high | very cold | long | moderately late | very good |
| 444 | high | very cold | long | late | good |
| 445 | high | very cold | long | very late | good |

| | | | | | |
|-----|-----------|-----------|------------|-----------------|-----------|
| 446 | high | cold | long | very early | very good |
| 447 | high | cold | long | early | very good |
| 448 | high | cold | long | moderately late | very good |
| 449 | high | cold | long | late | good |
| 450 | high | cold | long | very late | good |
| 451 | high | cool | long | very early | very good |
| 452 | high | cool | long | early | very good |
| 453 | high | cool | long | moderately late | very good |
| 454 | high | cool | long | late | good |
| 455 | high | cool | long | very late | good |
| 456 | high | mild | long | very early | very good |
| 457 | high | mild | long | early | very good |
| 458 | high | mild | long | moderately late | very good |
| 459 | high | mild | long | late | good |
| 460 | high | mild | long | very late | good |
| 461 | high | very cold | very long | very early | very good |
| 462 | high | very cold | very long | early | very good |
| 463 | high | very cold | very long | moderately late | very good |
| 464 | high | very cold | very long | late | good |
| 465 | high | very cold | very long | very late | good |
| 466 | high | cold | very long | very early | very good |
| 467 | high | cold | very long | early | very good |
| 468 | high | cold | very long | moderately late | very good |
| 469 | high | cold | very long | late | good |
| 470 | high | cold | very long | very late | good |
| 471 | high | cool | very long | very early | very good |
| 472 | high | cool | very long | early | very good |
| 473 | high | cool | very long | moderately late | very good |
| 474 | high | cool | very long | late | good |
| 475 | high | cool | very long | very late | good |
| 476 | high | mild | very long | very early | very good |
| 477 | high | mild | very long | early | very good |
| 478 | high | mild | very long | moderately late | very good |
| 479 | high | mild | very long | late | good |
| 480 | high | mild | very long | very late | good |
| 481 | very high | very cold | very short | very early | moderate |
| 482 | very high | very cold | very short | early | moderate |
| 483 | very high | very cold | very short | moderately late | moderate |
| 484 | very high | very cold | very short | late | low |
| 485 | very high | very cold | very short | very late | low |
| 486 | very high | cold | very short | very early | moderate |
| 487 | very high | cold | very short | early | moderate |
| 488 | very high | cold | very short | moderately late | moderate |
| 489 | very high | cold | very short | late | low |
| 490 | very high | cold | very short | very late | low |

| | | | | | |
|-----|-----------|-----------|------------------|-----------------|----------|
| 491 | very high | cool | very short | very early | moderate |
| 492 | very high | cool | very short | early | moderate |
| 493 | very high | cool | very short | moderately late | moderate |
| 494 | very high | cool | very short | late | low |
| 495 | very high | cool | very short | very late | low |
| 496 | very high | mild | very short | very early | moderate |
| 497 | very high | mild | very short | early | moderate |
| 498 | very high | mild | very short | moderately late | moderate |
| 499 | very high | mild | very short | late | low |
| 500 | very high | mild | very short | very late | low |
| 501 | very high | very cold | short | very early | good |
| 502 | very high | very cold | short | early | good |
| 503 | very high | very cold | short | moderately late | good |
| 504 | very high | very cold | short | late | moderate |
| 505 | very high | very cold | short | very late | moderate |
| 506 | very high | cold | short | very early | good |
| 507 | very high | cold | short | early | good |
| 508 | very high | cold | short | moderately late | good |
| 509 | very high | cold | short | late | moderate |
| 510 | very high | cold | short | very late | moderate |
| 511 | very high | cool | short | very early | good |
| 512 | very high | cool | short | early | good |
| 513 | very high | cool | short | moderately late | good |
| 514 | very high | cool | short | late | moderate |
| 515 | very high | cool | short | very late | moderate |
| 516 | very high | mild | short | very early | good |
| 517 | very high | mild | short | early | good |
| 518 | very high | mild | short | moderately late | good |
| 519 | very high | mild | short | late | moderate |
| 520 | very high | mild | short | very late | moderate |
| 521 | very high | very cold | moderately short | very early | good |
| 522 | very high | very cold | moderately short | early | good |
| 523 | very high | very cold | moderately short | moderately late | good |
| 524 | very high | very cold | moderately short | late | moderate |
| 525 | very high | very cold | moderately short | very late | moderate |
| 526 | very high | cold | moderately short | very early | good |
| 527 | very high | cold | moderately short | early | good |
| 528 | very high | cold | moderately short | moderately late | good |
| 529 | very high | cold | moderately short | late | moderate |
| 530 | very high | cold | moderately short | very late | moderate |
| 531 | very high | cool | moderately short | very early | good |
| 532 | very high | cool | moderately short | early | good |
| 533 | very high | cool | moderately short | moderately late | good |
| 534 | very high | cool | moderately short | late | moderate |
| 535 | very high | cool | moderately short | very late | moderate |

| | | | | | |
|-----|-----------|-----------|------------------|-----------------|----------|
| 536 | very high | mild | moderately short | very early | good |
| 537 | very high | mild | moderately short | early | good |
| 538 | very high | mild | moderately short | moderately late | good |
| 539 | very high | mild | moderately short | late | moderate |
| 540 | very high | mild | moderately short | very late | moderate |
| 541 | very high | very cold | moderately long | very early | good |
| 542 | very high | very cold | moderately long | early | good |
| 543 | very high | very cold | moderately long | moderately late | good |
| 544 | very high | very cold | moderately long | late | moderate |
| 545 | very high | very cold | moderately long | very late | moderate |
| 546 | very high | cold | moderately long | very early | good |
| 547 | very high | cold | moderately long | early | good |
| 548 | very high | cold | moderately long | moderately late | good |
| 549 | very high | cold | moderately long | late | moderate |
| 550 | very high | cold | moderately long | very late | moderate |
| 551 | very high | cool | moderately long | very early | good |
| 552 | very high | cool | moderately long | early | good |
| 553 | very high | cool | moderately long | moderately late | good |
| 554 | very high | cool | moderately long | late | moderate |
| 555 | very high | cool | moderately long | very late | moderate |
| 556 | very high | mild | moderately long | very early | good |
| 557 | very high | mild | moderately long | early | good |
| 558 | very high | mild | moderately long | moderately late | good |
| 559 | very high | mild | moderately long | late | moderate |
| 560 | very high | mild | moderately long | very late | moderate |
| 561 | very high | very cold | long | very early | good |
| 562 | very high | very cold | long | early | good |
| 563 | very high | very cold | long | moderately late | good |
| 564 | very high | very cold | long | late | moderate |
| 565 | very high | very cold | long | very late | moderate |
| 566 | very high | cold | long | very early | good |
| 567 | very high | cold | long | early | good |
| 568 | very high | cold | long | moderately late | good |
| 569 | very high | cold | long | late | moderate |
| 570 | very high | cold | long | very late | moderate |
| 571 | very high | cool | long | very early | good |
| 572 | very high | cool | long | early | good |
| 573 | very high | cool | long | moderately late | good |
| 574 | very high | cool | long | late | moderate |
| 575 | very high | cool | long | very late | moderate |
| 576 | very high | mild | long | very early | good |
| 577 | very high | mild | long | early | good |
| 578 | very high | mild | long | moderately late | good |
| 579 | very high | mild | long | late | good |
| 580 | very high | mild | long | very late | good |

| | | | | | |
|-----|-----------|-----------|-----------|-----------------|----------|
| 581 | very high | very cold | very long | very early | moderate |
| 582 | very high | very cold | very long | early | moderate |
| 583 | very high | very cold | very long | moderately late | moderate |
| 584 | very high | very cold | very long | late | low |
| 585 | very high | very cold | very long | very late | low |
| 586 | very high | cold | very long | very early | moderate |
| 587 | very high | cold | very long | early | moderate |
| 588 | very high | cold | very long | moderately late | moderate |
| 589 | very high | cold | very long | late | low |
| 590 | very high | cold | very long | very late | low |
| 591 | very high | cool | very long | very early | moderate |
| 592 | very high | cool | very long | early | moderate |
| 593 | very high | cool | very long | moderately late | moderate |
| 594 | very high | cool | very long | late | low |
| 595 | very high | cool | very long | very late | low |
| 596 | very high | mild | very long | very early | low |
| 597 | very high | mild | very long | early | low |
| 598 | very high | mild | very long | moderately late | low |
| 599 | very high | mild | very long | late | low |
| 600 | very high | mild | very long | very late | low |

1.3. *Fagus sylvatica*

| No. | IF | AND | AND | AND | THEN |
|-----|----------|-----------|------------|-----------------|----------|
| | GDD | WF | LVP | LF | SUI |
| 1 | very low | very cold | very short | very early | very low |
| 2 | very low | very cold | very short | early | very low |
| 3 | very low | very cold | very short | moderately late | very low |
| 4 | very low | very cold | very short | late | very low |
| 5 | very low | very cold | very short | very late | very low |
| 6 | very low | cold | very short | very early | very low |
| 7 | very low | cold | very short | early | very low |
| 8 | very low | cold | very short | moderately late | very low |
| 9 | very low | cold | very short | late | very low |
| 10 | very low | cold | very short | very late | very low |
| 11 | very low | cool | very short | very early | very low |
| 12 | very low | cool | very short | early | very low |
| 13 | very low | cool | very short | moderately late | very low |
| 14 | very low | cool | very short | late | very low |
| 15 | very low | cool | very short | very late | very low |
| 16 | very low | mild | very short | very early | very low |
| 17 | very low | mild | very short | early | very low |
| 18 | very low | mild | very short | moderately late | very low |
| 19 | very low | mild | very short | late | very low |
| 20 | very low | mild | very short | very late | very low |
| 21 | very low | very cold | short | very early | very low |
| 22 | very low | very cold | short | early | very low |
| 23 | very low | very cold | short | moderately late | very low |
| 24 | very low | very cold | short | late | very low |
| 25 | very low | very cold | short | very late | very low |
| 26 | very low | cold | short | very early | very low |
| 27 | very low | cold | short | early | very low |
| 28 | very low | cold | short | moderately late | very low |
| 29 | very low | cold | short | late | very low |
| 30 | very low | cold | short | very late | very low |
| 31 | very low | cool | short | very early | very low |
| 32 | very low | cool | short | early | very low |
| 33 | very low | cool | short | moderately late | very low |
| 34 | very low | cool | short | late | very low |
| 35 | very low | cool | short | very late | very low |
| 36 | very low | mild | short | very early | very low |
| 37 | very low | mild | short | early | very low |
| 38 | very low | mild | short | moderately late | very low |

| | | | | | |
|----|----------|-----------|------------------|-----------------|----------|
| 39 | very low | mild | short | late | very low |
| 40 | very low | mild | short | very late | very low |
| 41 | very low | very cold | moderately short | very early | very low |
| 42 | very low | very cold | moderately short | early | very low |
| 43 | very low | very cold | moderately short | moderately late | very low |
| 44 | very low | very cold | moderately short | late | very low |
| 45 | very low | very cold | moderately short | very late | very low |
| 46 | very low | cold | moderately short | very early | very low |
| 47 | very low | cold | moderately short | early | very low |
| 48 | very low | cold | moderately short | moderately late | very low |
| 49 | very low | cold | moderately short | late | very low |
| 50 | very low | cold | moderately short | very late | very low |
| 51 | very low | cool | moderately short | very early | very low |
| 52 | very low | cool | moderately short | early | very low |
| 53 | very low | cool | moderately short | moderately late | very low |
| 54 | very low | cool | moderately short | late | very low |
| 55 | very low | cool | moderately short | very late | very low |
| 56 | very low | mild | moderately short | very early | very low |
| 57 | very low | mild | moderately short | early | very low |
| 58 | very low | mild | moderately short | moderately late | very low |
| 59 | very low | mild | moderately short | late | very low |
| 60 | very low | mild | moderately short | very late | very low |
| 61 | very low | very cold | moderately long | very early | very low |
| 62 | very low | very cold | moderately long | early | very low |
| 63 | very low | very cold | moderately long | moderately late | very low |
| 64 | very low | very cold | moderately long | late | very low |
| 65 | very low | very cold | moderately long | very late | very low |
| 66 | very low | cold | moderately long | very early | very low |
| 67 | very low | cold | moderately long | early | very low |
| 68 | very low | cold | moderately long | moderately late | very low |
| 69 | very low | cold | moderately long | late | very low |
| 70 | very low | cold | moderately long | very late | very low |
| 71 | very low | cool | moderately long | very early | very low |
| 72 | very low | cool | moderately long | early | very low |
| 73 | very low | cool | moderately long | moderately late | very low |
| 74 | very low | cool | moderately long | late | very low |
| 75 | very low | cool | moderately long | very late | very low |
| 76 | very low | mild | moderately long | very early | very low |
| 77 | very low | mild | moderately long | early | very low |
| 78 | very low | mild | moderately long | moderately late | very low |
| 79 | very low | mild | moderately long | late | very low |
| 80 | very low | mild | moderately long | very late | very low |
| 81 | very low | very cold | long | very early | very low |
| 82 | very low | very cold | long | early | very low |
| 83 | very low | very cold | long | moderately late | very low |

| | | | | | |
|-----|----------|-----------|------------|-----------------|------------|
| 84 | very low | very cold | long | late | very low |
| 85 | very low | very cold | long | very late | very low |
| 86 | very low | cold | long | very early | very low |
| 87 | very low | cold | long | early | very low |
| 88 | very low | cold | long | moderately late | very low |
| 89 | very low | cold | long | late | very low |
| 90 | very low | cold | long | very late | very low |
| 91 | very low | cool | long | very early | low |
| 92 | very low | cool | long | early | low |
| 93 | very low | cool | long | moderately late | low |
| 94 | very low | cool | long | late | low |
| 95 | very low | cool | long | very late | low |
| 96 | very low | mild | long | very early | low |
| 97 | very low | mild | long | early | low |
| 98 | very low | mild | long | moderately late | low |
| 99 | very low | mild | long | late | low |
| 100 | very low | mild | long | very late | low |
| 101 | very low | very cold | very long | very early | very low |
| 102 | very low | very cold | very long | early | very low |
| 103 | very low | very cold | very long | moderately late | very low |
| 104 | very low | very cold | very long | late | very low |
| 105 | very low | very cold | very long | very late | very low |
| 106 | very low | cold | very long | very early | very low |
| 107 | very low | cold | very long | early | very low |
| 108 | very low | cold | very long | moderately late | very low |
| 109 | very low | cold | very long | late | very low |
| 110 | very low | cold | very long | very late | very low |
| 111 | very low | cool | very long | very early | low |
| 112 | very low | cool | very long | early | low |
| 113 | very low | cool | very long | moderately late | very low |
| 114 | very low | cool | very long | late | very low |
| 115 | very low | cool | very long | very late | very low |
| 116 | very low | mild | very long | very early | low |
| 117 | very low | mild | very long | early | low |
| 118 | very low | mild | very long | moderately late | low |
| 119 | very low | mild | very long | late | low |
| 120 | very low | mild | very long | very late | low |
| 121 | low | very cold | very short | very early | very low |
| 122 | low | very cold | very short | early | very low |
| 123 | low | very cold | very short | moderately late | very low |
| 124 | low | very cold | very short | late | very low |
| 125 | low | very cold | very short | very late | very low |
| 126 | low | cold | very short | very early | very low |
| 127 | low | cold | very short | early | very low |
| 128 | low | cold | very short | moderately late | very low |

| | | | | | |
|-----|-----|-----------|------------------|-----------------|------------|
| 129 | low | cold | very short | late | very low |
| 130 | low | cold | very short | very late | very low |
| 131 | low | cool | very short | very early | very low |
| 132 | low | cool | very short | early | very low |
| 133 | low | cool | very short | moderately late | very low |
| 134 | low | cool | very short | late | very low |
| 135 | low | cool | very short | very late | very low |
| 136 | low | mild | very short | very early | very low |
| 137 | low | mild | very short | early | very low |
| 138 | low | mild | very short | moderately late | very low |
| 139 | low | mild | very short | late | very low |
| 140 | low | mild | very short | very late | very low |
| 141 | low | very cold | short | very early | very low |
| 142 | low | very cold | short | early | very low |
| 143 | low | very cold | short | moderately late | very low |
| 144 | low | very cold | short | late | very low |
| 145 | low | very cold | short | very late | very low |
| 146 | low | cold | short | very early | very low |
| 147 | low | cold | short | early | very low |
| 148 | low | cold | short | moderately late | very low |
| 149 | low | cold | short | late | very low |
| 150 | low | cold | short | very late | very low |
| 151 | low | cool | short | very early | low |
| 152 | low | cool | short | early | low |
| 153 | low | cool | short | moderately late | low |
| 154 | low | cool | short | late | low |
| 155 | low | cool | short | very late | low |
| 156 | low | mild | short | very early | low |
| 157 | low | mild | short | early | low |
| 158 | low | mild | short | moderately late | low |
| 159 | low | mild | short | late | low |
| 160 | low | mild | short | very late | low |
| 161 | low | very cold | moderately short | very early | low |
| 162 | low | very cold | moderately short | early | low |
| 163 | low | very cold | moderately short | moderately late | low |
| 164 | low | very cold | moderately short | late | low |
| 165 | low | very cold | moderately short | very late | low |
| 166 | low | cold | moderately short | very early | very low |
| 167 | low | cold | moderately short | early | very low |
| 168 | low | cold | moderately short | moderately late | very low |
| 169 | low | cold | moderately short | late | very low |
| 170 | low | cold | moderately short | very late | very low |
| 171 | low | cool | moderately short | very early | moderate |
| 172 | low | cool | moderately short | early | moderate |
| 173 | low | cool | moderately short | moderately late | low |

| | | | | | |
|-----|-----|-----------|------------------|-----------------|----------|
| 174 | low | cool | moderately short | late | low |
| 175 | low | cool | moderately short | very late | low |
| 176 | low | mild | moderately short | very early | moderate |
| 177 | low | mild | moderately short | early | moderate |
| 178 | low | mild | moderately short | moderately late | low |
| 179 | low | mild | moderately short | late | low |
| 180 | low | mild | moderately short | very late | low |
| 181 | low | very cold | moderately long | very early | moderate |
| 182 | low | very cold | moderately long | early | moderate |
| 183 | low | very cold | moderately long | moderately late | low |
| 184 | low | very cold | moderately long | late | low |
| 185 | low | very cold | moderately long | very late | low |
| 186 | low | cold | moderately long | very early | very low |
| 187 | low | cold | moderately long | early | very low |
| 188 | low | cold | moderately long | moderately late | very low |
| 189 | low | cold | moderately long | late | very low |
| 190 | low | cold | moderately long | very late | very low |
| 191 | low | cool | moderately long | very early | moderate |
| 192 | low | cool | moderately long | early | moderate |
| 193 | low | cool | moderately long | moderately late | low |
| 194 | low | cool | moderately long | late | low |
| 195 | low | cool | moderately long | very late | low |
| 196 | low | mild | moderately long | very early | moderate |
| 197 | low | mild | moderately long | early | moderate |
| 198 | low | mild | moderately long | moderately late | low |
| 199 | low | mild | moderately long | late | low |
| 200 | low | mild | moderately long | very late | low |
| 201 | low | very cold | long | very early | low |
| 202 | low | very cold | long | early | low |
| 203 | low | very cold | long | moderately late | low |
| 204 | low | very cold | long | late | low |
| 205 | low | very cold | long | very late | low |
| 206 | low | cold | long | very early | very low |
| 207 | low | cold | long | early | very low |
| 208 | low | cold | long | moderately late | very low |
| 209 | low | cold | long | late | very low |
| 210 | low | cold | long | very late | very low |
| 211 | low | cool | long | very early | moderate |
| 212 | low | cool | long | early | moderate |
| 213 | low | cool | long | moderately late | low |
| 214 | low | cool | long | late | low |
| 215 | low | cool | long | very late | low |
| 216 | low | mild | long | very early | moderate |
| 217 | low | mild | long | early | moderate |
| 218 | low | mild | long | moderately late | low |

| | | | | | |
|-----|----------|-----------|------------|-----------------|----------|
| 219 | low | mild | long | late | low |
| 220 | low | mild | long | very late | low |
| 221 | low | very cold | very long | very early | low |
| 222 | low | very cold | very long | early | low |
| 223 | low | very cold | very long | moderately late | low |
| 224 | low | very cold | very long | late | low |
| 225 | low | very cold | very long | very late | low |
| 226 | low | cold | very long | very early | very low |
| 227 | low | cold | very long | early | very low |
| 228 | low | cold | very long | moderately late | very low |
| 229 | low | cold | very long | late | very low |
| 230 | low | cold | very long | very late | very low |
| 231 | low | cool | very long | very early | moderate |
| 232 | low | cool | very long | early | moderate |
| 233 | low | cool | very long | moderately late | low |
| 234 | low | cool | very long | late | low |
| 235 | low | cool | very long | very late | low |
| 236 | low | mild | very long | very early | moderate |
| 237 | low | mild | very long | early | moderate |
| 238 | low | mild | very long | moderately late | low |
| 239 | low | mild | very long | late | low |
| 240 | low | mild | very long | very late | low |
| 241 | moderate | very cold | very short | very early | low |
| 242 | moderate | very cold | very short | early | low |
| 243 | moderate | very cold | very short | moderately late | low |
| 244 | moderate | very cold | very short | late | low |
| 245 | moderate | very cold | very short | very late | low |
| 246 | moderate | cold | very short | very early | very low |
| 247 | moderate | cold | very short | early | very low |
| 248 | moderate | cold | very short | moderately late | very low |
| 249 | moderate | cold | very short | late | very low |
| 250 | moderate | cold | very short | very late | very low |
| 251 | moderate | cool | very short | very early | low |
| 252 | moderate | cool | very short | early | low |
| 253 | moderate | cool | very short | moderately late | low |
| 254 | moderate | cool | very short | late | low |
| 255 | moderate | cool | very short | very late | low |
| 256 | moderate | mild | very short | very early | low |
| 257 | moderate | mild | very short | early | low |
| 258 | moderate | mild | very short | moderately late | low |
| 259 | moderate | mild | very short | late | low |
| 260 | moderate | mild | very short | very late | low |
| 261 | moderate | very cold | short | very early | low |
| 262 | moderate | very cold | short | early | low |
| 263 | moderate | very cold | short | moderately late | low |

| | | | | | |
|-----|----------|-----------|------------------|-----------------|-----------------|
| 264 | moderate | very cold | short | late | low |
| 265 | moderate | very cold | short | very late | low |
| 266 | moderate | cold | short | very early | very low |
| 267 | moderate | cold | short | early | very low |
| 268 | moderate | cold | short | moderately late | very low |
| 269 | moderate | cold | short | late | very low |
| 270 | moderate | cold | short | very late | very low |
| 271 | moderate | cool | short | very early | moderate |
| 272 | moderate | cool | short | early | moderate |
| 273 | moderate | cool | short | moderately late | low |
| 274 | moderate | cool | short | late | low |
| 275 | moderate | cool | short | very late | low |
| 276 | moderate | mild | short | very early | moderate |
| 277 | moderate | mild | short | early | moderate |
| 278 | moderate | mild | short | moderately late | low |
| 279 | moderate | mild | short | late | low |
| 280 | moderate | mild | short | very late | low |
| 281 | moderate | very cold | moderately short | very early | low |
| 282 | moderate | very cold | moderately short | early | low |
| 283 | moderate | very cold | moderately short | moderately late | low |
| 284 | moderate | very cold | moderately short | late | low |
| 285 | moderate | very cold | moderately short | very late | low |
| 286 | moderate | cold | moderately short | very early | very low |
| 287 | moderate | cold | moderately short | early | very low |
| 288 | moderate | cold | moderately short | moderately late | very low |
| 289 | moderate | cold | moderately short | late | very low |
| 290 | moderate | cold | moderately short | very late | very low |
| 291 | moderate | cool | moderately short | very early | moderate |
| 292 | moderate | cool | moderately short | early | moderate |
| 293 | moderate | cool | moderately short | moderately late | low |
| 294 | moderate | cool | moderately short | late | low |
| 295 | moderate | cool | moderately short | very late | low |
| 296 | moderate | mild | moderately short | very early | moderate |
| 297 | moderate | mild | moderately short | early | moderate |
| 298 | moderate | mild | moderately short | moderately late | low |
| 299 | moderate | mild | moderately short | late | low |
| 300 | moderate | mild | moderately short | very late | low |
| 301 | moderate | very cold | moderately long | very early | low |
| 302 | moderate | very cold | moderately long | early | low |
| 303 | moderate | very cold | moderately long | moderately late | low |
| 304 | moderate | very cold | moderately long | late | low |
| 305 | moderate | very cold | moderately long | very late | low |
| 306 | moderate | cold | moderately long | very early | very low |
| 307 | moderate | cold | moderately long | early | very low |
| 308 | moderate | cold | moderately long | moderately late | very low |

| | | | | | |
|-----|----------|-----------|-----------------|-----------------|----------|
| 309 | moderate | cold | moderately long | late | very low |
| 310 | moderate | cold | moderately long | very late | very low |
| 311 | moderate | cool | moderately long | very early | moderate |
| 312 | moderate | cool | moderately long | early | moderate |
| 313 | moderate | cool | moderately long | moderately late | low |
| 314 | moderate | cool | moderately long | late | low |
| 315 | moderate | cool | moderately long | very late | low |
| 316 | moderate | mild | moderately long | very early | moderate |
| 317 | moderate | mild | moderately long | early | moderate |
| 318 | moderate | mild | moderately long | moderately late | low |
| 319 | moderate | mild | moderately long | late | low |
| 320 | moderate | mild | moderately long | very late | low |
| 321 | moderate | very cold | long | very early | low |
| 322 | moderate | very cold | long | early | low |
| 323 | moderate | very cold | long | moderately late | low |
| 324 | moderate | very cold | long | late | low |
| 325 | moderate | very cold | long | very late | low |
| 326 | moderate | cold | long | very early | very low |
| 327 | moderate | cold | long | early | very low |
| 328 | moderate | cold | long | moderately late | very low |
| 329 | moderate | cold | long | late | very low |
| 330 | moderate | cold | long | very late | very low |
| 331 | moderate | cool | long | very early | moderate |
| 332 | moderate | cool | long | early | moderate |
| 333 | moderate | cool | long | moderately late | low |
| 334 | moderate | cool | long | late | low |
| 335 | moderate | cool | long | very late | low |
| 336 | moderate | mild | long | very early | moderate |
| 337 | moderate | mild | long | early | moderate |
| 338 | moderate | mild | long | moderately late | low |
| 339 | moderate | mild | long | late | low |
| 340 | moderate | mild | long | very late | low |
| 341 | moderate | very cold | very long | very early | low |
| 342 | moderate | very cold | very long | early | low |
| 343 | moderate | very cold | very long | moderately late | low |
| 344 | moderate | very cold | very long | late | low |
| 345 | moderate | very cold | very long | very late | low |
| 346 | moderate | cold | very long | very early | very low |
| 347 | moderate | cold | very long | early | very low |
| 348 | moderate | cold | very long | moderately late | very low |
| 349 | moderate | cold | very long | late | very low |
| 350 | moderate | cold | very long | very late | very low |
| 351 | moderate | cool | very long | very early | good |
| 352 | moderate | cool | very long | early | good |
| 353 | moderate | cool | very long | moderately late | moderate |

| | | | | | |
|-----|----------|-----------|------------|-----------------|----------|
| 354 | moderate | cool | very long | late | moderate |
| 355 | moderate | cool | very long | very late | moderate |
| 356 | moderate | mild | very long | very early | good |
| 357 | moderate | mild | very long | early | good |
| 358 | moderate | mild | very long | moderately late | moderate |
| 359 | moderate | mild | very long | late | moderate |
| 360 | moderate | mild | very long | very late | moderate |
| 361 | high | very cold | very short | very early | low |
| 362 | high | very cold | very short | early | low |
| 363 | high | very cold | very short | moderately late | low |
| 364 | high | very cold | very short | late | low |
| 365 | high | very cold | very short | very late | low |
| 366 | high | cold | very short | very early | very low |
| 367 | high | cold | very short | early | very low |
| 368 | high | cold | very short | moderately late | very low |
| 369 | high | cold | very short | late | very low |
| 370 | high | cold | very short | very late | very low |
| 371 | high | cool | very short | very early | low |
| 372 | high | cool | very short | early | low |
| 373 | high | cool | very short | moderately late | low |
| 374 | high | cool | very short | late | low |
| 375 | high | cool | very short | very late | low |
| 376 | high | mild | very short | very early | low |
| 377 | high | mild | very short | early | low |
| 378 | high | mild | very short | moderately late | low |
| 379 | high | mild | very short | late | low |
| 380 | high | mild | very short | very late | low |
| 381 | high | very cold | short | very early | low |
| 382 | high | very cold | short | early | low |
| 383 | high | very cold | short | moderately late | low |
| 384 | high | very cold | short | late | low |
| 385 | high | very cold | short | very late | low |
| 386 | high | cold | short | very early | very low |
| 387 | high | cold | short | early | very low |
| 388 | high | cold | short | moderately late | very low |
| 389 | high | cold | short | late | very low |
| 390 | high | cold | short | very late | very low |
| 391 | high | cool | short | very early | moderate |
| 392 | high | cool | short | early | moderate |
| 393 | high | cool | short | moderately late | low |
| 394 | high | cool | short | late | low |
| 395 | high | cool | short | very late | low |
| 396 | high | mild | short | very early | moderate |
| 397 | high | mild | short | early | moderate |
| 398 | high | mild | short | moderately late | moderate |

| | | | | | |
|-----|------|-----------|------------------|-----------------|-----------|
| 399 | high | mild | short | late | low |
| 400 | high | mild | short | very late | low |
| 401 | high | very cold | moderately short | very early | low |
| 402 | high | very cold | moderately short | early | low |
| 403 | high | very cold | moderately short | moderately late | low |
| 404 | high | very cold | moderately short | late | low |
| 405 | high | very cold | moderately short | very late | low |
| 406 | high | cold | moderately short | very early | very low |
| 407 | high | cold | moderately short | early | very low |
| 408 | high | cold | moderately short | moderately late | very low |
| 409 | high | cold | moderately short | late | very low |
| 410 | high | cold | moderately short | very late | very low |
| 411 | high | cool | moderately short | very early | moderate |
| 412 | high | cool | moderately short | early | moderate |
| 413 | high | cool | moderately short | moderately late | low |
| 414 | high | cool | moderately short | late | low |
| 415 | high | cool | moderately short | very late | low |
| 416 | high | mild | moderately short | very early | moderate |
| 417 | high | mild | moderately short | early | moderate |
| 418 | high | mild | moderately short | moderately late | low |
| 419 | high | mild | moderately short | late | low |
| 420 | high | mild | moderately short | very late | low |
| 421 | high | very cold | moderately long | very early | low |
| 422 | high | very cold | moderately long | early | low |
| 423 | high | very cold | moderately long | moderately late | low |
| 424 | high | very cold | moderately long | late | low |
| 425 | high | very cold | moderately long | very late | low |
| 426 | high | cold | moderately long | very early | very low |
| 427 | high | cold | moderately long | early | very low |
| 428 | high | cold | moderately long | moderately late | very low |
| 429 | high | cold | moderately long | late | very low |
| 430 | high | cold | moderately long | very late | very low |
| 431 | high | cool | moderately long | very early | very good |
| 432 | high | cool | moderately long | early | very good |
| 433 | high | cool | moderately long | moderately late | good |
| 434 | high | cool | moderately long | late | good |
| 435 | high | cool | moderately long | very late | good |
| 436 | high | mild | moderately long | very early | very good |
| 437 | high | mild | moderately long | early | very good |
| 438 | high | mild | moderately long | moderately late | good |
| 439 | high | mild | moderately long | late | good |
| 440 | high | mild | moderately long | very late | good |
| 441 | high | very cold | long | very early | low |
| 442 | high | very cold | long | early | low |
| 443 | high | very cold | long | moderately late | low |

| | | | | | |
|-----|-----------|-----------|------------|-----------------|-----------|
| 444 | high | very cold | long | late | low |
| 445 | high | very cold | long | very late | low |
| 446 | high | cold | long | very early | very low |
| 447 | high | cold | long | early | very low |
| 448 | high | cold | long | moderately late | very low |
| 449 | high | cold | long | late | very low |
| 450 | high | cold | long | very late | very low |
| 451 | high | cool | long | very early | very good |
| 452 | high | cool | long | early | very good |
| 453 | high | cool | long | moderately late | good |
| 454 | high | cool | long | late | good |
| 455 | high | cool | long | very late | good |
| 456 | high | mild | long | very early | very good |
| 457 | high | mild | long | early | very good |
| 458 | high | mild | long | moderately late | good |
| 459 | high | mild | long | late | good |
| 460 | high | mild | long | very late | good |
| 461 | high | very cold | very long | very early | low |
| 462 | high | very cold | very long | early | low |
| 463 | high | very cold | very long | moderately late | low |
| 464 | high | very cold | very long | late | low |
| 465 | high | very cold | very long | very late | low |
| 466 | high | cold | very long | very early | very low |
| 467 | high | cold | very long | early | very low |
| 468 | high | cold | very long | moderately late | very low |
| 469 | high | cold | very long | late | very low |
| 470 | high | cold | very long | very late | very low |
| 471 | high | cool | very long | very early | very good |
| 472 | high | cool | very long | early | very good |
| 473 | high | cool | very long | moderately late | good |
| 474 | high | cool | very long | late | good |
| 475 | high | cool | very long | very late | good |
| 476 | high | mild | very long | very early | very good |
| 477 | high | mild | very long | early | very good |
| 478 | high | mild | very long | moderately late | good |
| 479 | high | mild | very long | late | good |
| 480 | high | mild | very long | very late | good |
| 481 | very high | very cold | very short | very early | low |
| 482 | very high | very cold | very short | early | low |
| 483 | very high | very cold | very short | moderately late | low |
| 484 | very high | very cold | very short | late | low |
| 485 | very high | very cold | very short | very late | low |
| 486 | very high | cold | very short | very early | very low |
| 487 | very high | cold | very short | early | very low |
| 488 | very high | cold | very short | moderately late | very low |

| | | | | | |
|-----|-----------|-----------|------------------|-----------------|----------|
| 489 | very high | cold | very short | late | very low |
| 490 | very high | cold | very short | very late | very low |
| 491 | very high | cool | very short | very early | low |
| 492 | very high | cool | very short | early | low |
| 493 | very high | cool | very short | moderately late | low |
| 494 | very high | cool | very short | late | low |
| 495 | very high | cool | very short | very late | low |
| 496 | very high | mild | very short | very early | low |
| 497 | very high | mild | very short | early | low |
| 498 | very high | mild | very short | moderately late | low |
| 499 | very high | mild | very short | late | low |
| 500 | very high | mild | very short | very late | low |
| 501 | very high | very cold | short | very early | low |
| 502 | very high | very cold | short | early | low |
| 503 | very high | very cold | short | moderately late | low |
| 504 | very high | very cold | short | late | low |
| 505 | very high | very cold | short | very late | low |
| 506 | very high | cold | short | very early | very low |
| 507 | very high | cold | short | early | very low |
| 508 | very high | cold | short | moderately late | very low |
| 509 | very high | cold | short | late | very low |
| 510 | very high | cold | short | very late | very low |
| 511 | very high | cool | short | very early | good |
| 512 | very high | cool | short | early | good |
| 513 | very high | cool | short | moderately late | moderate |
| 514 | very high | cool | short | late | moderate |
| 515 | very high | cool | short | very late | moderate |
| 516 | very high | mild | short | very early | good |
| 517 | very high | mild | short | early | good |
| 518 | very high | mild | short | moderately late | moderate |
| 519 | very high | mild | short | late | moderate |
| 520 | very high | mild | short | very late | moderate |
| 521 | very high | very cold | moderately short | very early | low |
| 522 | very high | very cold | moderately short | early | low |
| 523 | very high | very cold | moderately short | moderately late | low |
| 524 | very high | very cold | moderately short | late | low |
| 525 | very high | very cold | moderately short | very late | low |
| 526 | very high | cold | moderately short | very early | very low |
| 527 | very high | cold | moderately short | early | very low |
| 528 | very high | cold | moderately short | moderately late | very low |
| 529 | very high | cold | moderately short | late | very low |
| 530 | very high | cold | moderately short | very late | very low |
| 531 | very high | cool | moderately short | very early | good |
| 532 | very high | cool | moderately short | early | good |
| 533 | very high | cool | moderately short | moderately late | moderate |

| | | | | | |
|-----|-----------|-----------|------------------|-----------------|-----------|
| 534 | very high | cool | moderately short | late | moderate |
| 535 | very high | cool | moderately short | very late | moderate |
| 536 | very high | mild | moderately short | very early | good |
| 537 | very high | mild | moderately short | early | good |
| 538 | very high | mild | moderately short | moderately late | moderate |
| 539 | very high | mild | moderately short | late | moderate |
| 540 | very high | mild | moderately short | very late | moderate |
| 541 | very high | very cold | moderately long | very early | low |
| 542 | very high | very cold | moderately long | early | low |
| 543 | very high | very cold | moderately long | moderately late | low |
| 544 | very high | very cold | moderately long | late | low |
| 545 | very high | very cold | moderately long | very late | low |
| 546 | very high | cold | moderately long | very early | very low |
| 547 | very high | cold | moderately long | early | very low |
| 548 | very high | cold | moderately long | moderately late | very low |
| 549 | very high | cold | moderately long | late | very low |
| 550 | very high | cold | moderately long | very late | very low |
| 551 | very high | cool | moderately long | very early | very good |
| 552 | very high | cool | moderately long | early | very good |
| 553 | very high | cool | moderately long | moderately late | good |
| 554 | very high | cool | moderately long | late | good |
| 555 | very high | cool | moderately long | very late | good |
| 556 | very high | mild | moderately long | very early | very good |
| 557 | very high | mild | moderately long | early | very good |
| 558 | very high | mild | moderately long | moderately late | good |
| 559 | very high | mild | moderately long | late | good |
| 560 | very high | mild | moderately long | very late | good |
| 561 | very high | very cold | long | very early | low |
| 562 | very high | very cold | long | early | low |
| 563 | very high | very cold | long | moderately late | low |
| 564 | very high | very cold | long | late | low |
| 565 | very high | very cold | long | very late | low |
| 566 | very high | cold | long | very early | very low |
| 567 | very high | cold | long | early | very low |
| 568 | very high | cold | long | moderately late | very low |
| 569 | very high | cold | long | late | very low |
| 570 | very high | cold | long | very late | very low |
| 571 | very high | cool | long | very early | very good |
| 572 | very high | cool | long | early | very good |
| 573 | very high | cool | long | moderately late | good |
| 574 | very high | cool | long | late | good |
| 575 | very high | cool | long | very late | good |
| 576 | very high | mild | long | very early | very good |
| 577 | very high | mild | long | early | very good |
| 578 | very high | mild | long | moderately late | good |

| | | | | | |
|-----|-----------|-----------|-----------|-----------------|----------|
| 579 | very high | mild | long | late | good |
| 580 | very high | mild | long | very late | good |
| 581 | very high | very cold | very long | very early | low |
| 582 | very high | very cold | very long | early | low |
| 583 | very high | very cold | very long | moderately late | low |
| 584 | very high | very cold | very long | late | low |
| 585 | very high | very cold | very long | very late | low |
| 586 | very high | cold | very long | very early | very low |
| 587 | very high | cold | very long | early | very low |
| 588 | very high | cold | very long | moderately late | very low |
| 589 | very high | cold | very long | late | very low |
| 590 | very high | cold | very long | very late | very low |
| 591 | very high | cool | very long | very early | good |
| 592 | very high | cool | very long | early | good |
| 593 | very high | cool | very long | moderately late | moderate |
| 594 | very high | cool | very long | late | moderate |
| 595 | very high | cool | very long | very late | moderate |
| 596 | very high | mild | very long | very early | good |
| 597 | very high | mild | very long | early | good |
| 598 | very high | mild | very long | moderately late | moderate |
| 599 | very high | mild | very long | late | moderate |
| 600 | very high | mild | very long | very late | moderate |

1.4. *Quercus robur*

| No. | IF | AND | AND | AND | THEN |
|-----|----------|-----------|------------|-----------------|----------|
| | GDD | WF | LVP | LF | SUI |
| 1 | very low | very cold | very short | very early | very low |
| 2 | very low | very cold | very short | early | very low |
| 3 | very low | very cold | very short | moderately late | very low |
| 4 | very low | very cold | very short | late | very low |
| 5 | very low | very cold | very short | very late | very low |
| 6 | very low | cold | very short | very early | very low |
| 7 | very low | cold | very short | early | very low |
| 8 | very low | cold | very short | moderately late | very low |
| 9 | very low | cold | very short | late | very low |
| 10 | very low | cold | very short | very late | very low |
| 11 | very low | cool | very short | very early | very low |
| 12 | very low | cool | very short | early | very low |
| 13 | very low | cool | very short | moderately late | very low |
| 14 | very low | cool | very short | late | very low |
| 15 | very low | cool | very short | very late | very low |
| 16 | very low | mild | very short | very early | very low |
| 17 | very low | mild | very short | early | very low |
| 18 | very low | mild | very short | moderately late | very low |
| 19 | very low | mild | very short | late | very low |
| 20 | very low | mild | very short | very late | very low |
| 21 | very low | very cold | short | very early | very low |
| 22 | very low | very cold | short | early | very low |
| 23 | very low | very cold | short | moderately late | very low |
| 24 | very low | very cold | short | late | very low |
| 25 | very low | very cold | short | very late | very low |
| 26 | very low | cold | short | very early | very low |
| 27 | very low | cold | short | early | very low |
| 28 | very low | cold | short | moderately late | very low |
| 29 | very low | cold | short | late | very low |
| 30 | very low | cold | short | very late | very low |
| 31 | very low | cool | short | very early | very low |
| 32 | very low | cool | short | early | very low |
| 33 | very low | cool | short | moderately late | very low |
| 34 | very low | cool | short | late | very low |
| 35 | very low | cool | short | very late | very low |
| 36 | very low | mild | short | very early | very low |
| 37 | very low | mild | short | early | very low |
| 38 | very low | mild | short | moderately late | very low |

| | | | | | |
|----|----------|-----------|------------------|-----------------|----------|
| 39 | very low | mild | short | late | very low |
| 40 | very low | mild | short | very late | very low |
| 41 | very low | very cold | moderately short | very early | very low |
| 42 | very low | very cold | moderately short | early | very low |
| 43 | very low | very cold | moderately short | moderately late | very low |
| 44 | very low | very cold | moderately short | late | very low |
| 45 | very low | very cold | moderately short | very late | very low |
| 46 | very low | cold | moderately short | very early | very low |
| 47 | very low | cold | moderately short | early | very low |
| 48 | very low | cold | moderately short | moderately late | very low |
| 49 | very low | cold | moderately short | late | very low |
| 50 | very low | cold | moderately short | very late | very low |
| 51 | very low | cool | moderately short | very early | very low |
| 52 | very low | cool | moderately short | early | very low |
| 53 | very low | cool | moderately short | moderately late | very low |
| 54 | very low | cool | moderately short | late | very low |
| 55 | very low | cool | moderately short | very late | very low |
| 56 | very low | mild | moderately short | very early | very low |
| 57 | very low | mild | moderately short | early | very low |
| 58 | very low | mild | moderately short | moderately late | very low |
| 59 | very low | mild | moderately short | late | very low |
| 60 | very low | mild | moderately short | very late | very low |
| 61 | very low | very cold | moderately long | very early | very low |
| 62 | very low | very cold | moderately long | early | very low |
| 63 | very low | very cold | moderately long | moderately late | very low |
| 64 | very low | very cold | moderately long | late | very low |
| 65 | very low | very cold | moderately long | very late | very low |
| 66 | very low | cold | moderately long | very early | very low |
| 67 | very low | cold | moderately long | early | very low |
| 68 | very low | cold | moderately long | moderately late | very low |
| 69 | very low | cold | moderately long | late | very low |
| 70 | very low | cold | moderately long | very late | very low |
| 71 | very low | cool | moderately long | very early | very low |
| 72 | very low | cool | moderately long | early | very low |
| 73 | very low | cool | moderately long | moderately late | very low |
| 74 | very low | cool | moderately long | late | very low |
| 75 | very low | cool | moderately long | very late | very low |
| 76 | very low | mild | moderately long | very early | very low |
| 77 | very low | mild | moderately long | early | very low |
| 78 | very low | mild | moderately long | moderately late | very low |
| 79 | very low | mild | moderately long | late | very low |
| 80 | very low | mild | moderately long | very late | very low |
| 81 | very low | very cold | long | very early | very low |
| 82 | very low | very cold | long | early | very low |
| 83 | very low | very cold | long | moderately late | very low |

| | | | | | |
|-----|----------|-----------|------------|-----------------|------------|
| 84 | very low | very cold | long | late | very low |
| 85 | very low | very cold | long | very late | very low |
| 86 | very low | cold | long | very early | low |
| 87 | very low | cold | long | early | low |
| 88 | very low | cold | long | moderately late | low |
| 89 | very low | cold | long | late | low |
| 90 | very low | cold | long | very late | low |
| 91 | very low | cool | long | very early | low |
| 92 | very low | cool | long | early | low |
| 93 | very low | cool | long | moderately late | low |
| 94 | very low | cool | long | late | low |
| 95 | very low | cool | long | very late | low |
| 96 | very low | mild | long | very early | low |
| 97 | very low | mild | long | early | low |
| 98 | very low | mild | long | moderately late | low |
| 99 | very low | mild | long | late | low |
| 100 | very low | mild | long | very late | low |
| 101 | very low | very cold | very long | very early | very low |
| 102 | very low | very cold | very long | early | very low |
| 103 | very low | very cold | very long | moderately late | very low |
| 104 | very low | very cold | very long | late | very low |
| 105 | very low | very cold | very long | very late | very low |
| 106 | very low | cold | very long | very early | low |
| 107 | very low | cold | very long | early | very low |
| 108 | very low | cold | very long | moderately late | very low |
| 109 | very low | cold | very long | late | very low |
| 110 | very low | cold | very long | very late | very low |
| 111 | very low | cool | very long | very early | low |
| 112 | very low | cool | very long | early | very low |
| 113 | very low | cool | very long | moderately late | very low |
| 114 | very low | cool | very long | late | very low |
| 115 | very low | cool | very long | very late | very low |
| 116 | very low | mild | very long | very early | low |
| 117 | very low | mild | very long | early | very low |
| 118 | very low | mild | very long | moderately late | very low |
| 119 | very low | mild | very long | late | very low |
| 120 | very low | mild | very long | very late | very low |
| 121 | low | very cold | very short | very early | very low |
| 122 | low | very cold | very short | early | very low |
| 123 | low | very cold | very short | moderately late | very low |
| 124 | low | very cold | very short | late | very low |
| 125 | low | very cold | very short | very late | very low |
| 126 | low | cold | very short | very early | very low |
| 127 | low | cold | very short | early | very low |
| 128 | low | cold | very short | moderately late | very low |

| | | | | | |
|-----|-----|-----------|------------------|-----------------|----------|
| 129 | low | cold | very short | late | very low |
| 130 | low | cold | very short | very late | very low |
| 131 | low | cool | very short | very early | very low |
| 132 | low | cool | very short | early | very low |
| 133 | low | cool | very short | moderately late | very low |
| 134 | low | cool | very short | late | very low |
| 135 | low | cool | very short | very late | very low |
| 136 | low | mild | very short | very early | very low |
| 137 | low | mild | very short | early | very low |
| 138 | low | mild | very short | moderately late | very low |
| 139 | low | mild | very short | late | very low |
| 140 | low | mild | very short | very late | very low |
| 141 | low | very cold | short | very early | very low |
| 142 | low | very cold | short | early | very low |
| 143 | low | very cold | short | moderately late | very low |
| 144 | low | very cold | short | late | very low |
| 145 | low | very cold | short | very late | very low |
| 146 | low | cold | short | very early | very low |
| 147 | low | cold | short | early | very low |
| 148 | low | cold | short | moderately late | very low |
| 149 | low | cold | short | late | very low |
| 150 | low | cold | short | very late | very low |
| 151 | low | cool | short | very early | very low |
| 152 | low | cool | short | early | very low |
| 153 | low | cool | short | moderately late | very low |
| 154 | low | cool | short | late | very low |
| 155 | low | cool | short | very late | very low |
| 156 | low | mild | short | very early | very low |
| 157 | low | mild | short | early | very low |
| 158 | low | mild | short | moderately late | very low |
| 159 | low | mild | short | late | very low |
| 160 | low | mild | short | very late | very low |
| 161 | low | very cold | moderately short | very early | very low |
| 162 | low | very cold | moderately short | early | very low |
| 163 | low | very cold | moderately short | moderately late | very low |
| 164 | low | very cold | moderately short | late | very low |
| 165 | low | very cold | moderately short | very late | very low |
| 166 | low | cold | moderately short | very early | very low |
| 167 | low | cold | moderately short | early | very low |
| 168 | low | cold | moderately short | moderately late | very low |
| 169 | low | cold | moderately short | late | very low |
| 170 | low | cold | moderately short | very late | very low |
| 171 | low | cool | moderately short | very early | very low |
| 172 | low | cool | moderately short | early | very low |
| 173 | low | cool | moderately short | moderately late | very low |

| | | | | | |
|-----|-----|-----------|------------------|-----------------|----------|
| 174 | low | cool | moderately short | late | very low |
| 175 | low | cool | moderately short | very late | very low |
| 176 | low | mild | moderately short | very early | very low |
| 177 | low | mild | moderately short | early | very low |
| 178 | low | mild | moderately short | moderately late | very low |
| 179 | low | mild | moderately short | late | very low |
| 180 | low | mild | moderately short | very late | very low |
| 181 | low | very cold | moderately long | very early | very low |
| 182 | low | very cold | moderately long | early | very low |
| 183 | low | very cold | moderately long | moderately late | very low |
| 184 | low | very cold | moderately long | late | very low |
| 185 | low | very cold | moderately long | very late | very low |
| 186 | low | cold | moderately long | very early | very low |
| 187 | low | cold | moderately long | early | very low |
| 188 | low | cold | moderately long | moderately late | very low |
| 189 | low | cold | moderately long | late | very low |
| 190 | low | cold | moderately long | very late | very low |
| 191 | low | cool | moderately long | very early | very low |
| 192 | low | cool | moderately long | early | very low |
| 193 | low | cool | moderately long | moderately late | very low |
| 194 | low | cool | moderately long | late | very low |
| 195 | low | cool | moderately long | very late | very low |
| 196 | low | mild | moderately long | very early | very low |
| 197 | low | mild | moderately long | early | very low |
| 198 | low | mild | moderately long | moderately late | very low |
| 199 | low | mild | moderately long | late | very low |
| 200 | low | mild | moderately long | very late | very low |
| 201 | low | very cold | long | very early | very low |
| 202 | low | very cold | long | early | very low |
| 203 | low | very cold | long | moderately late | very low |
| 204 | low | very cold | long | late | very low |
| 205 | low | very cold | long | very late | very low |
| 206 | low | cold | long | very early | very low |
| 207 | low | cold | long | early | very low |
| 208 | low | cold | long | moderately late | very low |
| 209 | low | cold | long | late | very low |
| 210 | low | cold | long | very late | very low |
| 211 | low | cool | long | very early | very low |
| 212 | low | cool | long | early | very low |
| 213 | low | cool | long | moderately late | very low |
| 214 | low | cool | long | late | very low |
| 215 | low | cool | long | very late | very low |
| 216 | low | mild | long | very early | very low |
| 217 | low | mild | long | early | very low |
| 218 | low | mild | long | moderately late | very low |

| | | | | | |
|-----|----------|-----------|------------|-----------------|----------|
| 219 | low | mild | long | late | very low |
| 220 | low | mild | long | very late | very low |
| 221 | low | very cold | very long | very early | very low |
| 222 | low | very cold | very long | early | very low |
| 223 | low | very cold | very long | moderately late | very low |
| 224 | low | very cold | very long | late | very low |
| 225 | low | very cold | very long | very late | very low |
| 226 | low | cold | very long | very early | very low |
| 227 | low | cold | very long | early | very low |
| 228 | low | cold | very long | moderately late | very low |
| 229 | low | cold | very long | late | very low |
| 230 | low | cold | very long | very late | very low |
| 231 | low | cool | very long | very early | very low |
| 232 | low | cool | very long | early | very low |
| 233 | low | cool | very long | moderately late | very low |
| 234 | low | cool | very long | late | very low |
| 235 | low | cool | very long | very late | very low |
| 236 | low | mild | very long | very early | very low |
| 237 | low | mild | very long | early | very low |
| 238 | low | mild | very long | moderately late | very low |
| 239 | low | mild | very long | late | very low |
| 240 | low | mild | very long | very late | very low |
| 241 | moderate | very cold | very short | very early | very low |
| 242 | moderate | very cold | very short | early | very low |
| 243 | moderate | very cold | very short | moderately late | very low |
| 244 | moderate | very cold | very short | late | very low |
| 245 | moderate | very cold | very short | very late | very low |
| 246 | moderate | cold | very short | very early | very low |
| 247 | moderate | cold | very short | early | very low |
| 248 | moderate | cold | very short | moderately late | very low |
| 249 | moderate | cold | very short | late | very low |
| 250 | moderate | cold | very short | very late | very low |
| 251 | moderate | cool | very short | very early | very low |
| 252 | moderate | cool | very short | early | very low |
| 253 | moderate | cool | very short | moderately late | very low |
| 254 | moderate | cool | very short | late | very low |
| 255 | moderate | cool | very short | very late | very low |
| 256 | moderate | mild | very short | very early | very low |
| 257 | moderate | mild | very short | early | very low |
| 258 | moderate | mild | very short | moderately late | very low |
| 259 | moderate | mild | very short | late | very low |
| 260 | moderate | mild | very short | very late | very low |
| 261 | moderate | very cold | short | very early | very low |
| 262 | moderate | very cold | short | early | very low |
| 263 | moderate | very cold | short | moderately late | very low |

| | | | | | |
|-----|----------|-----------|------------------|-----------------|----------|
| 264 | moderate | very cold | short | late | very low |
| 265 | moderate | very cold | short | very late | very low |
| 266 | moderate | cold | short | very early | very low |
| 267 | moderate | cold | short | early | very low |
| 268 | moderate | cold | short | moderately late | very low |
| 269 | moderate | cold | short | late | very low |
| 270 | moderate | cold | short | very late | very low |
| 271 | moderate | cool | short | very early | very low |
| 272 | moderate | cool | short | early | very low |
| 273 | moderate | cool | short | moderately late | very low |
| 274 | moderate | cool | short | late | very low |
| 275 | moderate | cool | short | very late | very low |
| 276 | moderate | mild | short | very early | very low |
| 277 | moderate | mild | short | early | very low |
| 278 | moderate | mild | short | moderately late | very low |
| 279 | moderate | mild | short | late | very low |
| 280 | moderate | mild | short | very late | very low |
| 281 | moderate | very cold | moderately short | very early | very low |
| 282 | moderate | very cold | moderately short | early | very low |
| 283 | moderate | very cold | moderately short | moderately late | very low |
| 284 | moderate | very cold | moderately short | late | very low |
| 285 | moderate | very cold | moderately short | very late | very low |
| 286 | moderate | cold | moderately short | very early | low |
| 287 | moderate | cold | moderately short | early | very low |
| 288 | moderate | cold | moderately short | moderately late | very low |
| 289 | moderate | cold | moderately short | late | very low |
| 290 | moderate | cold | moderately short | very late | very low |
| 291 | moderate | cool | moderately short | very early | low |
| 292 | moderate | cool | moderately short | early | very low |
| 293 | moderate | cool | moderately short | moderately late | very low |
| 294 | moderate | cool | moderately short | late | very low |
| 295 | moderate | cool | moderately short | very late | very low |
| 296 | moderate | mild | moderately short | very early | low |
| 297 | moderate | mild | moderately short | early | very low |
| 298 | moderate | mild | moderately short | moderately late | very low |
| 299 | moderate | mild | moderately short | late | very low |
| 300 | moderate | mild | moderately short | very late | very low |
| 301 | moderate | very cold | moderately long | very early | very low |
| 302 | moderate | very cold | moderately long | early | very low |
| 303 | moderate | very cold | moderately long | moderately late | very low |
| 304 | moderate | very cold | moderately long | late | very low |
| 305 | moderate | very cold | moderately long | very late | very low |
| 306 | moderate | cold | moderately long | very early | low |
| 307 | moderate | cold | moderately long | early | low |
| 308 | moderate | cold | moderately long | moderately late | very low |

| | | | | | |
|-----|----------|-----------|-----------------|-----------------|-----------------|
| 309 | moderate | cold | moderately long | late | very low |
| 310 | moderate | cold | moderately long | very late | very low |
| 311 | moderate | cool | moderately long | very early | moderate |
| 312 | moderate | cool | moderately long | early | moderate |
| 313 | moderate | cool | moderately long | moderately late | low |
| 314 | moderate | cool | moderately long | late | low |
| 315 | moderate | cool | moderately long | very late | low |
| 316 | moderate | mild | moderately long | very early | moderate |
| 317 | moderate | mild | moderately long | early | moderate |
| 318 | moderate | mild | moderately long | moderately late | moderate |
| 319 | moderate | mild | moderately long | late | low |
| 320 | moderate | mild | moderately long | very late | low |
| 321 | moderate | very cold | long | very early | very low |
| 322 | moderate | very cold | long | early | very low |
| 323 | moderate | very cold | long | moderately late | very low |
| 324 | moderate | very cold | long | late | very low |
| 325 | moderate | very cold | long | very late | very low |
| 326 | moderate | cold | long | very early | moderate |
| 327 | moderate | cold | long | early | moderate |
| 328 | moderate | cold | long | moderately late | low |
| 329 | moderate | cold | long | late | low |
| 330 | moderate | cold | long | very late | low |
| 331 | moderate | cool | long | very early | moderate |
| 332 | moderate | cool | long | early | moderate |
| 333 | moderate | cool | long | moderately late | moderate |
| 334 | moderate | cool | long | late | low |
| 335 | moderate | cool | long | very late | low |
| 336 | moderate | mild | long | very early | moderate |
| 337 | moderate | mild | long | early | moderate |
| 338 | moderate | mild | long | moderately late | moderate |
| 339 | moderate | mild | long | late | low |
| 340 | moderate | mild | long | very late | low |
| 341 | moderate | very cold | very long | very early | very low |
| 342 | moderate | very cold | very long | early | very low |
| 343 | moderate | very cold | very long | moderately late | very low |
| 344 | moderate | very cold | very long | late | very low |
| 345 | moderate | very cold | very long | very late | very low |
| 346 | moderate | cold | very long | very early | moderate |
| 347 | moderate | cold | very long | early | moderate |
| 348 | moderate | cold | very long | moderately late | moderate |
| 349 | moderate | cold | very long | late | low |
| 350 | moderate | cold | very long | very late | low |
| 351 | moderate | cool | very long | very early | moderate |
| 352 | moderate | cool | very long | early | moderate |
| 353 | moderate | cool | very long | moderately late | moderate |

| | | | | | |
|-----|----------|-----------|------------|-----------------|----------|
| 354 | moderate | cool | very long | late | low |
| 355 | moderate | cool | very long | very late | low |
| 356 | moderate | mild | very long | very early | moderate |
| 357 | moderate | mild | very long | early | moderate |
| 358 | moderate | mild | very long | moderately late | moderate |
| 359 | moderate | mild | very long | late | low |
| 360 | moderate | mild | very long | very late | low |
| 361 | high | very cold | very short | very early | very low |
| 362 | high | very cold | very short | early | very low |
| 363 | high | very cold | very short | moderately late | very low |
| 364 | high | very cold | very short | late | very low |
| 365 | high | very cold | very short | very late | very low |
| 366 | high | cold | very short | very early | very low |
| 367 | high | cold | very short | early | very low |
| 368 | high | cold | very short | moderately late | very low |
| 369 | high | cold | very short | late | very low |
| 370 | high | cold | very short | very late | very low |
| 371 | high | cool | very short | very early | very low |
| 372 | high | cool | very short | early | very low |
| 373 | high | cool | very short | moderately late | very low |
| 374 | high | cool | very short | late | very low |
| 375 | high | cool | very short | very late | very low |
| 376 | high | mild | very short | very early | very low |
| 377 | high | mild | very short | early | very low |
| 378 | high | mild | very short | moderately late | very low |
| 379 | high | mild | very short | late | very low |
| 380 | high | mild | very short | very late | very low |
| 381 | high | very cold | short | very early | very low |
| 382 | high | very cold | short | early | very low |
| 383 | high | very cold | short | moderately late | very low |
| 384 | high | very cold | short | late | very low |
| 385 | high | very cold | short | very late | very low |
| 386 | high | cold | short | very early | very low |
| 387 | high | cold | short | early | very low |
| 388 | high | cold | short | moderately late | very low |
| 389 | high | cold | short | late | very low |
| 390 | high | cold | short | very late | very low |
| 391 | high | cool | short | very early | very low |
| 392 | high | cool | short | early | very low |
| 393 | high | cool | short | moderately late | very low |
| 394 | high | cool | short | late | very low |
| 395 | high | cool | short | very late | very low |
| 396 | high | mild | short | very early | very low |
| 397 | high | mild | short | early | very low |
| 398 | high | mild | short | moderately late | very low |

| | | | | | |
|-----|------|-----------|------------------|-----------------|----------|
| 399 | high | mild | short | late | very low |
| 400 | high | mild | short | very late | very low |
| 401 | high | very cold | moderately short | very early | very low |
| 402 | high | very cold | moderately short | early | very low |
| 403 | high | very cold | moderately short | moderately late | very low |
| 404 | high | very cold | moderately short | late | very low |
| 405 | high | very cold | moderately short | very late | very low |
| 406 | high | cold | moderately short | very early | moderate |
| 407 | high | cold | moderately short | early | moderate |
| 408 | high | cold | moderately short | moderately late | moderate |
| 409 | high | cold | moderately short | late | low |
| 410 | high | cold | moderately short | very late | low |
| 411 | high | cool | moderately short | very early | moderate |
| 412 | high | cool | moderately short | early | moderate |
| 413 | high | cool | moderately short | moderately late | moderate |
| 414 | high | cool | moderately short | late | low |
| 415 | high | cool | moderately short | very late | low |
| 416 | high | mild | moderately short | very early | moderate |
| 417 | high | mild | moderately short | early | moderate |
| 418 | high | mild | moderately short | moderately late | moderate |
| 419 | high | mild | moderately short | late | low |
| 420 | high | mild | moderately short | very late | low |
| 421 | high | very cold | moderately long | very early | very low |
| 422 | high | very cold | moderately long | early | very low |
| 423 | high | very cold | moderately long | moderately late | very low |
| 424 | high | very cold | moderately long | late | very low |
| 425 | high | very cold | moderately long | very late | very low |
| 426 | high | cold | moderately long | very early | moderate |
| 427 | high | cold | moderately long | early | moderate |
| 428 | high | cold | moderately long | moderately late | moderate |
| 429 | high | cold | moderately long | late | low |
| 430 | high | cold | moderately long | very late | low |
| 431 | high | cool | moderately long | very early | moderate |
| 432 | high | cool | moderately long | early | moderate |
| 433 | high | cool | moderately long | moderately late | moderate |
| 434 | high | cool | moderately long | late | low |
| 435 | high | cool | moderately long | very late | low |
| 436 | high | mild | moderately long | very early | moderate |
| 437 | high | mild | moderately long | early | moderate |
| 438 | high | mild | moderately long | moderately late | moderate |
| 439 | high | mild | moderately long | late | moderate |
| 440 | high | mild | moderately long | very late | low |
| 441 | high | very cold | long | very early | very low |
| 442 | high | very cold | long | early | very low |
| 443 | high | very cold | long | moderately late | very low |

| | | | | | |
|-----|-----------|-----------|------------|-----------------|-----------|
| 444 | high | very cold | long | late | very low |
| 445 | high | very cold | long | very late | very low |
| 446 | high | cold | long | very early | good |
| 447 | high | cold | long | early | good |
| 448 | high | cold | long | moderately late | good |
| 449 | high | cold | long | late | moderate |
| 450 | high | cold | long | very late | moderate |
| 451 | high | cool | long | very early | good |
| 452 | high | cool | long | early | good |
| 453 | high | cool | long | moderately late | good |
| 454 | high | cool | long | late | moderate |
| 455 | high | cool | long | very late | moderate |
| 456 | high | mild | long | very early | good |
| 457 | high | mild | long | early | good |
| 458 | high | mild | long | moderately late | good |
| 459 | high | mild | long | late | moderate |
| 460 | high | mild | long | very late | moderate |
| 461 | high | very cold | very long | very early | very low |
| 462 | high | very cold | very long | early | very low |
| 463 | high | very cold | very long | moderately late | very low |
| 464 | high | very cold | very long | late | very low |
| 465 | high | very cold | very long | very late | very low |
| 466 | high | cold | very long | very early | very good |
| 467 | high | cold | very long | early | very good |
| 468 | high | cold | very long | moderately late | very good |
| 469 | high | cold | very long | late | good |
| 470 | high | cold | very long | very late | good |
| 471 | high | cool | very long | very early | very good |
| 472 | high | cool | very long | early | very good |
| 473 | high | cool | very long | moderately late | very good |
| 474 | high | cool | very long | late | good |
| 475 | high | cool | very long | very late | good |
| 476 | high | mild | very long | very early | very good |
| 477 | high | mild | very long | early | very good |
| 478 | high | mild | very long | moderately late | very good |
| 479 | high | mild | very long | late | good |
| 480 | high | mild | very long | very late | good |
| 481 | very high | very cold | very short | very early | very low |
| 482 | very high | very cold | very short | early | very low |
| 483 | very high | very cold | very short | moderately late | very low |
| 484 | very high | very cold | very short | late | very low |
| 485 | very high | very cold | very short | very late | very low |
| 486 | very high | cold | very short | very early | very low |
| 487 | very high | cold | very short | early | very low |
| 488 | very high | cold | very short | moderately late | very low |

| | | | | | |
|-----|-----------|-----------|------------------|-----------------|----------|
| 489 | very high | cold | very short | late | very low |
| 490 | very high | cold | very short | very late | very low |
| 491 | very high | cool | very short | very early | very low |
| 492 | very high | cool | very short | early | very low |
| 493 | very high | cool | very short | moderately late | very low |
| 494 | very high | cool | very short | late | very low |
| 495 | very high | cool | very short | very late | very low |
| 496 | very high | mild | very short | very early | very low |
| 497 | very high | mild | very short | early | very low |
| 498 | very high | mild | very short | moderately late | very low |
| 499 | very high | mild | very short | late | very low |
| 500 | very high | mild | very short | very late | very low |
| 501 | very high | very cold | short | very early | very low |
| 502 | very high | very cold | short | early | very low |
| 503 | very high | very cold | short | moderately late | very low |
| 504 | very high | very cold | short | late | very low |
| 505 | very high | very cold | short | very late | very low |
| 506 | very high | cold | short | very early | moderate |
| 507 | very high | cold | short | early | moderate |
| 508 | very high | cold | short | moderately late | moderate |
| 509 | very high | cold | short | late | low |
| 510 | very high | cold | short | very late | low |
| 511 | very high | cool | short | very early | good |
| 512 | very high | cool | short | early | good |
| 513 | very high | cool | short | moderately late | good |
| 514 | very high | cool | short | late | moderate |
| 515 | very high | cool | short | very late | moderate |
| 516 | very high | mild | short | very early | good |
| 517 | very high | mild | short | early | good |
| 518 | very high | mild | short | moderately late | good |
| 519 | very high | mild | short | late | moderate |
| 520 | very high | mild | short | very late | moderate |
| 521 | very high | very cold | moderately short | very early | very low |
| 522 | very high | very cold | moderately short | early | very low |
| 523 | very high | very cold | moderately short | moderately late | very low |
| 524 | very high | very cold | moderately short | late | very low |
| 525 | very high | very cold | moderately short | very late | very low |
| 526 | very high | cold | moderately short | very early | good |
| 527 | very high | cold | moderately short | early | good |
| 528 | very high | cold | moderately short | moderately late | good |
| 529 | very high | cold | moderately short | late | moderate |
| 530 | very high | cold | moderately short | very late | moderate |
| 531 | very high | cool | moderately short | very early | good |
| 532 | very high | cool | moderately short | early | good |
| 533 | very high | cool | moderately short | moderately late | good |

| | | | | | |
|-----|-----------|-----------|------------------|-----------------|-----------|
| 534 | very high | cool | moderately short | late | moderate |
| 535 | very high | cool | moderately short | very late | moderate |
| 536 | very high | mild | moderately short | very early | good |
| 537 | very high | mild | moderately short | early | good |
| 538 | very high | mild | moderately short | moderately late | good |
| 539 | very high | mild | moderately short | late | moderate |
| 540 | very high | mild | moderately short | very late | moderate |
| 541 | very high | very cold | moderately long | very early | very low |
| 542 | very high | very cold | moderately long | early | very low |
| 543 | very high | very cold | moderately long | moderately late | very low |
| 544 | very high | very cold | moderately long | late | very low |
| 545 | very high | very cold | moderately long | very late | very low |
| 546 | very high | cold | moderately long | very early | good |
| 547 | very high | cold | moderately long | early | good |
| 548 | very high | cold | moderately long | moderately late | good |
| 549 | very high | cold | moderately long | late | moderate |
| 550 | very high | cold | moderately long | very late | moderate |
| 551 | very high | cool | moderately long | very early | good |
| 552 | very high | cool | moderately long | early | good |
| 553 | very high | cool | moderately long | moderately late | good |
| 554 | very high | cool | moderately long | late | moderate |
| 555 | very high | cool | moderately long | very late | moderate |
| 556 | very high | mild | moderately long | very early | good |
| 557 | very high | mild | moderately long | early | good |
| 558 | very high | mild | moderately long | moderately late | good |
| 559 | very high | mild | moderately long | late | moderate |
| 560 | very high | mild | moderately long | very late | moderate |
| 561 | very high | very cold | long | very early | very low |
| 562 | very high | very cold | long | early | very low |
| 563 | very high | very cold | long | moderately late | very low |
| 564 | very high | very cold | long | late | very low |
| 565 | very high | very cold | long | very late | very low |
| 566 | very high | cold | long | very early | very good |
| 567 | very high | cold | long | early | very good |
| 568 | very high | cold | long | moderately late | very good |
| 569 | very high | cold | long | late | good |
| 570 | very high | cold | long | very late | good |
| 571 | very high | cool | long | very early | very good |
| 572 | very high | cool | long | early | very good |
| 573 | very high | cool | long | moderately late | very good |
| 574 | very high | cool | long | late | good |
| 575 | very high | cool | long | very late | good |
| 576 | very high | mild | long | very early | very good |
| 577 | very high | mild | long | early | very good |
| 578 | very high | mild | long | moderately late | very good |

| | | | | | |
|-----|-----------|-----------|-----------|-----------------|-----------|
| 579 | very high | mild | long | late | good |
| 580 | very high | mild | long | very late | good |
| 581 | very high | very cold | very long | very early | very low |
| 582 | very high | very cold | very long | early | very low |
| 583 | very high | very cold | very long | moderately late | very low |
| 584 | very high | very cold | very long | late | very low |
| 585 | very high | very cold | very long | very late | very low |
| 586 | very high | cold | very long | very early | very good |
| 587 | very high | cold | very long | early | very good |
| 588 | very high | cold | very long | moderately late | very good |
| 589 | very high | cold | very long | late | good |
| 590 | very high | cold | very long | very late | good |
| 591 | very high | cool | very long | very early | very good |
| 592 | very high | cool | very long | early | very good |
| 593 | very high | cool | very long | moderately late | very good |
| 594 | very high | cool | very long | late | good |
| 595 | very high | cool | very long | very late | good |
| 596 | very high | mild | very long | very early | very good |
| 597 | very high | mild | very long | early | very good |
| 598 | very high | mild | very long | moderately late | very good |
| 599 | very high | mild | very long | late | good |
| 600 | very high | mild | very long | very late | good |

2. Rule bases for Nutrient Suitability model

2.1. Soil Adsorption Matrix model

| No. | IF | AND | AND | THEN |
|-----|-----------------|-----------------|-------------|----------|
| | SD | CF | ST | SAM |
| 1 | very shallow | very low | sandy soils | low |
| 2 | shallow | very low | sandy soils | low |
| 3 | moderately deep | very low | sandy soils | low |
| 4 | deep | very low | sandy soils | moderate |
| 5 | very deep | very low | sandy soils | moderate |
| 6 | very shallow | low | sandy soils | low |
| 7 | shallow | low | sandy soils | low |
| 8 | moderately deep | low | sandy soils | low |
| 9 | deep | low | sandy soils | moderate |
| 10 | very deep | low | sandy soils | moderate |
| 11 | very shallow | moderately high | sandy soils | low |
| 12 | shallow | moderately high | sandy soils | low |
| 13 | moderately deep | moderately high | sandy soils | low |
| 14 | deep | moderately high | sandy soils | low |
| 15 | very deep | moderately high | sandy soils | moderate |
| 16 | very shallow | high | sandy soils | low |
| 17 | shallow | high | sandy soils | low |
| 18 | moderately deep | high | sandy soils | low |
| 19 | deep | high | sandy soils | low |
| 20 | very deep | high | sandy soils | low |
| 21 | very shallow | very high | sandy soils | low |
| 22 | shallow | very high | sandy soils | low |
| 23 | moderately deep | very high | sandy soils | low |
| 24 | deep | very high | sandy soils | low |
| 25 | very deep | very high | sandy soils | low |
| 26 | very shallow | very low | loamy sands | low |
| 27 | shallow | very low | loamy sands | low |
| 28 | moderately deep | very low | loamy sands | moderate |
| 29 | deep | very low | loamy sands | good |
| 30 | very deep | very low | loamy sands | good |
| 31 | very shallow | low | loamy sands | low |
| 32 | shallow | low | loamy sands | low |
| 33 | moderately deep | low | loamy sands | low |
| 34 | deep | low | loamy sands | moderate |
| 35 | very deep | low | loamy sands | good |
| 36 | very shallow | moderately high | loamy sands | low |
| 37 | shallow | moderately high | loamy sands | low |
| 38 | moderately deep | moderately high | loamy sands | low |

| | | | | |
|----|-----------------|-----------------|-------------|-----------|
| 39 | deep | moderately high | loamy sands | moderate |
| 40 | very deep | moderately high | loamy sands | moderate |
| 41 | very shallow | high | loamy sands | low |
| 42 | shallow | high | loamy sands | low |
| 43 | moderately deep | high | loamy sands | low |
| 44 | deep | high | loamy sands | low |
| 45 | very deep | high | loamy sands | moderate |
| 46 | very shallow | very high | loamy sands | low |
| 47 | shallow | very high | loamy sands | low |
| 48 | moderately deep | very high | loamy sands | low |
| 49 | deep | very high | loamy sands | low |
| 50 | very deep | very high | loamy sands | moderate |
| 51 | very shallow | very low | loamy soils | low |
| 52 | shallow | very low | loamy soils | low |
| 53 | moderately deep | very low | loamy soils | moderate |
| 54 | deep | very low | loamy soils | good |
| 55 | very deep | very low | loamy soils | very good |
| 56 | very shallow | low | loamy soils | low |
| 57 | shallow | low | loamy soils | low |
| 58 | moderately deep | low | loamy soils | moderate |
| 59 | deep | low | loamy soils | good |
| 60 | very deep | low | loamy soils | very good |
| 61 | very shallow | moderately high | loamy soils | low |
| 62 | shallow | moderately high | loamy soils | low |
| 63 | moderately deep | moderately high | loamy soils | moderate |
| 64 | deep | moderately high | loamy soils | moderate |
| 65 | very deep | moderately high | loamy soils | good |
| 66 | very shallow | high | loamy soils | low |
| 67 | shallow | high | loamy soils | low |
| 68 | moderately deep | high | loamy soils | moderate |
| 69 | deep | high | loamy soils | moderate |
| 70 | very deep | high | loamy soils | moderate |
| 71 | very shallow | very high | loamy soils | low |
| 72 | shallow | very high | loamy soils | low |
| 73 | moderately deep | very high | loamy soils | low |
| 74 | deep | very high | loamy soils | moderate |
| 75 | very deep | very high | loamy soils | moderate |
| 76 | very shallow | very low | clay soils | low |
| 77 | shallow | very low | clay soils | moderate |
| 78 | moderately deep | very low | clay soils | moderate |
| 79 | deep | very low | clay soils | good |
| 80 | very deep | very low | clay soils | very good |
| 81 | very shallow | low | clay soils | low |
| 82 | shallow | low | clay soils | moderate |
| 83 | moderately deep | low | clay soils | moderate |

| | | | | |
|-----|-----------------|-----------------|------------|-----------|
| 84 | deep | low | clay soils | good |
| 85 | very deep | low | clay soils | very good |
| 86 | very shallow | moderately high | clay soils | low |
| 87 | shallow | moderately high | clay soils | moderate |
| 88 | moderately deep | moderately high | clay soils | moderate |
| 89 | deep | moderately high | clay soils | good |
| 90 | very deep | moderately high | clay soils | good |
| 91 | very shallow | high | clay soils | low |
| 92 | shallow | high | clay soils | low |
| 93 | moderately deep | high | clay soils | moderate |
| 94 | deep | high | clay soils | moderate |
| 95 | very deep | high | clay soils | good |
| 96 | very shallow | very high | clay soils | low |
| 97 | shallow | very high | clay soils | low |
| 98 | moderately deep | very high | clay soils | moderate |
| 99 | deep | very high | clay soils | moderate |
| 100 | very deep | very high | clay soils | moderate |

2.2. Nutrient Suitability model

2.2.1. *Picea abies*

| No. | IF SAM | AND BS | AND pH | THEN SUI |
|-----|-----------|------------------------|-----------------------------|-------------|
| 1 | low | (low & unbalanced) | extremely acidic | low |
| 2 | low | (low & unbalanced) | very acidic | low |
| 3 | low | (low & unbalanced) | moderately acidic | low |
| 4 | low | (low & unbalanced) | weak acidic / weak alkaline | low |
| 5 | low | low supply | extremely acidic | low |
| 6 | low | low supply | very acidic | low |
| 7 | low | low supply | moderately acidic | low |
| 8 | low | low supply | weak acidic / weak alkaline | low |
| 9 | low | moderately good supply | extremely acidic | low |
| 10 | low | moderately good supply | very acidic | low |
| 11 | low | moderately good supply | moderately acidic | low |
| 12 | low | moderately good supply | weak acidic / weak alkaline | low |
| 13 | low | good supply | extremely acidic | low |
| 14 | low | good supply | very acidic | moderate |
| 15 | low | good supply | moderately acidic | moderate |
| 16 | low | good supply | weak acidic / weak alkaline | moderate |
| 17 | moderate | (low & unbalanced) | extremely acidic | low |
| 18 | moderate | (low & unbalanced) | very acidic | low |
| 19 | moderate | (low & unbalanced) | moderately acidic | low |

| | | | | |
|----|-----------|------------------------|-----------------------------|-----------|
| 20 | moderate | (low & unbalanced) | weak acidic / weak alkaline | moderate |
| 21 | moderate | low supply | extremely acidic | low |
| 22 | moderate | low supply | very acidic | moderate |
| 23 | moderate | low supply | moderately acidic | moderate |
| 24 | moderate | low supply | weak acidic / weak alkaline | moderate |
| 25 | moderate | moderately good supply | extremely acidic | low |
| 26 | moderate | moderately good supply | very acidic | moderate |
| 27 | moderate | moderately good supply | moderately acidic | good |
| 28 | moderate | moderately good supply | weak acidic / weak alkaline | good |
| 29 | moderate | good supply | extremely acidic | moderate |
| 30 | moderate | good supply | very acidic | good |
| 31 | moderate | good supply | moderately acidic | very good |
| 32 | moderate | good supply | weak acidic / weak alkaline | very good |
| 33 | good | (low & unbalanced) | extremely acidic | moderate |
| 34 | good | (low & unbalanced) | very acidic | moderate |
| 35 | good | (low & unbalanced) | moderately acidic | moderate |
| 36 | good | (low & unbalanced) | weak acidic / weak alkaline | moderate |
| 37 | good | low supply | extremely acidic | low |
| 38 | good | low supply | very acidic | moderate |
| 39 | good | low supply | moderately acidic | good |
| 40 | good | low supply | weak acidic / weak alkaline | good |
| 41 | good | moderately good supply | extremely acidic | moderate |
| 42 | good | moderately good supply | very acidic | good |
| 43 | good | moderately good supply | moderately acidic | very good |
| 44 | good | moderately good supply | weak acidic / weak alkaline | very good |
| 45 | good | good supply | extremely acidic | good |
| 46 | good | good supply | very acidic | good |
| 47 | good | good supply | moderately acidic | very good |
| 48 | good | good supply | weak acidic / weak alkaline | very good |
| 49 | very good | (low & unbalanced) | extremely acidic | low |
| 50 | very good | (low & unbalanced) | very acidic | moderate |
| 51 | very good | (low & unbalanced) | moderately acidic | moderate |
| 52 | very good | (low & unbalanced) | weak acidic / weak alkaline | moderate |
| 53 | very good | low supply | extremely acidic | moderate |
| 54 | very good | low supply | very acidic | good |
| 55 | very good | low supply | moderately acidic | good |
| 56 | very good | low supply | weak acidic / weak alkaline | good |
| 57 | very good | moderately good supply | extremely acidic | moderate |
| 58 | very good | moderately good supply | very acidic | good |
| 59 | very good | moderately good supply | moderately acidic | very good |
| 60 | very good | moderately good supply | weak acidic / weak alkaline | very good |
| 61 | very good | good supply | extremely acidic | moderate |
| 62 | very good | good supply | very acidic | very good |
| 63 | very good | good supply | moderately acidic | very good |
| 64 | very good | good supply | weak acidic / weak alkaline | very good |

2.2.2. *Abies alba*

| No. | IF | AND | AND | THEN |
|-----|----------|------------------------|-----------------------------|------------|
| | SAM | BS | pH | SUI |
| 1 | low | (low & unbalanced) | extremely acidic | unsuitable |
| 2 | low | (low & unbalanced) | very acidic | unsuitable |
| 3 | low | (low & unbalanced) | moderately acidic | unsuitable |
| 4 | low | (low & unbalanced) | weak acidic / weak alkaline | unsuitable |
| 5 | low | low supply | extremely acidic | unsuitable |
| 6 | low | low supply | very acidic | unsuitable |
| 7 | low | low supply | moderately acidic | low |
| 8 | low | low supply | weak acidic / weak alkaline | low |
| 9 | low | moderately good supply | extremely acidic | unsuitable |
| 10 | low | moderately good supply | very acidic | unsuitable |
| 11 | low | moderately good supply | moderately acidic | low |
| 12 | low | moderately good supply | weak acidic / weak alkaline | low |
| 13 | low | good supply | extremely acidic | unsuitable |
| 14 | low | good supply | very acidic | unsuitable |
| 15 | low | good supply | moderately acidic | moderate |
| 16 | low | good supply | weak acidic / weak alkaline | moderate |
| 17 | moderate | (low & unbalanced) | extremely acidic | unsuitable |
| 18 | moderate | (low & unbalanced) | very acidic | low |
| 19 | moderate | (low & unbalanced) | moderately acidic | low |
| 20 | moderate | (low & unbalanced) | weak acidic / weak alkaline | moderate |
| 21 | moderate | low supply | extremely acidic | unsuitable |
| 22 | moderate | low supply | very acidic | low |
| 23 | moderate | low supply | moderately acidic | moderate |
| 24 | moderate | low supply | weak acidic / weak alkaline | moderate |
| 25 | moderate | moderately good supply | extremely acidic | unsuitable |
| 26 | moderate | moderately good supply | very acidic | low |
| 27 | moderate | moderately good supply | moderately acidic | moderate |
| 28 | moderate | moderately good supply | weak acidic / weak alkaline | good |
| 29 | moderate | good supply | extremely acidic | low |
| 30 | moderate | good supply | very acidic | moderate |
| 31 | moderate | good supply | moderately acidic | very good |
| 32 | moderate | good supply | weak acidic / weak alkaline | very good |
| 33 | good | (low & unbalanced) | extremely acidic | low |
| 34 | good | (low & unbalanced) | very acidic | moderate |
| 35 | good | (low & unbalanced) | moderately acidic | moderate |
| 36 | good | (low & unbalanced) | weak acidic / weak alkaline | moderate |
| 37 | good | low supply | extremely acidic | low |
| 38 | good | low supply | very acidic | moderate |
| 39 | good | low supply | moderately acidic | moderate |

| | | | | |
|----|-----------|------------------------|-----------------------------|-----------|
| 40 | good | low supply | weak acidic / weak alkaline | moderate |
| 41 | good | moderately good supply | extremely acidic | low |
| 42 | good | moderately good supply | very acidic | moderate |
| 43 | good | moderately good supply | moderately acidic | very good |
| 44 | good | moderately good supply | weak acidic / weak alkaline | very good |
| 45 | good | good supply | extremely acidic | low |
| 46 | good | good supply | very acidic | moderate |
| 47 | good | good supply | moderately acidic | very good |
| 48 | good | good supply | weak acidic / weak alkaline | very good |
| 49 | very good | (low & unbalanced) | extremely acidic | low |
| 50 | very good | (low & unbalanced) | very acidic | moderate |
| 51 | very good | (low & unbalanced) | moderately acidic | moderate |
| 52 | very good | (low & unbalanced) | weak acidic / weak alkaline | moderate |
| 53 | very good | low supply | extremely acidic | low |
| 54 | very good | low supply | very acidic | moderate |
| 55 | very good | low supply | moderately acidic | moderate |
| 56 | very good | low supply | weak acidic / weak alkaline | good |
| 57 | very good | moderately good supply | extremely acidic | low |
| 58 | very good | moderately good supply | very acidic | moderate |
| 59 | very good | moderately good supply | moderately acidic | very good |
| 60 | very good | moderately good supply | weak acidic / weak alkaline | very good |
| 61 | very good | good supply | extremely acidic | low |
| 62 | very good | good supply | very acidic | very good |
| 63 | very good | good supply | moderately acidic | very good |
| 64 | very good | good supply | weak acidic / weak alkaline | very good |

2.2.3. *Fagus sylvatica*

| No. | IF | AND | AND | THEN |
|-----|-----|------------------------|-----------------------------|------------|
| | SAM | BS | pH | SUI |
| 1 | low | (low & unbalanced) | extremely acidic | unsuitable |
| 2 | low | (low & unbalanced) | very acidic | unsuitable |
| 3 | low | (low & unbalanced) | moderately acidic | unsuitable |
| 4 | low | (low & unbalanced) | weak acidic / weak alkaline | unsuitable |
| 5 | low | low supply | extremely acidic | unsuitable |
| 6 | low | low supply | very acidic | unsuitable |
| 7 | low | low supply | moderately acidic | low |
| 8 | low | low supply | weak acidic / weak alkaline | low |
| 9 | low | moderately good supply | extremely acidic | unsuitable |
| 10 | low | moderately good supply | very acidic | unsuitable |
| 11 | low | moderately good supply | moderately acidic | low |
| 12 | low | moderately good supply | weak acidic / weak alkaline | low |

| | | | | |
|----|-----------|------------------------|-----------------------------|------------|
| 13 | low | good supply | extremely acidic | low |
| 14 | low | good supply | very acidic | low |
| 15 | low | good supply | moderately acidic | moderate |
| 16 | low | good supply | weak acidic / weak alkaline | moderate |
| 17 | moderate | (low & unbalanced) | extremely acidic | low |
| 18 | moderate | (low & unbalanced) | very acidic | low |
| 19 | moderate | (low & unbalanced) | moderately acidic | moderate |
| 20 | moderate | (low & unbalanced) | weak acidic / weak alkaline | moderate |
| 21 | moderate | low supply | extremely acidic | unsuitable |
| 22 | moderate | low supply | very acidic | low |
| 23 | moderate | low supply | moderately acidic | moderate |
| 24 | moderate | low supply | weak acidic / weak alkaline | moderate |
| 25 | moderate | moderately good supply | extremely acidic | unsuitable |
| 26 | moderate | moderately good supply | very acidic | low |
| 27 | moderate | moderately good supply | moderately acidic | moderate |
| 28 | moderate | moderately good supply | weak acidic / weak alkaline | good |
| 29 | moderate | good supply | extremely acidic | low |
| 30 | moderate | good supply | very acidic | moderate |
| 31 | moderate | good supply | moderately acidic | very good |
| 32 | moderate | good supply | weak acidic / weak alkaline | very good |
| 33 | good | (low & unbalanced) | extremely acidic | low |
| 34 | good | (low & unbalanced) | very acidic | moderate |
| 35 | good | (low & unbalanced) | moderately acidic | good |
| 36 | good | (low & unbalanced) | weak acidic / weak alkaline | good |
| 37 | good | low supply | extremely acidic | low |
| 38 | good | low supply | very acidic | good |
| 39 | good | low supply | moderately acidic | good |
| 40 | good | low supply | weak acidic / weak alkaline | good |
| 41 | good | moderately good supply | extremely acidic | low |
| 42 | good | moderately good supply | very acidic | good |
| 43 | good | moderately good supply | moderately acidic | very good |
| 44 | good | moderately good supply | weak acidic / weak alkaline | very good |
| 45 | good | good supply | extremely acidic | low |
| 46 | good | good supply | very acidic | moderate |
| 47 | good | good supply | moderately acidic | very good |
| 48 | good | good supply | weak acidic / weak alkaline | very good |
| 49 | very good | (low & unbalanced) | extremely acidic | low |
| 50 | very good | (low & unbalanced) | very acidic | good |
| 51 | very good | (low & unbalanced) | moderately acidic | good |
| 52 | very good | (low & unbalanced) | weak acidic / weak alkaline | good |
| 53 | very good | low supply | extremely acidic | low |
| 54 | very good | low supply | very acidic | good |
| 55 | very good | low supply | moderately acidic | good |
| 56 | very good | low supply | weak acidic / weak alkaline | good |
| 57 | very good | moderately good supply | extremely acidic | low |

| | | | | |
|----|-----------|------------------------|-----------------------------|-----------|
| 58 | very good | moderately good supply | very acidic | moderate |
| 59 | very good | moderately good supply | moderately acidic | very good |
| 60 | very good | moderately good supply | weak acidic / weak alkaline | very good |
| 61 | very good | good supply | extremely acidic | low |
| 62 | very good | good supply | very acidic | very good |
| 63 | very good | good supply | moderately acidic | very good |
| 64 | very good | good supply | weak acidic / weak alkaline | very good |

2.3.4. *Quercus robur*

| No. | IF | AND | AND | THEN |
|-----|----------|------------------------|-----------------------------|------------|
| | SAM | BS | pH | SUI |
| 1 | low | (low & unbalanced) | extremely acidic | unsuitable |
| 2 | low | (low & unbalanced) | very acidic | unsuitable |
| 3 | low | (low & unbalanced) | moderately acidic | unsuitable |
| 4 | low | (low & unbalanced) | weak acidic / weak alkaline | unsuitable |
| 5 | low | low supply | extremely acidic | unsuitable |
| 6 | low | low supply | very acidic | unsuitable |
| 7 | low | low supply | moderately acidic | unsuitable |
| 8 | low | low supply | weak acidic / weak alkaline | unsuitable |
| 9 | low | moderately good supply | extremely acidic | unsuitable |
| 10 | low | moderately good supply | very acidic | unsuitable |
| 11 | low | moderately good supply | moderately acidic | low |
| 12 | low | moderately good supply | weak acidic / weak alkaline | low |
| 13 | low | good supply | extremely acidic | unsuitable |
| 14 | low | good supply | very acidic | unsuitable |
| 15 | low | good supply | moderately acidic | moderate |
| 16 | low | good supply | weak acidic / weak alkaline | moderate |
| 17 | moderate | (low & unbalanced) | extremely acidic | unsuitable |
| 18 | moderate | (low & unbalanced) | very acidic | unsuitable |
| 19 | moderate | (low & unbalanced) | moderately acidic | low |
| 20 | moderate | (low & unbalanced) | weak acidic / weak alkaline | low |
| 21 | moderate | low supply | extremely acidic | unsuitable |
| 22 | moderate | low supply | very acidic | unsuitable |
| 23 | moderate | low supply | moderately acidic | low |
| 24 | moderate | low supply | weak acidic / weak alkaline | moderate |
| 25 | moderate | moderately good supply | extremely acidic | unsuitable |
| 26 | moderate | moderately good supply | very acidic | low |
| 27 | moderate | moderately good supply | moderately acidic | moderate |
| 28 | moderate | moderately good supply | weak acidic / weak alkaline | moderate |
| 29 | moderate | good supply | extremely acidic | low |
| 30 | moderate | good supply | very acidic | moderate |

| | | | | |
|----|-----------|------------------------|-----------------------------|-----------|
| 31 | moderate | good supply | moderately acidic | moderate |
| 32 | moderate | good supply | weak acidic / weak alkaline | moderate |
| 33 | good | (low & unbalanced) | extremely acidic | low |
| 34 | good | (low & unbalanced) | very acidic | moderate |
| 35 | good | (low & unbalanced) | moderately acidic | moderate |
| 36 | good | (low & unbalanced) | weak acidic / weak alkaline | moderate |
| 37 | good | low supply | extremely acidic | low |
| 38 | good | low supply | very acidic | moderate |
| 39 | good | low supply | moderately acidic | moderate |
| 40 | good | low supply | weak acidic / weak alkaline | moderate |
| 41 | good | moderately good supply | extremely acidic | low |
| 42 | good | moderately good supply | very acidic | moderate |
| 43 | good | moderately good supply | moderately acidic | good |
| 44 | good | moderately good supply | weak acidic / weak alkaline | good |
| 45 | good | good supply | extremely acidic | low |
| 46 | good | good supply | very acidic | moderate |
| 47 | good | good supply | moderately acidic | good |
| 48 | good | good supply | weak acidic / weak alkaline | very good |
| 49 | very good | (low & unbalanced) | extremely acidic | low |
| 50 | very good | (low & unbalanced) | very acidic | low |
| 51 | very good | (low & unbalanced) | moderately acidic | moderate |
| 52 | very good | (low & unbalanced) | weak acidic / weak alkaline | moderate |
| 53 | very good | low supply | extremely acidic | low |
| 54 | very good | low supply | very acidic | low |
| 55 | very good | low supply | moderately acidic | moderate |
| 56 | very good | low supply | weak acidic / weak alkaline | moderate |
| 57 | very good | moderately good supply | extremely acidic | low |
| 58 | very good | moderately good supply | very acidic | moderate |
| 59 | very good | moderately good supply | moderately acidic | good |
| 60 | very good | moderately good supply | weak acidic / weak alkaline | good |
| 61 | very good | good supply | extremely acidic | low |
| 62 | very good | good supply | very acidic | good |
| 63 | very good | good supply | moderately acidic | very good |
| 64 | very good | good supply | weak acidic / weak alkaline | very good |

3. Rule bases for Water Suitability model

3.1. *Picea abies*

| No. | IF | AND | AND | THEN |
|-----|---------------------------|---------------------|--------------------|-----------------------|
| | SMI | GW | Gley | SUI |
| 1 | good water supply | no ground water | no gley | very good suitability |
| 2 | good water supply | no ground water | weak gleyic soil | moderate |
| 3 | good water supply | no ground water | strong gleyic soil | unsuitable |
| 4 | good water supply | ground water weak | no gley | good suitability |
| 5 | good water supply | ground water weak | weak gleyic soil | moderate suitability |
| 6 | good water supply | ground water weak | strong gleyic soil | unsuitable |
| 7 | good water supply | ground water strong | no gley | low suitability |
| 8 | good water supply | ground water strong | weak gleyic soil | low suitability |
| 9 | good water supply | ground water strong | strong gleyic soil | unsuitable |
| 10 | moderate water supply | no ground water | no gley | moderate suitability |
| 11 | moderate water supply | no ground water | weak gleyic soil | moderate suitability |
| 12 | moderate water supply | no ground water | strong gleyic soil | unsuitable |
| 13 | moderate water supply | ground water weak | no gley | good suitability |
| 14 | moderate water supply | ground water weak | weak gleyic soil | moderate suitability |
| 15 | moderate water supply | ground water weak | strong gleyic soil | unsuitable |
| 16 | moderate water supply | ground water strong | no gley | low suitability |
| 17 | moderate water supply | ground water strong | weak gleyic soil | low suitability |
| 18 | moderate water supply | ground water strong | strong gleyic soil | unsuitable |
| 19 | limited water supply | no ground water | no gley | low suitability |
| 20 | limited water supply | no ground water | weak gleyic soil | low suitability |
| 21 | limited water supply | no ground water | strong gleyic soil | unsuitable |
| 22 | limited water supply | ground water weak | no gley | moderate suitability |
| 23 | limited water supply | ground water weak | weak gleyic soil | moderate suitability |
| 24 | limited water supply | ground water weak | strong gleyic soil | unsuitable |
| 25 | limited water supply | ground water strong | no gley | low suitability |
| 26 | limited water supply | ground water strong | weak gleyic soil | low suitability |
| 27 | limited water supply | ground water strong | strong gleyic soil | unsuitable |
| 28 | very limited water supply | no ground water | no gley | unsuitable |
| 29 | very limited water supply | no ground water | weak gleyic soil | unsuitable |
| 30 | very limited water supply | no ground water | strong gleyic soil | unsuitable |

| | | | | |
|----|---------------------------|---------------------|--------------------|-----------------|
| 31 | very limited water supply | ground water weak | no gley | low suitability |
| 32 | very limited water supply | ground water weak | weak gleyic soil | low suitability |
| 33 | very limited water supply | ground water weak | strong gleyic soil | unsuitable |
| 34 | very limited water supply | ground water strong | no gley | low suitability |
| 35 | very limited water supply | ground water strong | weak gleyic soil | low suitability |
| 36 | very limited water supply | ground water strong | strong gleyic soil | unsuitable |

3.2. *Abies alba*

| No. | IF | AND | AND | THEN |
|-----|-----------------------|-----------------------|--------------------|-----------------------|
| | SMI | GW | Gley | SUI |
| 1 | good water supply | no ground water | no gley | very good suitability |
| 2 | good water supply | no ground water | weak gleyic soil | very good suitability |
| 3 | good water supply | no ground water | strong gleyic soil | good suitability |
| 4 | good water supply | ground water weak | no gley | very good suitability |
| 5 | good water supply | ground water weak | weak gleyic soil | very good suitability |
| 6 | good water supply | ground water weak | strong gleyic soil | good suitability |
| 7 | good water supply | ground water strong | no gley | very good suitability |
| 8 | good water supply | ground water strong | weak gleyic soil | very good suitability |
| 9 | good water supply | ground water strong | strong gleyic soil | good suitability |
| 10 | moderate water supply | no ground water | no gley | good suitability |
| 11 | moderate water supply | no ground water | weak gleyic soil | good suitability |
| 12 | moderate water supply | no ground water | strong gleyic soil | good suitability |
| 13 | moderate water supply | ground water weak | no gley | very good suitability |
| 14 | moderate water supply | ground water weak | weak gleyic soil | very good suitability |
| 15 | moderate water supply | ground water weak | strong gleyic soil | good suitability |
| 16 | moderate water supply | ground water strong | no gley | very good suitability |
| 17 | moderate water supply | moderate water supply | weak gleyic soil | very good suitability |
| 18 | moderate water supply | moderate water supply | strong gleyic soil | good suitability |
| 19 | limited water supply | no ground water | no gley | moderate suitability |

| | | | | |
|----|---------------------------|---------------------|--------------------|----------------------|
| 20 | limited water supply | no ground water | weak gleyic soil | moderate suitability |
| 21 | limited water supply | no ground water | strong gleyic soil | moderate suitability |
| 22 | limited water supply | ground water weak | no gley | good suitability |
| 23 | limited water supply | ground water weak | weak gleyic soil | good suitability |
| 24 | limited water supply | ground water weak | strong gleyic soil | good suitability |
| 25 | limited water supply | ground water strong | no gley | good suitability |
| 26 | limited water supply | ground water strong | weak gleyic soil | good suitability |
| 27 | limited water supply | ground water strong | strong gleyic soil | good suitability |
| 28 | very limited water supply | no ground water | no gley | unsuitable |
| 29 | very limited water supply | no ground water | weak gleyic soil | unsuitable |
| 30 | very limited water supply | no ground water | strong gleyic soil | unsuitable |
| 31 | very limited water supply | ground water weak | no gley | low suitability |
| 32 | very limited water supply | ground water weak | weak gleyic soil | low suitability |
| 33 | very limited water supply | ground water weak | strong gleyic soil | low suitability |
| 34 | very limited water supply | ground water strong | no gley | moderate suitability |
| 35 | very limited water supply | ground water strong | weak gleyic soil | moderate suitability |
| 36 | very limited water supply | ground water strong | strong gleyic soil | moderate suitability |

3.3. *Fagus sylvatica*

| No. | IF | AND | AND | THEN |
|-----|-----------------------|---------------------|--------------------|-----------------------|
| | SMI | GW | Gley | SUI |
| 1 | good water supply | no ground water | no gley | very good suitability |
| 2 | good water supply | no ground water | weak gleyic soil | moderate suitability |
| 3 | good water supply | no ground water | strong gleyic soil | low suitability |
| 4 | good water supply | ground water weak | no gley | very good suitability |
| 5 | good water supply | ground water weak | weak gleyic soil | moderate suitability |
| 6 | good water supply | ground water weak | strong gleyic soil | unsuitable |
| 7 | good water supply | ground water strong | no gley | very good suitability |
| 8 | good water supply | ground water strong | weak gleyic soil | moderate suitability |
| 9 | good water supply | ground water strong | strong gleyic soil | unsuitable |
| 10 | moderate water supply | no ground water | no gley | good suitability |

| | | | | |
|----|---------------------------|---------------------|--------------------|-----------------------|
| 11 | moderate water supply | no ground water | weak gleyic soil | moderate suitability |
| 12 | moderate water supply | no ground water | strong gleyic soil | unsuitable |
| 13 | moderate water supply | ground water weak | no gley | very good suitability |
| 14 | moderate water supply | ground water weak | weak gleyic soil | moderate suitability |
| 15 | moderate water supply | ground water weak | strong gleyic soil | unsuitable |
| 16 | moderate water supply | ground water strong | no gley | very good suitability |
| 17 | moderate water supply | ground water strong | weak gleyic soil | moderate suitability |
| 18 | moderate water supply | ground water strong | strong gleyic soil | unsuitable |
| 19 | limited water supply | no ground water | no gley | low suitability |
| 20 | limited water supply | no ground water | weak gleyic soil | low suitability |
| 21 | limited water supply | no ground water | strong gleyic soil | unsuitable |
| 22 | limited water supply | ground water weak | no gley | moderate suitability |
| 23 | limited water supply | ground water weak | weak gleyic soil | moderate suitability |
| 24 | limited water supply | ground water weak | strong gleyic soil | unsuitable |
| 25 | limited water supply | ground water strong | no gley | good suitability |
| 26 | limited water supply | ground water strong | weak gleyic soil | moderate suitability |
| 27 | limited water supply | ground water strong | strong gleyic soil | unsuitable |
| 28 | very limited water supply | no ground water | no gley | unsuitable |
| 29 | very limited water supply | no ground water | weak gleyic soil | unsuitable |
| 30 | very limited water supply | no ground water | strong gleyic soil | unsuitable |
| 31 | very limited water supply | ground water weak | no gley | unsuitable |
| 32 | very limited water supply | ground water weak | weak gleyic soil | unsuitable |
| 33 | very limited water supply | ground water weak | strong gleyic soil | unsuitable |
| 34 | very limited water supply | ground water strong | no gley | moderate suitability |
| 35 | very limited water supply | ground water strong | weak gleyic soil | moderate suitability |
| 36 | very limited water supply | ground water strong | strong gleyic soil | unsuitable |

3.4. Quercus robur

| No. | IF | AND | AND | THEN |
|-----|-----------------------|---------------------|--------------------|-----------------------|
| | SMI | GW | Gley | SUI |
| 1 | good water supply | no ground water | no gley | very good suitability |
| 2 | good water supply | no ground water | weak gleyic soil | very good suitability |
| 3 | good water supply | no ground water | strong gleyic soil | very good suitability |
| 4 | good water supply | ground water weak | no gley | very good suitability |
| 5 | good water supply | ground water weak | weak gleyic soil | very good suitability |
| 6 | good water supply | ground water weak | strong gleyic soil | very good suitability |
| 7 | good water supply | ground water strong | no gley | very good suitability |
| 8 | good water supply | ground water strong | weak gleyic soil | very good suitability |
| 9 | good water supply | ground water strong | strong gleyic soil | very good suitability |
| 10 | moderate water supply | no ground water | no gley | good suitability |
| 11 | moderate water supply | no ground water | weak gleyic soil | good suitability |
| 12 | moderate water supply | no ground water | strong gleyic soil | good suitability |
| 13 | moderate water supply | ground water weak | no gley | very good suitability |
| 14 | moderate water supply | ground water weak | weak gleyic soil | very good suitability |
| 15 | moderate water supply | ground water weak | strong gleyic soil | very good suitability |
| 16 | moderate water supply | ground water strong | no gley | very good suitability |
| 17 | moderate water supply | ground water strong | weak gleyic soil | very good suitability |
| 18 | moderate water supply | ground water strong | strong gleyic soil | very good suitability |
| 19 | limited water supply | no ground water | no gley | moderate suitability |
| 20 | limited water supply | no ground water | weak gleyic soil | moderate suitability |
| 21 | limited water supply | no ground water | strong gleyic soil | moderate suitability |
| 22 | limited water supply | ground water weak | no gley | good suitability |
| 23 | limited water supply | ground water weak | weak gleyic soil | good suitability |
| 24 | limited water supply | ground water weak | strong gleyic soil | good suitability |
| 25 | limited water supply | ground water strong | no gley | good suitability |
| 26 | limited water supply | ground water strong | weak gleyic soil | good suitability |
| 27 | limited water supply | ground water strong | strong gleyic soil | good suitability |

| | | | | |
|----|---------------------------|---------------------|--------------------|----------------------|
| 28 | very limited water supply | no ground water | no gley | low suitability |
| 29 | very limited water supply | no ground water | weak gleyic soil | low suitability |
| 30 | very limited water supply | no ground water | strong gleyic soil | low suitability |
| 31 | very limited water supply | ground water weak | no gley | moderate suitability |
| 32 | very limited water supply | ground water weak | weak gleyic soil | moderate suitability |
| 33 | very limited water supply | ground water weak | strong gleyic soil | moderate suitability |
| 34 | very limited water supply | ground water strong | no gley | good suitability |
| 35 | very limited water supply | ground water strong | weak gleyic soil | good suitability |
| 36 | very limited water supply | ground water strong | strong gleyic soil | good suitability |