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Possibilities of differentiating between forest community types with topographic variables in the canton of Appenzell Ausserrhoden

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Abstract

Forests often play an important role in mitigating the effects of natural hazards on humans and infrastructure, in particular in mountainous and densely populated countries like Switzerland. The protective function of forests depends on the forest community and its condition. Consequently, knowledge about forest communities is crucial to ensure site-adapted silvicultural measures. The low fraction of mapped forest communities and their expense of mapping call for ways of classifying forest communities remotely. The use of Digital Terrain Models (DTM) to do so arises because of their widespread availability, and the correlation between variables driving the distribution of forest communities and variables derived from DTMs. This thesis examined how well elevation and derivatives of DTMs can be used to distinguish between forest communities.

Topographic Wetness Indices (TWI) were calculated for three different spatial resolutions using two different Multiple Flow Direction (MFD) and one Single Flow Direction (SFD) flow routing algorithm. Additionally, the TWI was weighted with mean yearly precipitation. The data were extracted using a proportional stratified regular sampling. The analysis was conducted by looking at the differences between the forest communities descriptively and by calculating different Random Forest models.

Forest communities were found to occur at rather distinct elevation and slope values, while the variation of the aspect values was much higher. The coarsest DTM resolution performed best at explaining the distribution of forest communities regarding the correlation between TWI values and the humidity values. The two MFD algorithms were able to match TWI values with the position on the ecogram better than the SFD algorithm. The weighting of the TWI with precipitation data showed no clear improvement with regards to distinguishing between forest communities. Overall, Random Forest proved to be an appropriate algorithm to perform multivariate analysis of the distribution of forest communities.

This thesis showed that topographic variables have a high potential to distinguish between forest communities, when calculated with the right DTM resolution and flow routing algorithm. Therefore, topographic variables could be used complimentary to traditional field mapping methods to save time and costs.

Contents

List of Abbreviations

AR	Canton **A**ppenzell Ausser**r**hoden
AUC	**A**rea **U**nder the **C**urve
DTM	**D**igital **T**errain **M**odel
GIS	**G**eographic **I**nformation **S**ystem
LIDAR	**Li**ght **D**etection **a**nd **R**anging
mad	**m**edian **a**bsolute **d**eviation
MFD	**M**ultiple **F**low **D**irection
NaiS	**Na**chhaltigkeit und Erfolgskontrolle **i**m **S**chutzwald (German)
ROC	**R**eceiver **O**perating **C**haracteristics
SAGA	**S**ystem for **A**utomated **G**eoscientific **A**nalysis
SCA	**S**pecific **C**atchment **A**rea
SFD	**S**ingle **F**low **D**irection
SLF	Institut für **S**chnee- und **L**awinen**f**orschung (German)
TCA	**T**otal **C**atchment **A**rea
TWI	**T**opographic **W**etness **I**ndex

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1 Introduction

Switzerland's topography is characterized by the Alps, spanning across the whole country (BAFU 2015). The steep slopes of this mountain range make Switzerland prone to gravitational natural hazard processes such as rockfall, avalanches and shallow landslides (BAFU 2015; Breschan et al. 2018; Rickli et al. 2019). Where slopes are steep enough, shallow landslides (up to 2 m depth) can be triggered by intense rainfall and pose a danger to humans and infrastructure, especially when the shallow landslides turn into debris flows with run-out zones that can reach populated regions (Rickli et al. 2019). With the growing population and the increase in settlement area that has occurred in the last decades, the damage potential of such gravitational natural hazards has increased (Hilker et al. 2009). Additionally to the increasing damage potential, the probability of landslide occurrences is also predicted to increase in the future due to the intensification of heavy rainstorm events induced by climatic change (Beniston et al. 2011).

Forests have shown to play an important role in protecting populated regions from gravitational natural hazards (Schwarz et al. 2010; Breschan et al. 2018; Rickli et al. 2019). Forests cover roughly a third of Switzerland's land area. Of this third, approximately 42% of the forest area provides people with protection against natural hazards like avalanches, rockfall and landslides (Brang et al. 2006; Brändli et al. 2015). These forests that potentially reduce the risk of damage to humans or infrastructure, caused by natural hazards, are called protective forests (Losey and Wehrli 2013).

A protective forest can reduce the susceptibility to shallow landslides in two main ways. Firstly, forests can reduce the soil water content by withholding precipitation from the soil (interception) and by drawing water that they need for photosynthesis from the soil (evapotranspiration)(Sidle and Ochiai 2006; Graf et al. 2019). Secondly, forests can impact the soil mechanically by improving soil aggregation and ameliorating the cohesion between different soil layers through root reinforcement (Sidle and Ochiai 2006; Frei 2009;

Schwarz et al. 2010; Yildiz et al. 2015; Graf et al. 2019; Rickli et al. 2019). Generally, a slope is regarded as marginally stable when the slope angle is equal to the internal friction angle of dry soil. The aforementioned soil-stabilizing functions of forests can increase the angle at which a dry slope is still stable and does not slide off (Yildiz et al. 2019).

The extent of the protective function of a forest against gravitational natural hazards does not solely depend on the presence of forest but also on its structure (Rickli et al. 2019). The forest structure entails variables such as "layering", "cover", "development" and "mixture", and depends on the forest community type and the forest's condition (BAFU 2016). Targeted silvicultural measures help to ensure that the forest fulfils its desired protective function by improving its condition (Brändli et al. 2015; BAFU 2016). A guideline called *NaiS* was composed to help foresters know what the aspired forest condition is, depending on the forest community type, and how to reach the desired level of the forest's protective function with a minimal level of site-adapted silvicultural measures (Frehner et al. 2005). That being said, it becomes apparent that knowledge about the different forest community types is of fundamental importance (Kimmins 2004; Frehner et al. 2005; von Wyl et al. 2014). With the future challenges of climate change, the proper choice of tree species will become even more important than it is now when conducting silvicultural measures. Therefore, knowledge about different forest communities will gain importance (Brang et al. 2017).

Unfortunately, only 50% of Switzerland's forests are mapped (Brang et al. 2017), and the field mapping of these forest communities is expensive, time-consuming and has a low degree of reproducibility (Brzeziecki et al. 1993). Furthermore, the knowledge about the different forest community types in Switzerland is guarded and passed on by only a handful of specialists, of which most of them are close to retirement (Brang et al. 2017). So while knowledge about different forest community types is becoming increasingly important, only half of Switzerland's forests are currently mapped, and the knowledge about the forest communities is expected to decrease in the next decades (Brang et al. 2017). For these reasons, it would be desirable to be able to facilitate the mapping of forest communities.

The distribution of forest communities is determined by different biotic and abiotic factors. Temperature, solar radiation, soil water content and soil acidity are some of the important environmental factors that drive the distribution of forest communities (Ott et al. 1997; Kimmins 2004). In Switzerland, forest communities are classified in ecograms according to soil acidity and the humidity value. The latter is a term that quantifies the soil moisture content and comes from the ecological indicator values given e.g. in Landolt 1977. Up to a certain extent, these factors can be explained using geomorphometry as they highly correlate with the topography of the landscape (Guisan and Zimmermann 2000; Hörsch 2003).

Geomorphometry is the science of quantitative land-surface analysis (Pike 1995). As the land-surface plays a fundamental role in ecological and hydrologic processes, a better understanding of the land-surface can be beneficial to better understand the ecological and hydrologic processes (Montgomery and Dietrich 1988; Wilson 2012). The basis that underlies any geomorphometric analysis is a Digital Terrain Model (DTM). It is a digital representation of the bare ground surface, without any vegetation or buildings (Li et al. 2005). Elevation can be extracted from a DTM without any calculations. Additionally, three different types of derivatives can be extracted from a DTM. First-order derivatives include slope and aspect. Second-order derivatives are the profile curvature and the plan curvature. They are determined by calculating the rate of change of the aforementioned slope. Compound derivatives are terrain indices that combine two or more terrain attributes (Kienzle 2004). The widespread availability of high-resolution DTMs (0.5 m - 5 m) in Switzerland combined with the diverse geomorphometric analysis possibilities makes the previously mentioned derivatives potentially interesting to explain the distribution of forest communities (Guisan and Zimmermann 2000; Hörsch 2003).

Soil moisture is one of the main factors determining the composition of vegetation (Raduła et al. 2018). The movement of water can be mainly explained by gravity and the material the water flows over or through. The effect of gravity on the flow path of water can be approximated well with a DTM (Wilson 2012). Therefore, DTMs are commonly used in humid regions to better understand the soil moisture patterns by calculating the compound DTM derivative called *Topographic Wetness Index* (TWI)(Buchanan et al. 2014). The index describes the tendency of a raster cell to accumulate water by dividing the Specific Catchment Area (SCA) of a given point by the local slope, and then scaling it by the natural logarithm (Equation 2.1)(Mattivi et al. 2019). Preliminary to the calculation of the TWI, a flow routing algorithm has to be chosen that determines the way the outflow from a given cell will be distributed to one or more neighbouring cells (Wilson et al. 2008). Over the years, a variety of such algorithms has been developed (Fairfield and Leymarie 1991; Freeman 1991; Quinn et al. 1991; Holmgren 1994; Quinn et al. 1995; Qin et al. 2007). These algorithms can be divided into two main groups. Single Flow Direction algorithms (SFD) pass their entire flow on to a single neighbouring cell. Multiple Flow Direction algorithms (MFD) possibly pass on their flow to multiple down-slope neighbouring cells. The MFD algorithms can be further differentiated depending on the number of neighbouring cells they pass on flow to and by the way the flow partitioning is calculated.

Over the last couple of decades, both accuracy of DTMs and computing power have increased drastically, opening up new possibilities in research. Machine learning algorithms have been becoming more popular to classify land cover, plant communities and tree species (Adelabu et al. 2013; Ghimire et al. 2012). Ensemble machine learning algorithms such as the Random Forest algorithm (Breiman 2001) are particularly popular algorithms to use for complex classification problems (Zhang and Ma 2012). The idea of ensemble machine learning algorithms is to combine hundreds of different classification trees to a single model, taking advantage of the power of the collective (Zhang and Ma 2012).

The usage of DTM derivatives such as slope, aspect and TWI has become common practice in species distributions models (Brzeziecki et al. 1993; Hörsch 2003; Zimmermann et al. 2007; Kopecký and Čížková 2010). The TWI is widely accepted to give a good representation of the local hydrological conditions (Raduła et al. 2018). Nevertheless, there is a lack of understanding how the choice of the DTM resolution and the flow routing algorithm affects the TWI values with regards to matching the humidity value of forest communities. Furthermore, no research has been conducted to investigate whether weighting the TWI with mean yearly precipitation data portrays the hydrological conditions of an area better than without the weighting. In addition, ensemble machine learning algorithms such as Random Forest are yet to be used to classify forest community types, although their use is well established in other ecological research fields (Ghimire et al. 2012; Adelabu et al. 2013).

The objective of this thesis is to better understand the impact the DTM resolution and the flow routing algorithm have on TWI values with regards to matching humidity values of forest communities and, therefore, possibly facilitate the mapping of forest communities. Moreover, it shall be evaluated whether the weighting of the TWI with precipitation data poses an improvement with regards to matching humidity value of forest community types. Finally, it shall be evaluated whether Random Forest is a suitable method to explain forest communities using topographic variables. This thesis aims to investigate the following questions:

1. How well can elevation and first-order DTM derivatives explain the occurrence of different forest community types?
2. Which DTM resolution is most suitable when calculating a TWI to match the humidity value of forest communities?
3. Which flow routing algorithm is best used to calculate a TWI with regards to matching the humidity value of forest communities?
4. Does weighting the TWI with mean annual precipitation data pose an improvement with regards to differentiating between forest communities?
5. Is the Random Forest a suitable algorithm to classify forest community types based on topographic variables?

2 Methods and Materials

2.1 Study area

The study area is located in the canton of Appenzell Ausserrhoden (AR) in Switzerland. It is located in the north-east of Switzerland and borders to both the cantons of Appenzell Innerrhoden and St. Gallen, in the alpine foothills (Figure 2.1).

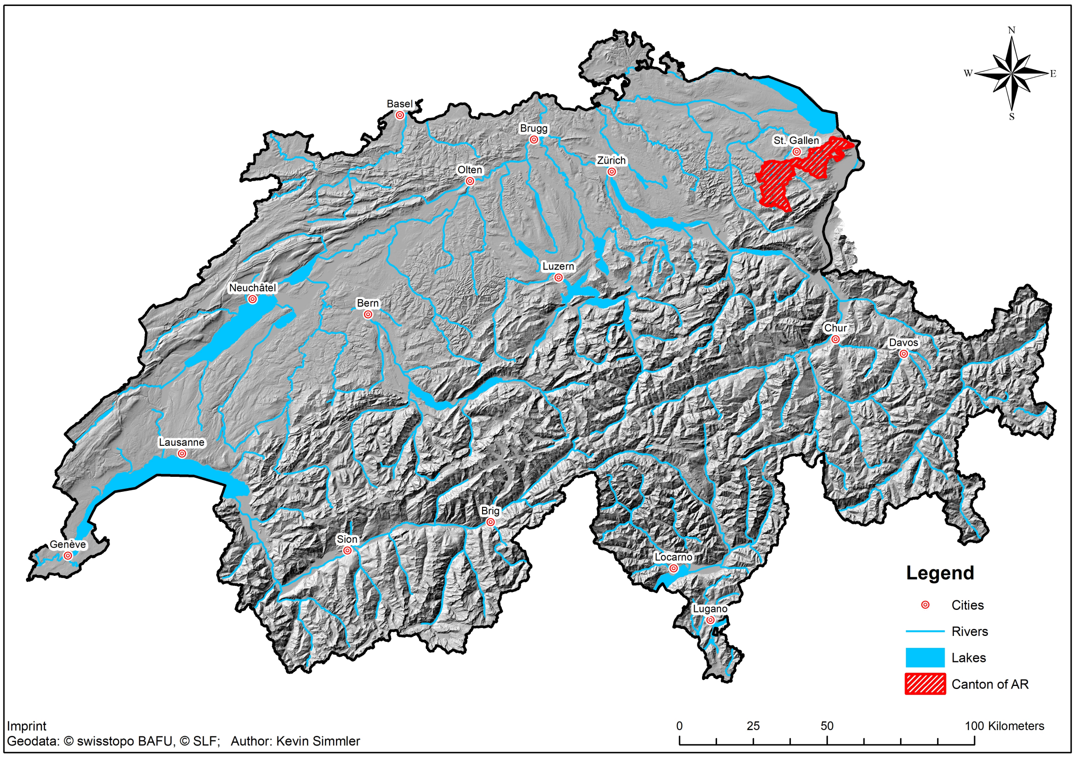


FIGURE 2.1: Map showing Switzerland and the study area of the canton of Appenzell Ausserrhoden (red).

The topography of the canton of AR can be described as hilly. The elevation stretches from 450 m.a.s.l. (Lutzenberg) to 2502 m.a.s.l. (Säntis)(Kanton Appenzell Ausserrhoden 2011).

Looking at the climate data of the reference period of 1981-2010 of the canton of AR, the mean yearly temperatures range from 0°C to 9°C (median = 7°C). Annual precipitation ranges from 1089 $mm * year^{-1}$ to 2735 $mm * year^{-1}$ (median = 1509 $mm * year^{-1}$)(MeteoSwiss).

2.2 The forest in the canton of Appenzell Ausserrhoden

2.2.1 Forest community types

Roughly a third of the canton of AR is covered by forest (Kanton Appenzell Ausserrhoden 2011). Within this forest area, 83 different forest communities were mapped (Burnand et al. 2013). The forest communities range across four elevational zones called *Submontan*, *Untermontan*, *Obermontan* and *Hochmontan* in Switzerland. Some areas show a variety of different forest community types on a very small spatial scale (Figure 2.2).

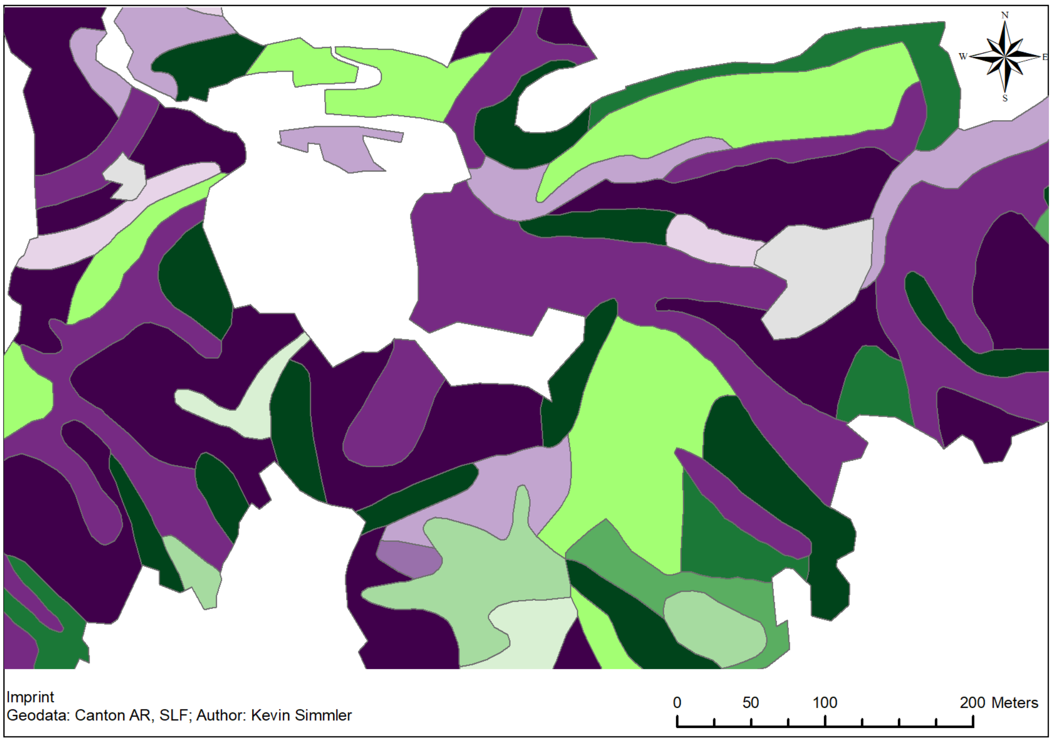


FIGURE 2.2: An excerpt of the forest communities in the canton of AR. Each colour represents a different forest community type.

The mapped forest communities vary significantly in their sizes and area fractions of the canton. While there is a large diversity of forest community types in the canton of AR, many of them only occur very rarely. As visible in Table 2.1, six of the 83 forest community types already account for more than half of the forest area. A complete list of forest community statistics can be found in Table A.2.

TABLE 2.1: Area fraction, total area, number of polygons and mean area per polygon of the 15 most common forest community types in the canton of AR.

Forest community	Area fraction [%]	Total area [m^2]	Number of polygons	Mean area per polygon [m^2]
19	15.5	7142730.6	1954	3655.4
20	8.2	3776563.4	1150	3284.0
8a	7.8	3592891.4	1124	3196.5
18	7.8	3589254.0	1087	3302.0
8d	6.9	3191648.7	1042	3063.0
19f	6.8	3142261.2	553	5682.2
20E	4.8	2200190.8	587	3748.2
8S	4.3	1966046.5	832	2363.0
12	3.9	1815085.1	696	2607.9
18M	3.3	1522651.1	497	3063.7
12S	2.4	1090368.7	566	1926.4
8f	2.2	1017408.3	201	5061.7
12w	1.9	878768.7	426	2062.8
18w	1.8	811063.2	401	2022.6
26	1.4	665515.0	579	1149.4

2.2.2 Preprocessing and exclusion of forest communities

A clear spatial delineation between different forest community types in the field only occurs if an environmental factor such as bedrock suddenly changes. Usually the transition from one forest community type to another is gradual and the mapped border man-made for practical reasons as it facilitates planning for forestry workers (Frehner et al. 2005).

As the difference between the extracted data of different forest community is the key interest of this study, several measures were taken to enhance the delineation between the different forest community types. Firstly, all forest communities that were mapped as a transition between two forest community types, indicated by a bracket with the forest community type that this mapped area transitions into inside the bracket (e.g. 12g(26h)), were excluded from the analysis. These "transition areas" make up 11% of the canton's forest area. The remaining 89% of the canton's forest areas were mapped as "main" forest community that does not transition into another forest community type.

As a second measure to increase the difference of the extracted data of different forest community types, a negative buffer of 5 m was applied to all forest community polygons with the *Buffer* function in ArcMap (ESRI), leaving a gap of 10 m between two polygons. A bigger buffer would have been preferred with regards to the enhanced delineation between different forest community types, but was not applicable because the mapped forest communities are extremely heterogeneous on a small spatial scale (Figure 2.2). Further enlarging the negative buffer would have led to a loss of too many forest community polygons.

As a third measure, all "special forest communities" (*Sonderwald* in German) were excluded from the analysis because, by definition, they cannot be classified solely by soil moisture and acidity as other "normal" forest communities can. Therefore, drawing conclusions based on their TWI values might be misleading. Furthermore, all forest communities whose name ends on a *k* were excluded from the analysis. These are versions of already existing forest community types that are influenced by the close proximity of bedrock. They were excluded because distinguishing between these bedrock-influenced forest communities and their "original" forest community would not be possible without any lithological variables. Finally, all forest communities with less than 50 extracted data points were excluded from the analysis to guarantee a certain robustness of the averages calculated per forest community (Congalton and Green 2019).

While all 52 forest community types left after the previously described exclusions were used for the analysis, some are more frequently displayed in the results section (chapter 3). The Latin and German name of the most commonly displayed forest communities can be found in Table 2.2.

TABLE 2.2: Number, German and Latin name, elevational zone and humidity category of the most frequently displayed forest communities in the results section.

number	German name	Latin name	elevational zone (german)	humidity category
1	Typischer Hainsimsen-Buchenwald	Luzulo-Fagetum typicum	submontan/ untermontan	
10	Platterbsen-Buchenwald mit Weisssegge	Lathyro-Fagetum caricetosum albae	submontan	
14	Seggen-Buchenwald mit Weisssegge	Carici albae-Fagetum typicum	submontan/ untermontan	dry
15	Seggen-Buchenwald mit Bergsegge	Carici-Fagetum caricetosum montanae	submontan/ untermontan	
16	Blaugras-Buchenwald	Seslerio-Fagetum	untermontan	
18*	Karbonat-Tannen-Buchenwald mit Weisssegge	Adenostylo-Abieti-Fagetum caricetosum albae	obermontan	
18M	Typischer Karbonat-Tannen-Buchenwald	Adenostylo-Abieti-Fagetum typycum	obermontan	
20C	Hochstauden-Tannen-Buchenwald mit Kitaibels Zahnwurz	Adenostylo alliariae-Abieti-Fagetum cardaminetosum kitaibelii	obermontan	average
20g	Hochstauden-Tannen-Buchenwald mit Barlauch	Adenostylo alliariae-Abieti-Fagetum allietosum	obermontan	
50*	Karbonat-Tannen-Fichtenwald mit Kahlem Alpendost	Adenostylo glabrae-Abieti-Piceetum typicum	hochmontan	
26h	Ahorn-Eschenwald, Höhenausbildung	Aceri-Fagetum	obermontan/ hochmontan	
27h	Bach-Eschenwald, Hohenausbildung	Carici remotae-Fraxinetum	obermontan	
27f	Bach-Eschenwald mit Riesenschachtelhalm	Carici-remotae-Fraxinetum equisetetosum telmateiae	submontan/ untermontan	wet
46*	Heidelbeer-Tannen-Fichtenwald mit Torfmoos	Vaccinio myrtilli-Abieti-Piceetum sphagnetosum	obermontan/ hochmontan	
56	Moorrand-Fichtenwald	Sphagno-Piceetum	obermontan/ hochmontan	
71	Torfmoos-Bergföhrenwald	Sphagno-Pinetum montanae	obtermontan/ hochmontan	

2.3 Precipitation data

The precipitation values are mean yearly values of the reference period of 1981-2010. The unit of the of precipitation is $cm * year^{-1}$. All forms of precipitation were converted to water-equivalent.

The data comes in a 100 m resolution for the whole of Switzerland. The precipitation values were calculated by interpolating *MeteoSwiss* weather stations using the *daymet* software (Thornton et al. 1997). The data processing was conducted by the *Land Change Science* group of the Swiss Federal Institute for Forest, Snow and Landscape Research in Birmensdorf (Switzerland).

The precipitation data was then broken down further into higher resolutions (5 m/2 m/0.5 m) by using the *disaggregate* function of the *raster* package in R (R Core Team 2013). This function allows to change the raster cell size to a smaller size without doing any further interpolations.

2.4 Topographic Wetness Index

2.4.1 Definition

The TWI is a commonly used index in humid regions to describe relative soil moisture patterns (Kopecký and Čížková 2010; Buchanan et al. 2014; Mattivi et al. 2019). The index describes the tendency of a cell to accumulate water and is calculated as follows.

The TWI is calculated by diving the *SCA* by the tan of the local slope β and then scaling this by the natural logarithm (Equation 2.1). The index assumes that conditions are steady-state and that the infiltration rate of the water into the soil is homogeneous (Mattivi et al. 2019).

$$TWI = ln\frac{SCA}{tan\beta} \tag{2.1}$$

Looking at the parameters of the equation of the TWI index, the SCA is a measure for the tendency for a cell to receive water, whereas the local slope is a measure of how well the water can drain. A cell prone to water accumulation, represented by high TWI values could, therefore, be described by a large up-slope contributing area and a low local slope. On the other hand, a well-drained cell, represented by a low TWI value, could be described by a small up-slope contribution area and a high local slope (Gruber and Peckham 2009; Mattivi et al. 2019).

To be able to calculate a SCA, the way water flows down-slope from cell to cell has to be defined. This is done by choosing a flow routing algorithm which defines the up-slope contribution area (Sørensen et al. 2006).

There are two main groups of algorithms that can be distinguished by how the water flow passes from cell to cell (Gruber and Peckham 2009). SFD algorithms allow the flow to only one neighbouring down-slope cell. The second group is called MFD algorithms. This group of algorithms allows the water to flow to more than one neighbouring down-slope cell. The group can be further divided by looking at the maximum number of down-slope cells that receive flow, ranging from two to eight cells (Kopecký and Čížková 2010).

The choice of the flow routing algorithm can have a considerable effect on the TWI and therefore is something to be considered (Kopecký and Čížková 2010).

2.4.2 Selection of flow routing algorithms

Overall, MFD algorithms have shown to perform better than SFD (Pan et al. 2004; Kopecký and Čížková 2010; Qin et al. 2011; Wittwer 2019). For that reason, the focus will be on MFD algorithms when computing the TWI. Specifically, the MFD-md algorithm (Qin et al. 2007) and the FD8-algorithm (Freeman 1991; Quinn et al. 1991) have shown the best explanatory abilities for soil moisture (Kopecký and Čížková 2010; Raduła et al. 2018) and will therefore be used for the calculations. Nevertheless, the Rho8-algorithm (SFD) has also shown a relatively high ability to predict soil moisture in a well differentiated topography (Raduła et al. 2018) and will therefore also be included in the analysis as the canton of AR has such a topography (Kanton Appenzell Ausserrhoden 2011).

TABLE 2.3: Description of the different flow routing algorithms used in this thesis

Algorithm	Type[a]	Maximum number of cells	Description	Author
Rho8	SFD	1	The algorithm randomly runs the flow to an adjacent cell with a probability proportional to the slope gradient.	Fairfield and Leymarie 1991
FD8	MFD	8	The algorithm drives the flow to all downslope neighbours through a flow partition exponent.	Freeman 1991 Quinn et al. 1991 Quinn et al. 1995 Holmgren 1994
MFD-md	MFD	8	The algorithm drives the flow to all downslope neighbours based on the linear function of the maximum downslope gradient.	Qin et al. 2007

[a] *SFD : singleflowdirectionalgorithm; MFD : multipleflowdirectionalgorithm.*

2.4.3 Calculation of TWI

Preprocessing of DTM

Topography is of fundamental importance to the analysis of a stream system and the calculation of variables like the TWI. DTMs are used to represent the topography of an area. From a DTM, flow direction, up-slope contributing areas, drainage divides and channel networks can be calculated (Band 1986). All these hydrological calculations are based on the simulation of overland water flow. In order to obtain the desired results from these hydrological calculations, the drainage network and watershed partition has to be fully connected. In an unprocessed DTM, this is not always guaranteed due to depressions in the landscape (Wang and Liu 2006).

A depression, also known as sink or pit, is a local minimum of the DTM that does not have a down-slope flow path to any adjacent cell. The depression can be a natural feature or an imperfection of the DTM. The surrounding overland flow therefore drains into the depression rather than the basin perimeter as it usually does (Wang and Liu 2006).

Surface depressions lead to undesirable results of hydrologic modelling. Therefore, it is common practise to remove them from a DTM before making any further calculations to ensure a continuous flow path (Wang and Liu 2006)(Figure 2.3).

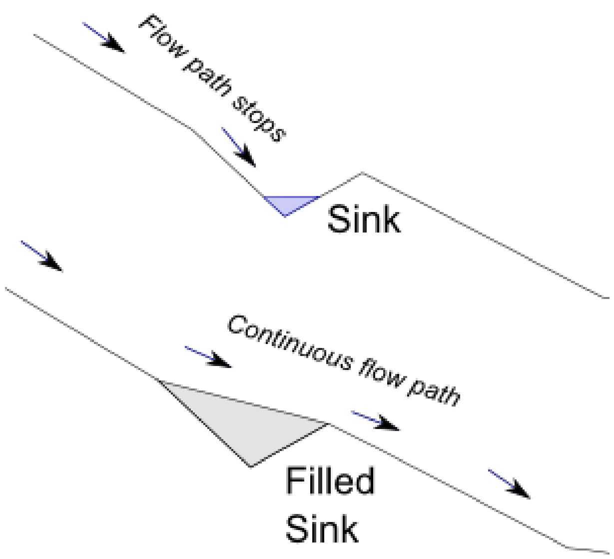


FIGURE 2.3: Illustration of how a surface depression is filled up (*Preprocessing and catchment deliniation*).

Workflow of calculating the TWI

All calculations described in this section were conducted with the geographic information system (GIS) called "System for Automated Geoscientific Analyses" (SAGA)(Conrad et al. 2015). For the resolution of 5 m and 2 m, the swissALTI3D DTM (Swisstopo 2019) was used. For the higher resolution of 0.5 m, a DTM was used that was created by processing LIDAR data of the canton of AR from 2014 with *rapidlasso* tools (van Rees 2013) at the Institute for Snow and Avalanche Research (SLF) in Davos (Switzerland).

From the DTM, slope and aspect were calculated using the *Slope, Aspect, Curvature* module. The method was set to *least squares fitted plane* (Costa-Cabral and Burges 1994). The units were set to *degree* for aspect, and to *radians* for slope. Furthermore, a Filled DTM was calculated from the DTM by using the the *Fill Sinks XXL (Wang Liu)* module (Wang and Liu 2006)(Figure 2.4). The *Minimum Slope* was set to 0.1.

The previously calculated Filled DTM was then used as input for the *Flow Accumulation (Top-Down)* module to calculate a Flow Accumulation (Total Catchment Area (TCA))(Figure 2.4). *Step* was set to one, the *Flow Accumulation Unit* set to cell area and the three *Methods* used to calculate the Flow Accumulation were *Rho8, Multiple Flow Direction* and *Multiple Maximum Downslope Gradient Based Flow Direction*.

The final step to calculate the TWI in SAGA was to input the Flow Accumulation as *Catchment Area* from the previous step and the slope (in radians) into the *Topographic Wetness Index (TWI)* module to get a Topographic Wetness Index as output (Figure 2.4). The *Method* was set to *Standard* and the *Area Conversion* to *1 / cell size (pseudo specific catchment area* because the Catchment Area used as Input in this module was not a SCA but a TCA.

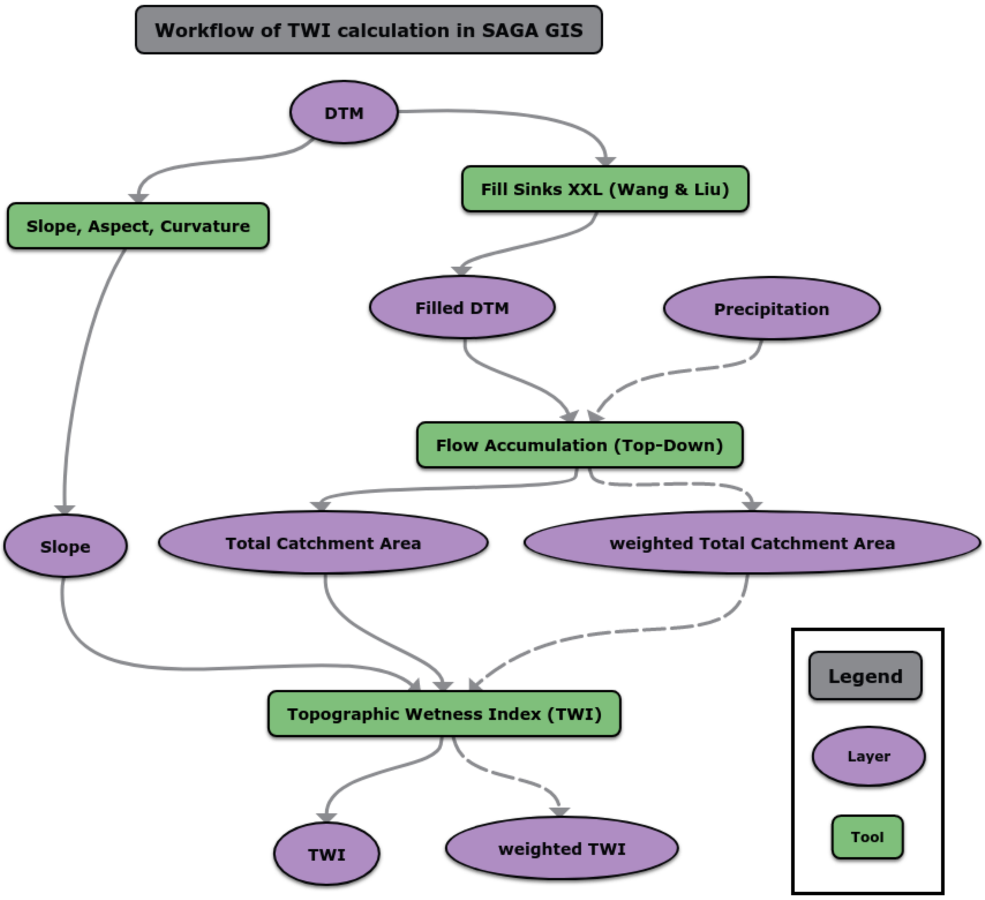


FIGURE 2.4: Workflow of the TWI calculation in SAGA. The green boxes represent SAGA tools, the purple layers.

Weighting the TWI with precipitation data

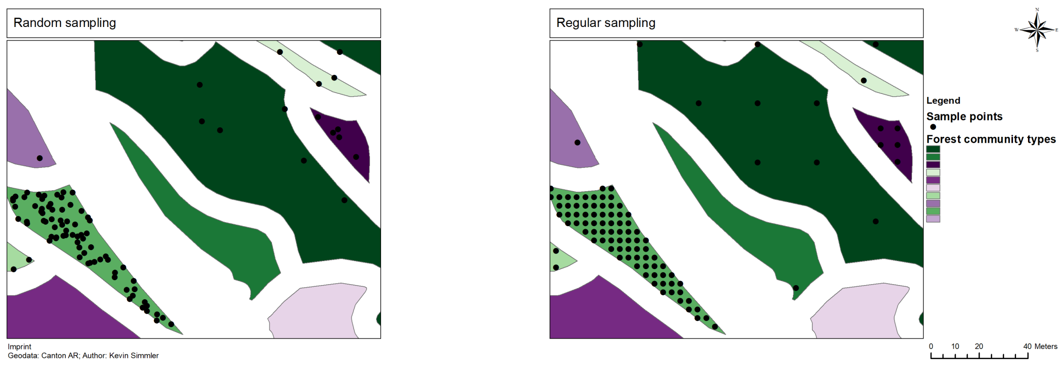
The TWI was weighted by setting the grid of the mean yearly precipitation for the reference period of 1981-2010 (in $cm * year^{-1}$) as *Weights* in the *Flow Accumulation (Top-Down)* module in SAGA (Figure 2.4).

If the flow accumulation is initialized without being weighted, each cell has the value of its cell area (if the *Flow Accumulation Unit* is set to *Cell Area*). From those values, the procedure starts and the higher cells "pass on" their values to lower cells. In a weighted flow accumulation, the procedure remains the same but the initial cell area values are multiplied with the precipitation data before the calculation procedure is started (*Weighting "Flow accumulation" with precipitation data*).

2.5 Sampling scheme and data extraction

Spatial sampling design is an important aspect to be considered in an environmental study involving spatial data, as the sampling design affects the quality of the data and, therefore, the final quality of the analysis (Müller 2007). The goal of every sampling design is to acquire a representative sample of the whole data set. In order to achieve this, both the distribution of the data points and the number of sampling points have to be considered in a sampling design (Grafström et al. 2012).

Auto-correlation is a common challenge to be faced with natural resource data that can affect the way the sampling points should be distributed in space. It describes the phenomena of locations that are close to each other being more likely to have similar values than locations far apart from each other (Tobler 1970). Auto-correlation can surely also be observed in the variables derived from a DTM and therefore it makes sense to spread out sampling points as much as possible. For this reason, a regular distribution of the sampling points was chosen over a random or clustered distribution as firstly, a regular distribution of sample points should lead to the most representative sample (Grafström et al. 2012) and also avoid sampling the same raster cell more than once (Figure 2.5).



(a) (b)

FIGURE 2.5: Comparison of **(a)** random sampling vs. **(b)** regular sampling. The black dots represent sampling points that are distributed in the different (buffered) forest community types, represented by the different colours of the polygons.

Besides the distribution of the sampling points, the number of sampling points taken per strata is the second important part of a sampling design.

For a sample to be representative, the strata should be included in the sample with equal probability (Grafström et al. 2012). As the sizes and fractions of the strata (forest community types) vary considerably (Table A.2), allocating the same number of sampling points to each strata would lead to much smaller sampling density in the large strata and therefore to a less representative sample (Gregoire and Valentine 2007)(Figure 2.6). For this reason, the number of points extracted per strata were proportional to the total area of each forest community.

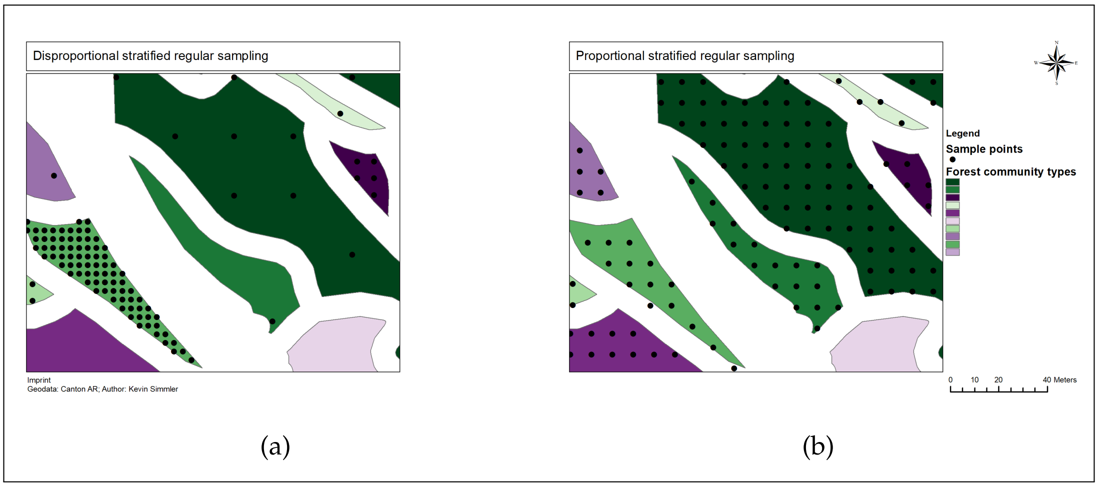


FIGURE 2.6: Comparison of **(a)** disproportional stratified regular sampling vs. **(b)** proportional stratified regular sampling. The black dots represent sampling points that are distributed in the different (buffered) forest community types, represented by the different colours of the polygons.

2.6 Statistical analysis

For the multivariate analysis, Random Forest was used (Breiman 2001).

Random Forest is a decision-tree-based ensemble machine learning algorithm. The main idea of it is to combine hundreds of individual classification trees to a single model and make it much more powerful by doing so (Zhang and Ma 2012). For this thesis, the number of trees calculated for each model was set to 500.

The number of input variables randomly sampled to make the split (mtry) was set to two input variables. This procedure of not considering all input variables at every split adds randomness and increases the variability of the decision trees, making the ensemble of trees more powerful (Zhang and Ma 2012).

For any classification, it is important to estimate the error made by the model. If no independent set of test samples is available, as it is the case in this study, the model can be tested "internally" by conducting a cross-validation (Kim 2009). In a cross-validation, the data set is split up into a predefined number of so called "folds". The model is then trained using all folds but one, to then test it on the left-out fold. This process is repeated until every fold was left out of the training process and instead used to test the model on. Finally, the error is calculated by averaging the errors attained from the testing of each "fold". For this thesis, a three times repeated 10-fold cross-validation was chosen to estimate the model error, as moderate fold values (10-20) have been found to reduce the variance (Kohavi 1995).

Due to limitations in computational power and time, the original data set was reduced in size by half. To ensure the proportions of the forest communities were preserved, this step was conducted with the *createDataPartition* function of the *caret* package in R (Kuhn 2012).

The predictive performance was assessed with the Receiver Operating Characteristic (ROC) curves. The curve is created by plotting the true positive rate (sensitivity) against the false positive rate (1 - specificity). The Area under the ROC curve (AUC) can then be calculated as a measure of model performance. AUC values of 0.5 stand for completely random, 0.7 for acceptable and 0.8 and higher for excellent (Moos et al. 2016).

3 Results

3.1 Values of extracted and calculated variables

Subsequent results are based on 523656 data points that were extracted from 52 different forest communities across the whole canton of AR. The number of data points extracted from each forest community can be found in Table A.3 and ranges from 63 to 95332. The basic descriptive statistics of all extracted and calculated values are listed in Table 3.1.

The forest communities addresses in this section are referred to by numbers. The corresponding German and Latin names of the most frequently presented communities are listed in Table 2.2 in the section *Methods and Materials*.

TABLE 3.1: Location and dispersion parameters of the DTM, its deduced variables and climate data in the canton of AR.
*median absolute deviation

	traits	unit	mean	median	sd	mad*	percentile 25	percentile 75	range
DTM and derivatives	altitude	m	944.40	941.10	157.35	159.18	837.80	1053.00	445.40 - 1587.60
	slope	°	23.36	23.16	9.50	9.92	16.38	29.75	0.08 - 77.74
	aspect	°	200.50	208.15	117.56	163.09	94.44	316.83	0.00 - 359.99
TWI	Rho8	-	4.28	3.79	2.02	1.53	2.89	5.09	0.08 - 19.94
	FD8	-	5.20	4.99	1.63	1.18	4.22	5.81	0.25 - 19.94
	MFD-md	-	4.91	4.66	1.75	1.31	3.82	5.59	0.08 - 19.94
Weighted TWI	weighted Rho8	-	9.36	8.87	2.02	1.54	7.97	10.18	5.36 - 24.99
	weighted FD8	-	10.40	10.14	1.72	1.24	9.34	11.03	5.52 - 25.00
	weighted MFDmd	-	10.06	9.78	1.82	1.35	8.92	10.76	5.36 - 24.99
Climate data	precipitation	mm^{-year}	1622.00	1589.00	186.84	175.99	1485.00	1742.00	1168.00 - 2167.00

The elevation at which the different forest communities are found varies significantly. The median values of the different forest communities range from 500.3 m (7g) to 1498.8 m (50*). The total median of all elevation values is 941.1 m (Figure 3.1). Most forest communities occur between 600 m and 1200 m. Only few are found below or above that range (Figure A.3).

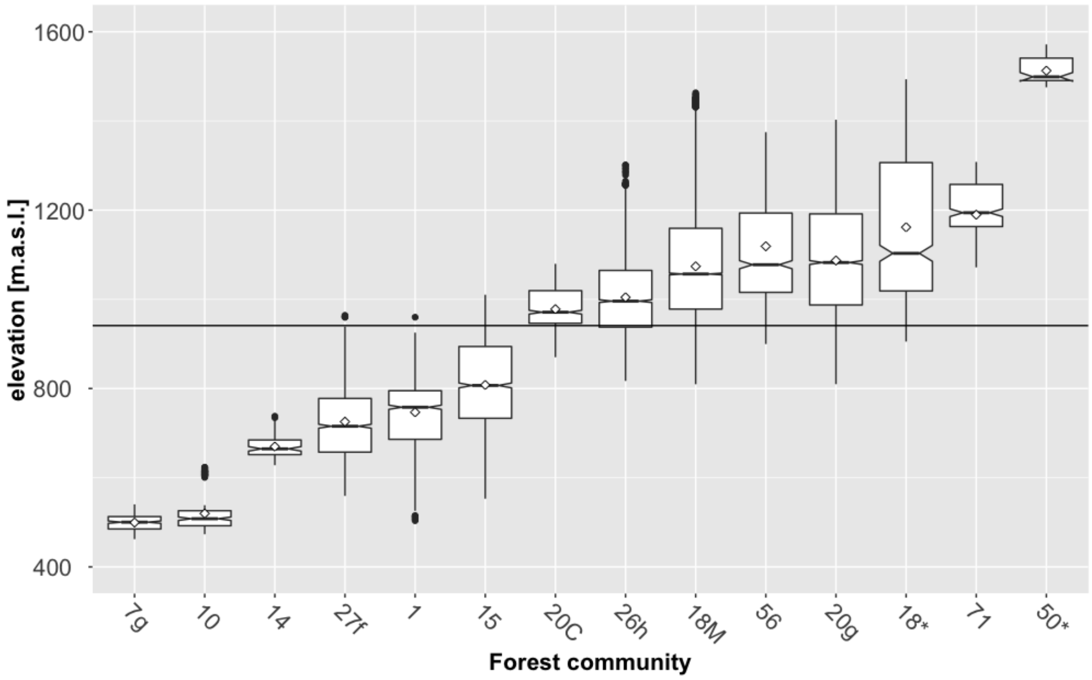


FIGURE 3.1: Elevation values of a selection of forest communities. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table 2.2. The black horizontal line represents the total median elevation value.

The median aspect of different forest communities also differs significantly. It is also obvious that the variation of the aspect values is exceptionally high (Figure 3.2). The median absolute deviation (mad; robust dispersion parameter) of 163.1°underlines the considerable variation.

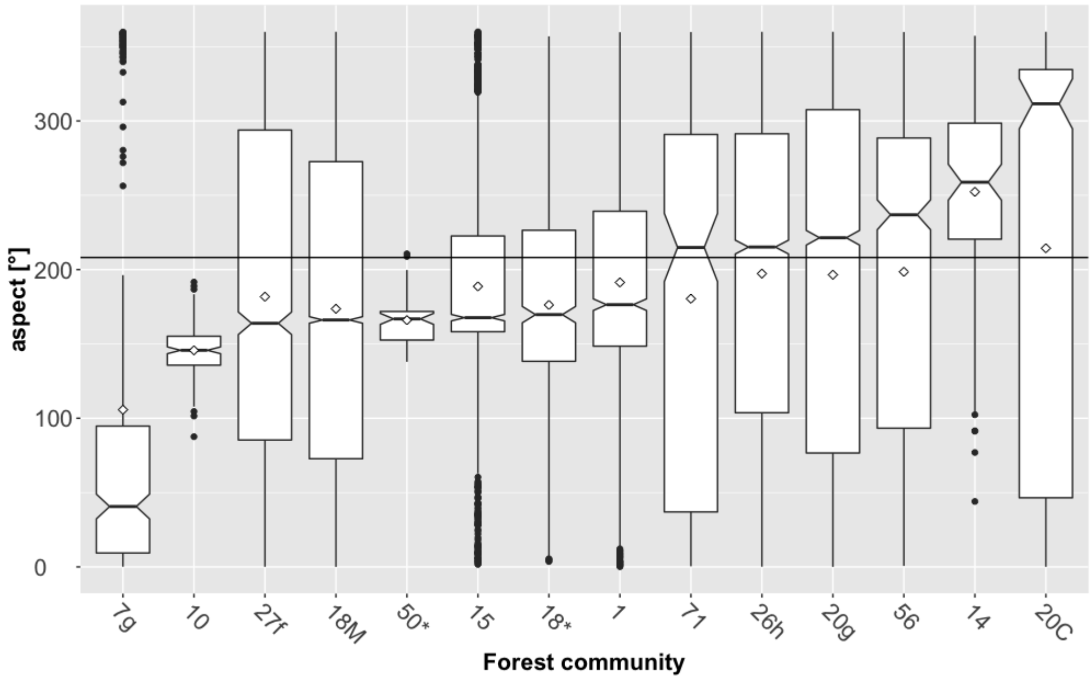


FIGURE 3.2: Aspect values of a selection of forest communities. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table 2.2. The black horizontal line represents the total median aspect value.

Opposed to the large variation of the aspect values, the slope values show a much clearer differentiation between the different forest communities. The median slope values range from 2.3°to 45.1°with a total median of 23.2°. While some forest communities as for example 71 and 56 are restricted to flat terrain, other forest communities such as number 10 and 50* are predominantly found on steep slopes (Figure 3.3).

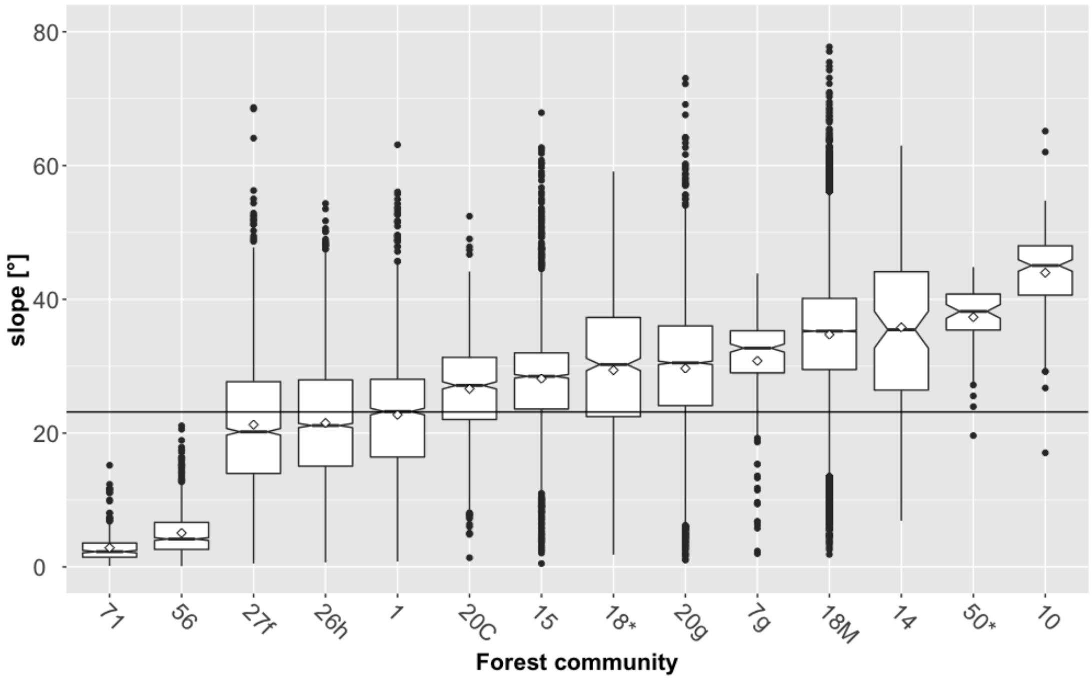


FIGURE 3.3: Slope values of a selection of forest communities. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table 2.2. The black horizontal line represents the total median slope value.

A display of the elevation, aspect and slope values of all forest community types can be found in section A.4.

Apart from a few exceptions, the distribution of the TWI values can be described as right-skewed. This means that the median is shifted towards the lower quartile. For almost all forest community types, the median for the TWI is lower compared to the corresponding mean value (section A.5). Outliers are present quite numerously in most of the forest community types, and the vast majority of them have abnormally high values while only very few have extremely low values.

As TWI values depend on the DTM resolution and the flow routing algorithm used as a basis of the calculation, the values cannot be seen as an absolute measure of humidity. They are a relative measure of humidity compared to the other values calculated with the same DTM resolution and the same flow routing algorithm. Nevertheless, a comparison between the median TWI values of the different forest communities and how these values fit into the ranking of the community's humidity according to the ecogram, allows to judge how well a resolution and a flow routing algorithm is suited to represent the humidity of forest communities. In the subsequent section, differences between various resolutions and flow routing algorithms are explained.

In Figure 3.4 the ecogram of a sequence of forest communities is presented from the *Obermontane* elevational zone to demonstrate how median TWI values can be evaluated in view of their ability to represent the humidity value of the forest communities.

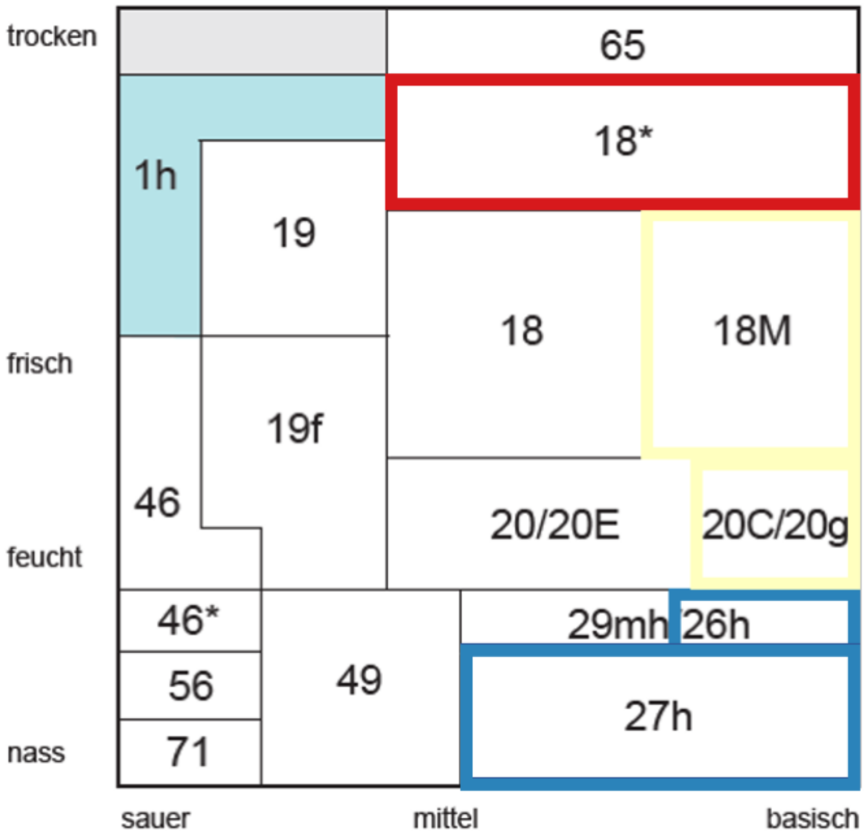


FIGURE 3.4: Ecogram of the *Obermontane* elevational zone. The TWI values of the framed forest community types are listed in Figure 3.5.

Figure 3.5 shows how the median TWI values, calculated for the forest communities shown in Figure 3.4, correspond to their position in the ecogram. Forest community 18* is found at the top of the ecogram. This means that it represents dry conditions. Correspondingly, low TWI values would be expected for this forest community. The other extreme is represented by forest community 27h. It is found at the very bottom of the ecogram representing wet conditions and, therefore, high TWI values are expected. The other four communities that were chosen from the ecogram for this exemplary presentation (18M, 20C, 20g, 26h) lie in between the two extremes. Therefore, each of the median TWI values are expected to follow the same pattern. For all three resolutions and all three flow routing algorithms, a general trend can be observed that dry forest communities found at the top of the ecogram (18*, 18M) have relatively low median TWI values. The opposite can be observed for wet forest communities found at the bottom of the ecogram (27h, 26h).

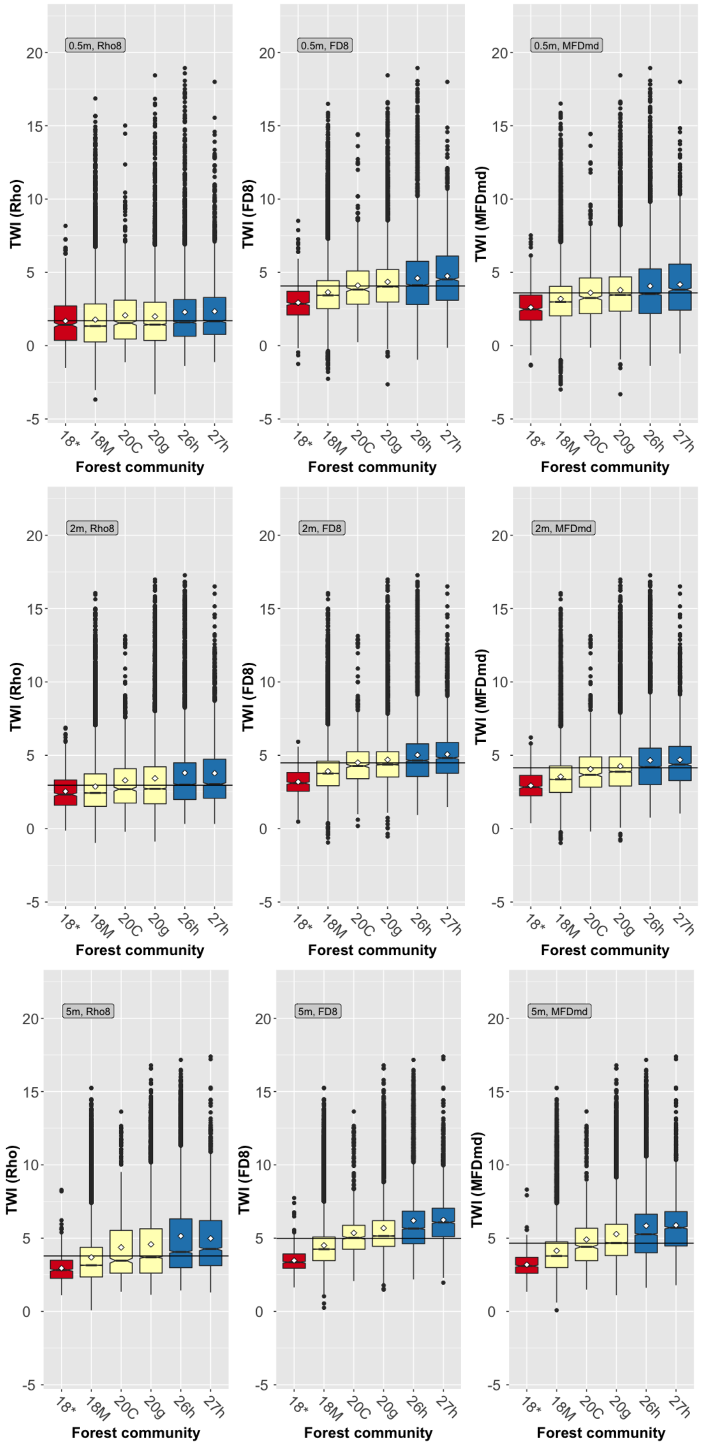


FIGURE 3.5: TWI values from a selection of forest communities from the *Obermontane* elevational zone. The forest communities are ordered from dry (left, red) to wet (right, blue). Each row of boxplots represents one resolution. At the top data from the 0.5 m, in the middle from the 2 m, and at the bottom from the 5 m resolution. Each column represents one flow routing algorithm. The Rho8 algorithm is presented in the left, the FD8 algorithm in the middle and the MFD-md algorithm in the right column. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table 2.2. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

The matching trends of the median TWI values and the position in the ecogram can also be seen for forest communities other than the ones shown in Figure 3.5. From the drier forest communities, several are identified as such by all flow routing algorithms in all resolutions. In the ecogram, forest community 18* can be found at the very top of the *Obermontane* elevational zone (Figure 3.4) and with one exception, it is always found to have the lowest median TWI values. Similarly, the mean TWI value of the communities 12e, 1h, 53 and 7e are always clearly below the total median of all communities. Two dry communities that stand out are number 10 and 14 (Figure A.24). Their median TWI values are always considerably lower than the average of all communities and 14 is always correctly recognized as drier than 10. Wet communities are well represented too by the median TWI value of all resolutions and flow routing algorithms. Community 26h, which is moist according to the ecogram (Figure 3.4), is always found to have a median TWI value slightly above the total median of all the communities. Furthermore, 27f and 27h too have a median TWI value above the average and 27h always has a higher value than 27f which corresponds well to their position in the ecogram (Figure A.24, Figure 3.4).

While the humidity value of some forest communities is represented well by the median TWI values for all resolutions and algorithms, there are also forest communities that are poorly represented by all resolutions or flow routing algorithms. This applies, for example, to the forest communities 14, 15 and 16. Out of these three, 14 always has the lowest median TWI value. Number 14's median TWI value is always slightly lower than number 16's even though 16 is classified drier according to the ecogram (Figure A.24). Moreover, the median TWI value of 14 is always considerably lower than the one of 15 even though they should be almost equal with regards to their classification in the ecogram (Figure A.24).

The humidity value [1] of some forest communities is represented well by the median TWI value calculated from all three resolutions. Nevertheless, the humidity value of other communities is represented better by TWI values calculated from one or the other DTM resolution. These differences are shown in the next section.

[1]The term "humidity value" comes from the "ecological indicator values" given e.g. in Landolt 1977.

3.2 DTM resolution

The choice of the DTM resolution affects the TWI values calculated from the DTM. The high-resolution DTM (0.5 m) leads to a more detailed representation of the terrain, whereas the lower-resolution DTM (5 m) represents the terrain smoother (Figure 3.6). The range of the TWI values changes depending on the resolution. Relative thereto, absolute TWI values change. Furthermore, a change in the ability of representing the humidity value of a forest community (as classified in the ecogram) is observed.

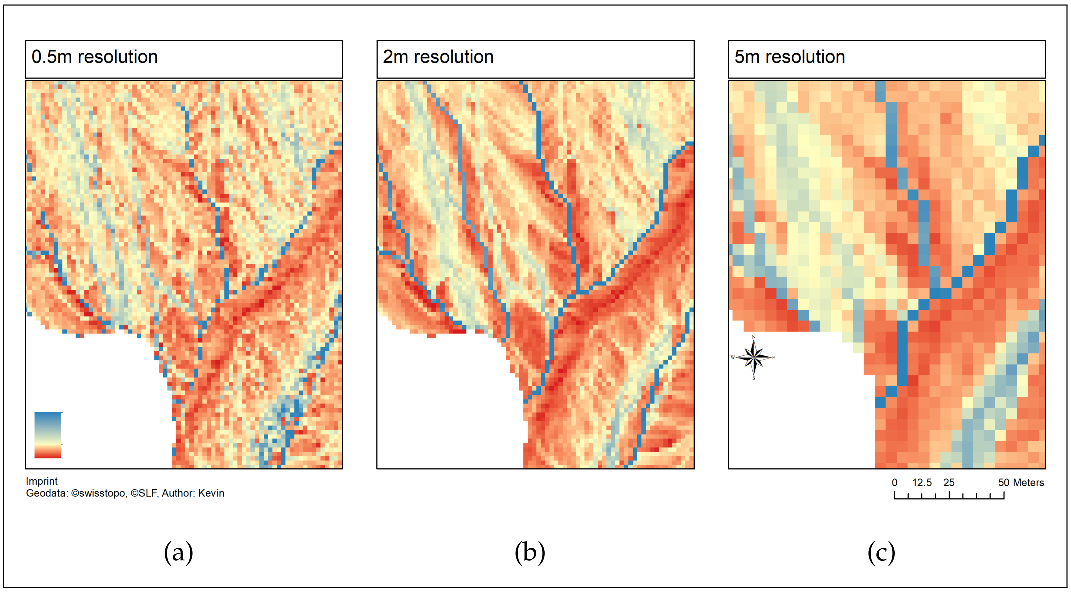


FIGURE 3.6: Map selection of the canton of AR showing differences in TWIs when using different resolution of the DTM for their calculation (MFD-md flow routing algorithm); (a) 0.5m resolution (b) 2m resolution (c) 5m resolution.

The position of forest communities that carry minimum or maximum median TWI values (within that ecogram, resolution and flow routing algorithm) could be regarded as a possible indicator of how well a resolution performs at matching TWI values with the humidity value classified in the ecogram. The position of the minimum and maximum median TWI values of the three different resolutions is shown in Figure 3.7.

In the highest resolution of 0.5 m, maximum and minimum median TWI values did not match the humidity value of the ecograms well in various cases (Figure 3.7(a)). The red minus symbol found at the bottom of the figure represents the median TWI value calculated with the FD8 algorithm for the forest community number 71. Despite this forest community being classified as the wettest forest community for the *Hochmontan* elevational zone, it had the lowest median TWI value of all forest communities in this ecogram. Consequently, its actual humidity value is poorly represented by the FD8 algorithm of the 0.5 m resolution. Another minimum value that stands out in the 0.5 m resolution is the one calculated with the MFD-md algorithm for the forest community number 46*. Within this calculation framework, this forest community had the lowest median TWI value (dry) in the *Hochmontan* elevational zone although, it is in fact, one of the wetter forest communities. With the 0.5 m resolution, only 11 out of 24 minimum/maximum median TWI values were found at the respective position of the ecograms.

With the slightly coarser resolution of 2 m matching minimum and maximum median TWI values with the "very wet" and "very dry" forest communities was more successful. Out of the 24 minimum and maximum median TWI values, 16 belonged to a forest community that is classified as driest or wettest in the corresponding ecograms (Figure 3.7(b)). Furthermore, three minimum values belonged to forest communities classified as "rather dry" within that ecogram, one maximum value to a community that is "rather wet", and four maximum values to forest communities that are found in the middle of the humidity range of the ecograms.

Best matching of minimum and maximum median TWI values, with forest communities classified as driest or wettest within the ecogram, was achieved with the coarsest resolution of 5 m. Of the 24 minimum and maximum median TWI values, 17 belonged to a forest community that is found at the very dry or wet end of the ecogram (Figure 3.7(c)). While the number of perfectly matched median TWI values with forest communities is only marginally higher compared to the 2 m resolution, a closer look shows that the median TWI values not found at the wet or dry end of the ecogram performed better than with the 2 m resolution. The three minimum values (dry) that were not found at the dry end of an ecogram were at least found in forest communities that are still classified as clearly dry. The same is true for the maximum values that were not found at the wet end of the ecogram. Finally, four maximum values were found representing above-average moisture conditions for forest communities.

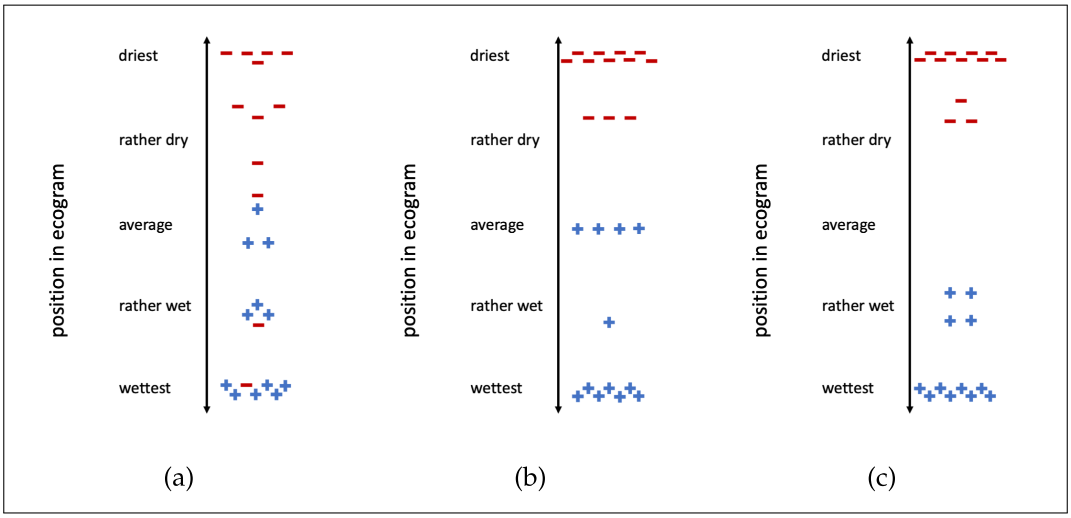


FIGURE 3.7: Qualitative assessment of the lowest and highest median TWI values related to the position in the ecograms of the four elevational zones. (a) 0.5 m resolution (b) 2 m resolution (c) 5 m resolution. The scale ranges from the wettest (bottom) to the driest forest community (top) classified in the ecogram.
+ : maximum values (wet) - : minimum values (dry)

The trend of better separation between wet and dry with a coarser DTM can not only be observed for the driest and wettest forest communities, as shown in Figure 3.7. For all three flow routing the following pattern can be seen for the "rather dry - dry" and the "rather wet - wet" forest communities, respectively. The median TWI values calculated from the high-resolution DTM of 0.5 m are inverted in several forest communities, meaning that dry communities according to the ecogram have clearly above the average median TWI values and vice versa. The TWI values calculated from the coarser DTM of 2 m resolution already show better separation than the 0.5 m resolution. Here the majority of dry forest communities in the ecogram also have a median TWI value that is below the median of the whole data set. The TWI values calculated from the coarsest DTM of 5 m resolution show a similar pattern such as those calculated from the 2 m DTM. However, with the former, the relative differences between the dry and wet forest communities are even more pronounced.

To sum up, the TWI values calculated from the coarsest DTM of 5 m resolution correspond better to the humidity value of forest communities than the TWI values calculated from the higher-resolution DTMs of 2 m and 0.5 m resolution do. The random forest model performances further support these findings from the descriptive analysis. For every model, the AUC decreases from lower (5 m) to higher DTM resolution (0.5 m), suggesting better model performance for the values calculated from the coarser DTM of 5 m resolution (Table 3.2).

Within different resolutions (0.5 m, 2 m, 5 m) of the DTM, TWI values vary depending on the flow routing algorithm applied for calculating the TWI. These differences will be explored in the next section.

3.3 Flow routing algorithm

The choice of the flow routing algorithm for calculating the TCA changes the flow paths of the water and, therefore, the TWI values. A clear difference can be observed between the SFD algorithm (Rho8) and the two MFD algorithms (FD8 and MFD-md). The SFD algorithm produces coarser screening than the two MFD algorithms that yield smooth screening with regards to the flow paths. There is no apparent difference between the two MFD algorithms (Figure 3.8).

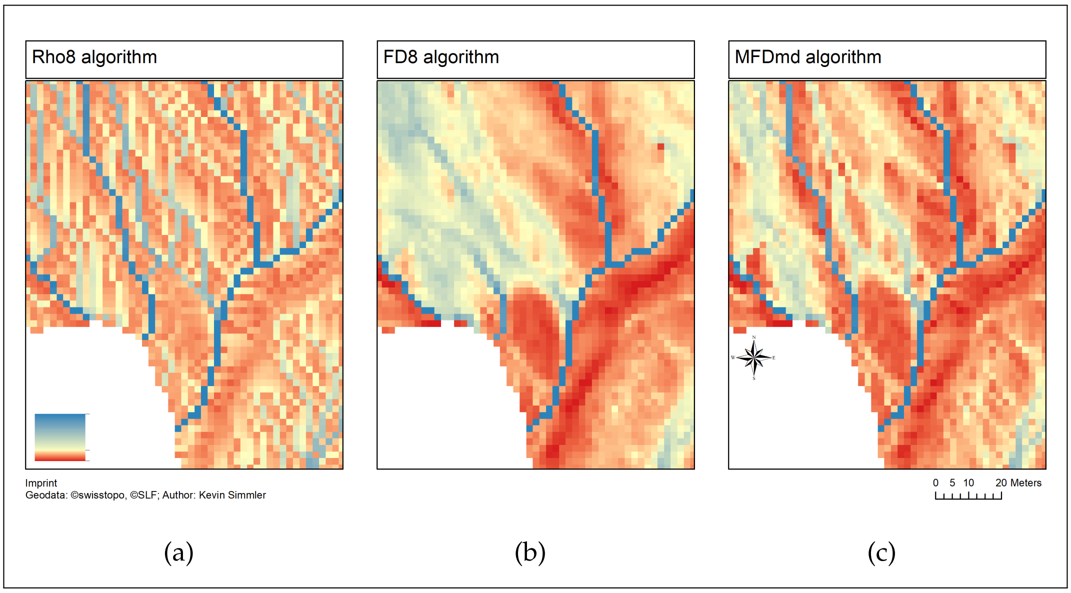


FIGURE 3.8: Map selection of the canton of AR showing differences in TWIs depending on flow routing algorithms applied for the calculation of the TCA; (a) Rho8 algorithm (b) FD8 algorithm (c) MFD-md algorithm.

The effect of the flow routing algorithm on the TWI value is illustrated in Figure 3.9. The SFD algorithm correctly recognizes both forest communities classified as drier than and as wetter than average (boxplots 1-4 (dry) and 5-8 (wet) in Figure 3.9). This classification of dry and wet is much more distinct for the two MFD algorithms. Contrary to the TWI values calculated with the SFD algorithm, not only the median lies above or below the total median value but most of the values. Therefore, the accuracy is higher for the MFD algorithms compared to the SFD algorithm.

In contrast to the noticeable differences between the TWI values of SFD and MFD algorithms (Figure 3.9), the variation between the TWI values calculated with the two MFD methods (FD8 and MFD-md) is marginal. Based on descriptive statistics and figures, it is difficult to distinguish between their performance in matching TWI values with the humidity value of the forest communities as classified in the ecograms. As regards this subject, the random forest models suggest that the FD8 algorithm performs slightly better compared to the MFD-md algorithm. Regardless of the DTM resolution used for the calculation of the TWI, the AUC of the FD8 algorithm was always higher than the AUC of the MFD-md algorithm, for both the weighted and unweighted TWI (Table 3.2).

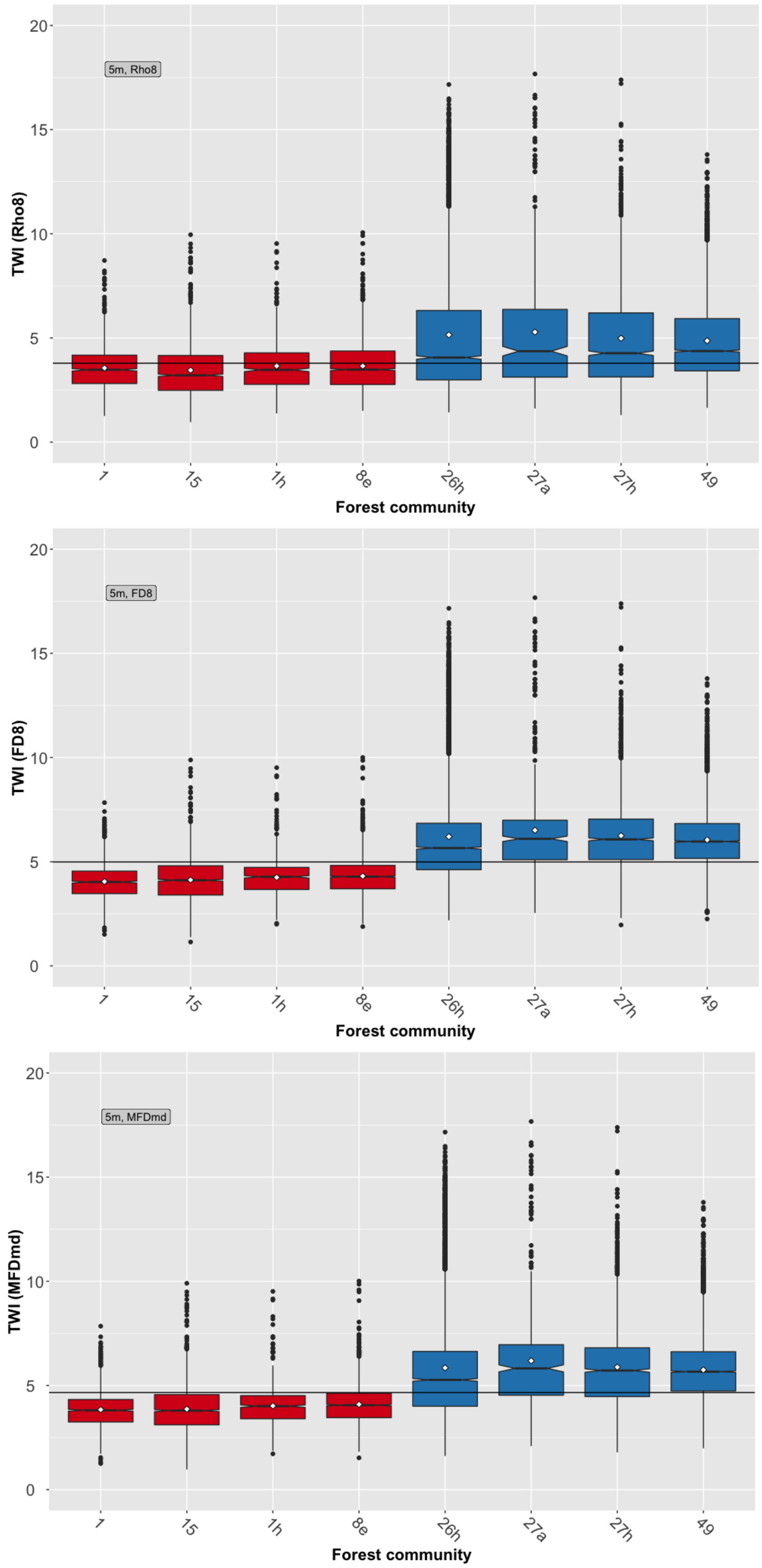


FIGURE 3.9: TWI values of four selected "rather dry - dry" (red) and four "rather wet - wet" (blue) forest communities. The values were calculated from the 5 m resolution DTM. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table 2.2. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

The humidity value of forest communities is (more or less directly) coupled with the local precipitation regime. Thus, in a next step this information was used for calculating corresponding weighted TWI values. In the subsequent section their performance with regards to classifying the humidity of forest communities is compared to unweighted TWI values.

3.4 Weighting the TWI with precipitation data

The absolute values of the weighted TWI are higher than those of the unweighted TWI (Table 3.1). However, the weighting does not change much with regards to the relative relationship between the median values of the different forest communities and the total median value of all communities (Figure 3.10).

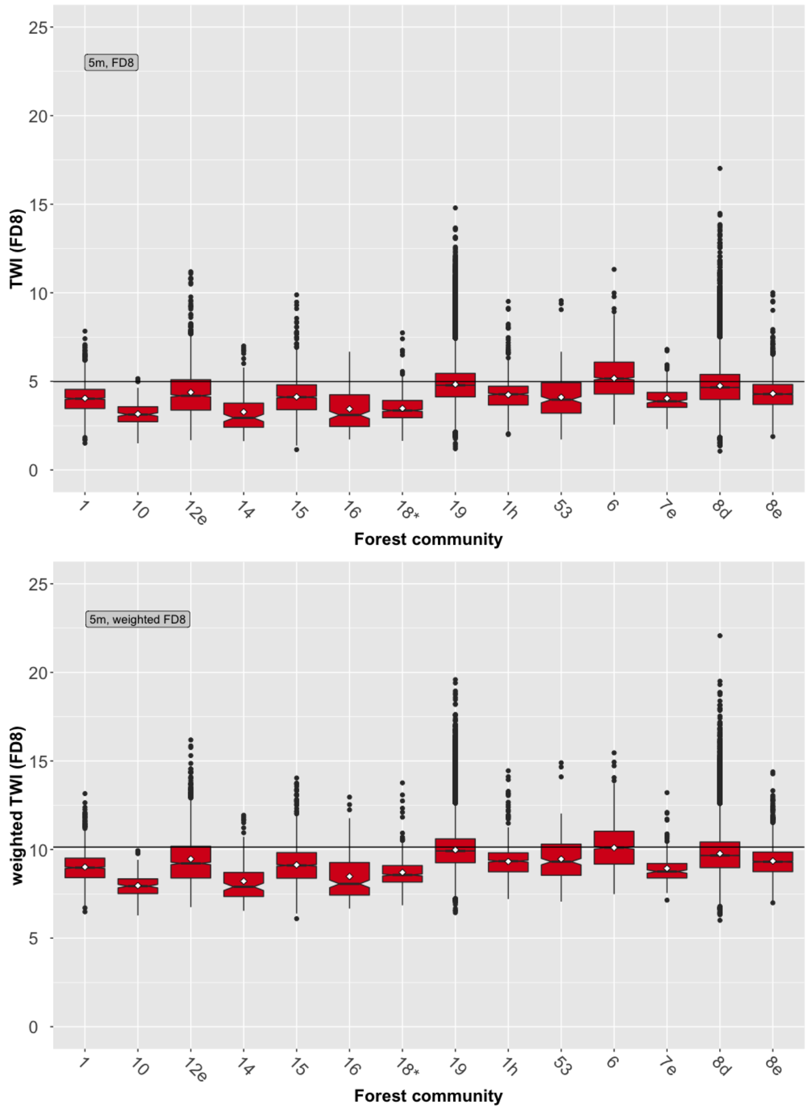


FIGURE 3.10: TWI values (top) and weighted TWI values (bottom) of dry forest communities calculated with FD8 algorithm and 5 m DTM resolution. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table 2.2. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

Figure 3.11 illustrates the impact of TWI weighting on the median value of the individual forest communities and their relative relationship to the total median value, representative for all DTM resolution and flow routing algorithms. As previously mentioned, the weighting increases the absolute values (Figure 3.10). The absolute difference between the median TWI and the total median TWI is found to be very similar after the weighting as it was before the weighting (section A.5). Therefore, the relative position of the weighted median TWI value to the total weighted median changes, i.e. both the median TWI values of "rather dry - dry" and "rather wet - wet" forest communities come closer to the total median TWI (relatively). Nevertheless, both the dry and wet forest communities are still clearly recognized as such after the weighting. In very few cases, the order of the forest community's humidity differs between the unweighted median TWI and the weighted median TWI values (10, 53, 27h) while it remains unchanged for most (Figure 3.11).

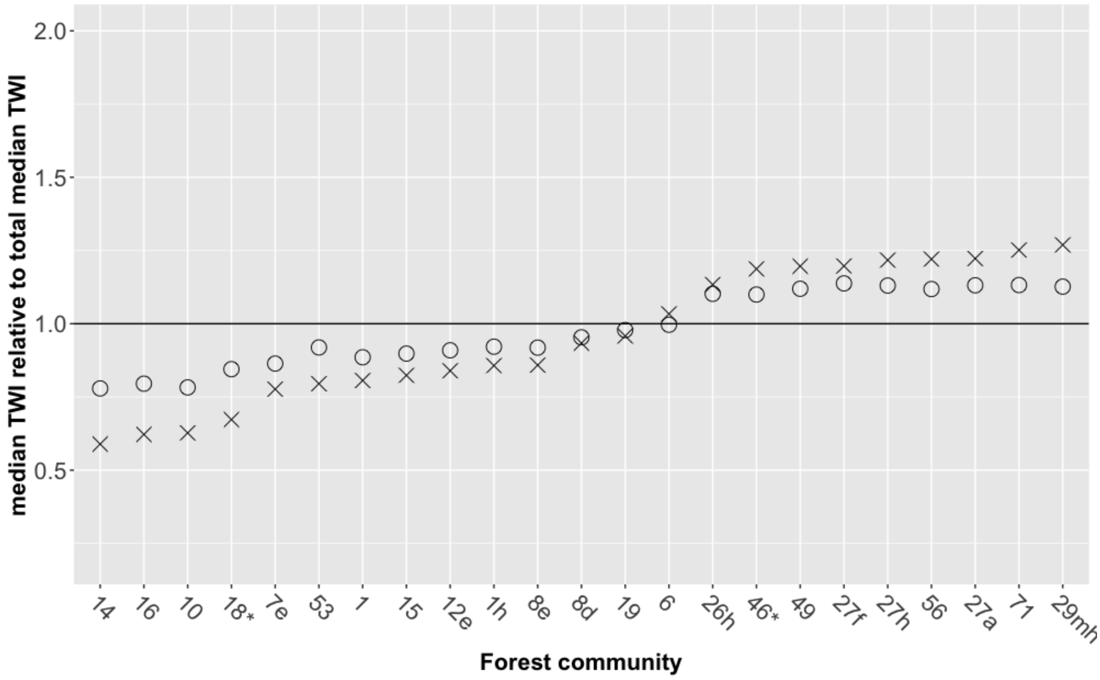


FIGURE 3.11: Median TWI values and median weighted TWI values relative to the total median TWI value and the total median weighted TWI value of "rather dry - dry" and "rather wet - wet" forest communities. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table 2.2.
x : unweighted median TWI, o : weighted median TWI.

The random forest models ambiguously unravel whether the weighting of the TWI improves the representation of the different forest community's humidity value. For the highest DTM resolution of 0.5 m, the weighting worsens the model performance for the two MFD while marginally improving it for the Rho8 flow routing algorithm. For the 2 m DTM resolution, the weighting improves the model performance of the two MFD algorithms while the Rho8 algorithm's model performance remains unchanged. The model performances of the 5 m DTM resolution show the opposite results of the 0.5 m resolution. Here the weighting improves the model performance for the two

MFD algorithms but worsens the model performance of the Rho8 algorithm (Table 3.2).

TABLE 3.2: Random forest outputs of different models explaining forest community types.

DTM resolultion	nr	model	AUC	accuracy	mean balanced accuracy	sensitivity	specificity
0.5m	1	forest community ~ elevation + aspect + slope	0.83	0.26	0.57	0.15	0.98
	2	forest community ~ elevation + aspect + TWI (Rho8)	0.80	0.23	0.55	0.11	0.98
	3	forest community ~ elevation + aspect + TWI (FD8)	0.81	0.23	0.55	0.12	0.98
	4	forest community ~ elevation + aspect + TWI (MFDmd)	0.81	0.23	0.55	0.12	0.98
	5	forest community ~ elevation + aspect + weighted TWI (Rho8)	0.80	0.23	0.55	0.11	0.98
	6	forest community ~ elevation + aspect + weighted TWI (FD8)	0.81	0.23	0.55	0.12	0.98
	7	forest community ~ elevation + aspect + weighted TWI (MFDmd)	0.80	0.23	0.55	0.12	0.98
2m	8	forest community ~ elevation + aspect + slope	0.85	0.29	0.59	0.20	0.98
	9	forest community ~ elevation + aspect + TWI (Rho8)	0.82	0.24	0.56	0.14	0.98
	10	forest community ~ elevation + aspect + TWI (FD8)	0.84	0.25	0.57	0.15	0.98
	11	forest community ~ elevation + aspect + TWI (MFDmd)	0.83	0.25	0.56	0.14	0.98
	12	forest community ~ elevation + aspect + weighted TWI (Rho8)	0.82	0.24	0.56	0.13	0.98
	13	forest community ~ elevation + aspect + weighted TWI (FD8)	0.84	0.26	0.57	0.15	0.98
	14	forest community ~ elevation + aspect + weighted TWI (MFDmd)	0.83	0.25	0.57	0.15	0.98
5m	15	forest community ~ elevation + aspect + slope	0.87	0.32	0.61	0.24	0.99
	16	forest community ~ elevation + aspect + TWI (Rho8)	0.84	0.26	0.57	0.16	0.98
	17	forest community ~ elevation + aspect + TWI (FD8)	0.87	0.29	0.59	0.19	0.98
	18	forest community ~ elevation + aspect + TWI (MFDmd)	0.86	0.28	0.58	0.18	0.98
	19	forest community ~ elevation + aspect + weighted TWI (Rho8)	0.84	0.26	0.57	0.16	0.98
	20	forest community ~ elevation + aspect + weighted TWI (FD8)	0.87	0.30	0.59	0.20	0.99
	21	forest community ~ elevation + aspect + weighted TWI (MFDmd)	0.86	0.28	0.58	0.18	0.98

4 Discussion

4.1 Elevation and first-order DTM derivatives

The results showed that the elevation, slope and aspect values at which the different forest community types occur differ significantly. This confirms and supports previous research that based its predictive vegetation models mainly on topographic variables, especially in mountainous regions (Brzeziecki et al. 1993; Guisan et al. 1998; Guisan et al. 1999; Womack and Carter 2011). The reason for this might be that several of the factors that drive the distribution of forest communities, such as warmth, snow cover duration and solar radiation, correlate highly with topographic variables (Ott et al. 1997).

While the variation of the elevation and slope values in the investigation area is relatively small, the aspect values vary much more relative thereto. These findings are in agreement with the description of the different forest communities. According to these, the forest communities are usually restricted to a rather distinct elevation and slope angle. In comparison to that, the range of aspect values at which the forest communities can be found is much broader (Burnand et al. 2013). A possible explanation for this large variation of aspect values at which the communities are found could be that the forest regeneration is not primarily limited by light in these forest communities. Most of the analyzed forest communities are different variations of beech forests. This tree species is known to be extraordinarily shade-tolerant and can, therefore, excel at all aspects. A clearer differentiating between forest communities based on aspect values could be expected in coniferous forests close to the tree line. For the regeneration of these forest communities, direct sunlight is essential due to a lack of warmth and, therefore, the exposition becomes more important (Ott et al. 1997).

To further enhance the differentiation of forest communities based on topographic variables, future studies should not extract single slope and aspect values as done in this study but rather calculate an average of the surrounding terrain for each extracted point. The reason for this is that high-resolution

DTMs (0.5 m - 5 m) used in this study also identify tiny terrain features. Slope and aspect values extracted from these small features most probably do not affect the presence or absence of a forest community and, therefore, create unnecessary noise.

4.2 DTM resolution

In agreement with previous studies, the results showed that both the absolute TWI values and their ability to match the humidity value of different forest communities are impacted considerably by choice of the DTM resolution, regardless of the flow routing algorithm used (Sørensen and Seibert 2007; Vaze et al. 2010; Qin et al. 2011; Buchanan et al. 2014; Hoang et al. 2018). Keeping in mind that the TWI is calculated by dividing the SCA by the local slope and then scaling it by the natural logarithm, there are two parameters that can be affected by the DTM resolution and, therefore, explain the variation of the TWI values depending on the chosen resolution. Previous work suggests that the differences in slope are generally small and, consequently, only account for the TWI variation depending on the resolution to a small degree (Sørensen and Seibert 2007). The more substantial part of the variation is thought to be explained by the impact the DTM resolution has on the SCA. For points along the main flow pathways, the SCA might remain similar for different resolutions. In contrast thereto, slightly elevated points from a high-resolution DTM might have a considerably smaller SCA compared to the coarser resolution (Wolock and Price 1994; Zhang and Montgomery 1994; Sørensen and Seibert 2007). This reduction of the resolution increases the proportion of low TWI values. The incredibly detailed representation of the terrain shown by the highest resolution DTM might be beneficial for certain applications. However, one has to keep in mind that the groundwater flow only matches the topography to a certain degree. Therefore, the increased frequency of low TWI values calculated from the high-resolution DTM can be seen as increased noise that worsens the representation of the groundwater flow which is crucial to explain the occurrences of different forest communities.

The optimal resolution for calculating TWI values depends on the local topography and the field of research. It has been shown that for the purpose of differentiating between forest communities based on TWI values, the highest resolution DTM used in this study (0.5 m) performs poorer than the coarser

DTMs (2 m and 5 m). Nevertheless, the questions about the optimal resolution in this context remains unsolved as it is unclear whether a DTM coarser than 5 m would perform even better at matching TWI and humidity values. Therefore, further work is needed to find the optimal DTM resolution with regards to matching TWI values and humidity values of forest communities.

4.3 Flow routing algorithm

The median TWI values of different forest communities differ significantly. In general, the median TWI matched the humidity value of the forest community as classified in the ecogram quite well. Nevertheless, in accordance with previous studies, considerable differences in TWI values are visible depending on the flow routing algorithm used (Pan et al. 2004; Kopecký and Čížková 2010; Raduła et al. 2018).

The TWI values calculated with the two MFD algorithms are able to match the position of the forest communities in the ecogram much better than the values calculated with the SFD algorithm, which confirms previous work (Quinn et al. 1991; Wolock and McCabe Jr. 1995; Pan et al. 2004; Raduła et al. 2018). The main difference between the two types of flow routing algorithms (SFD and MFD) is the number of neighbouring down-slope cells that potentially receive water. While the SFD algorithms looked at in this thesis only passed on flow to one neighbouring cell, the two MFD algorithms (FD8 and MFD-md) both potentially pass on flow to eight neighbouring cells. The results suggest that the natural flow of water is much better portrayed by MFD algorithms that create a smoother screening of the flow paths by passing on flow to several neighbouring cells.

Compared to the aforementioned differences between SFD and MFD algorithms, the differences between the two MFD algorithms are marginal. Their main difference lies in the way flow partitioning between the central cell and its neighbouring down-slope cells is calculated. An earlier study claims that the MFD-md algorithm portrays the terrain hydrology more accurately because the flow partitioning exponent accounts for the local terrain topography by including a maximum down-slope gradient while the FD8 algorithm does not account for the local topography, and used a global partitioning exponent instead (Qin et al. 2011). Nevertheless, in the present study, the FD8 algorithm in fact performed slightly better at matching median TWI values with the position of forest communities in the ecogram. The study of Qin et al. 2011 favouring the MFD-md algorithm was conducted in an area with low relief. In contrast, the present investigations were performed in a high-relief area which may be a possible explanation for the opposing results. Possibly, the importance of the flow partitioning exponent decreases if the topography is very hilly.

This study shows that for calculating TWIs within the scope of this work, the choice of the flow routing algorithms is crucial and needs careful consideration. MFD algorithms seem to give a more realistic representation of how the water flows. Despite the slight inferiority of the MFD-md algorithm compared to the FD8 algorithm, one has to keep in mind that both performed well at matching median TWI values with the humidity value of forest communities. Thus, I recommend using MFD flow routing algorithms with eight potential neighbouring cells to pass the flow on to when calculating a TWI. A more in-depth statistical analysis is needed to better assess the differences between the FD8 and MFD-md algorithm. Firstly, the differences between the model performance parameters of the models entailing the two MFD algorithms are too small to clearly favour one algorithm or the other. Secondly, the Random Forest models lack transparency with regards to the importance of the different explanatory variables. The TWIs were always combined with elevation and aspect in the models. Therefore, it is unclear if the slightly better model performances of the FD8 algorithm compared to the MFD-md algorithm can be ascribed to the higher capability of the FD8 algorithm to match TWI values and humidity values.

4.4 Weighting of TWI with precipitation data

The weighted TWI values were higher than the unweighted ones. This comes as no surprise looking at the way the weighting works. Before the flow accumulation is initiated, the starting value of one is multiplied with the weight grid, which is in this case, the mean yearly precipitation. Therefore, it can be expected that for the same cell, the weighted TWI value is equal or higher than the unweighted TWI value.

While the values of the weighted TWI are generally higher, the deviation of the forest community's median to the total median remains roughly the same for most forest communities. This leads to weighted mean values of each forest community being closer to the total median value. Therefore, the dry and wet forest communities differ less when weighted with regards to the mean TWI value.

Neither descriptively nor based on the Random Forest outputs a general conclusion can be made whether weighting the TWI values is beneficial with regards to matching the median values with the humidity value of the ecogram of the different forest communities. For some resolutions and flow routing algorithms weighting seems to be a slight improvement, while for others it appears to be neutral or even a change to the worse.

There could be three different argumentations to explain why the weighting of the TWI with mean yearly precipitation data did not yield significant results for differentiating forest community types according to their humidity value. Firstly, the TWI does not take water infiltration into consideration (Gruber and Peckham 2009). The calculated potential of each cell to accumulate water assumes that the water runs across the terrain heterogeneously, regardless of the underlying surface. Secondly, mean yearly precipitation data might not be the climatic variable that can explain the occurrence of different forest communities best. Previous work has shown that climatic extremes correlate better with spatial patterns of different tree species than long-term averaged data like used in this study (Zimmermann et al. 2009). Thirdly, the accuracy of the precipitation data has to be questioned. The map with the amount of mean yearly precipitation was generated by interpolating measuring stations. These so-called "macro-climatic" variables have been found not to consider local conditions enough and, therefore, not accurately explain the distribution of vegetation (Slavich et al. 2014). Precipitation amounts can vary significantly on a small spatial scale, especially within mountainous regions like the present study area. Interpolating between measuring stations might lead to unrepresentative data.

Nevertheless, weighting the TWI remains an interesting concept as the potential wetness based on the topography can be weighted with actual precipitation data. For further work, it may be better to weight the TWI with climatic extremes rather than mean annual values. Furthermore, a profound statistical analysis is needed to see whether the weighting of the TWI brings out the forest community types that are especially susceptible to shallow landslides. Random Forest models of this thesis do not show classification performance of the different forest communities which only allows general conclusions for all forest communities, but not for specific ones.

4.5 Methodological approach

The methodology of any research project can affect the outcome of the results and should, therefore, be critically evaluated. For any classification, the choice of the explanatory variables has to be made. For this thesis, only topo-climatic variables were selected for the models. Ecograms of forest communities suggest that elevation, soil humidity and acidity are fitting variables to classify forest communities in Switzerland. Elevation values were extracted directly from the DTM. Soil humidity was approximated by calculating TWIs. Thus, two out of the three variables used in the forest ecograms were accounted for. Soil acidity was not taken into consideration in this thesis due to time constraints. Recent research suggests that adding edaphic (soil-related) variables to topo-climatic variables can improve the prediction of plant species distribution (Dubuis et al. 2013).

In addition to the choice of the explanatory variables, the spatial sampling design is an important component of any environmental study involving spatial data as it affects the quality of the data and, therefore, the final analysis (Müller 2007). For this study, a proportional stratified regular sampling design was chosen, with the goal to obtain a spatially representative sample with minimized auto-correlation. Since the area fractions of the different forest communities vary drastically, this sampling design resulted in a highly unbalanced data frame. This sampling design has both advantages and disadvantages. On the one hand, the data is spatially representative as the chance of a forest community being sampled is directly correlated with its area. On the other hand, this sampling design is not the best choice combined with a decision-tree based algorithm such as Random Forest, as they are highly sensitive to class imbalance. The big differences between the "accuracy" and "mean balanced accuracy" of the Random Forest output point out that the data set is highly unbalanced and some forest communities achieve a much higher accuracy than others. Even though a "regular" sampling was chosen and the sampling points are roughly 15 m apart from each other, it is likely that there is still auto-correlation between the sampling points.

For future research projects involving the classification of forest communities, edaphic variables should be considered to be included as explanatory variables. If the multivariate analysis is conducted with a classification-tree based machine learning algorithm, big class imbalances should be avoided by adjusting the spatial sampling design accordingly.

5 Conclusions

Elevation and first-order DTM derivatives account for a large part regarding the distribution of the different forest community types. The elevation, aspect and slope values varied significantly between different forest community types and the Random Forest models that considered these three variables all showed good performance with AUC values higher than 0.8. Consequently, elevation and first-order derivatives of a DTM could be used in future by forestry practitioners to facilitate the mapping of forest communities. DTMs are available for the whole of Switzerland and the first-order derivatives can be calculated with basic knowledge of a GIS program which further increases to potential of these variables to differentiate between forest communities.

Apparent differences were shown between the DTM resolution used to calculate the TWI values and how these match the position of the forest communities in the ecogram. The results showed that within the chosen range of DTM resolutions (0.5 m - 5 m), the delineation between forest communities based on TWI values improves with a coarser DTM resolution. Conclusively, a DTM with a 5 m resolution seems more suitable to represent the local hydrological conditions relevant for tree growth than the 0.5 m resolution and should, therefore, be preferred when calculating TWIs. This finding of the coarser DTM resolution working better to differentiate between forest communities makes this method more applicable for forestry practitioners. Calculations for bigger areas are doable with normal computers when using the coarser DTM resolution of 5 m. On the contrary, the computation time when using the DTM of 0.5 m resolution increases immensely, making it difficult to calculate topographic variables for larger areas.

The median TWI values matched the position of the forest communities differently depending on the flow routing algorithm that was used to calculate them. The two MFD algorithms performed better than the SFD algorithm. Between the two MFD algorithms, differences at matching TWI values with the forest communities were only marginal. The AUC values of the Random Forest models suggest that the FD8 flow routing algorithm slightly outcompetes the MFD-md algorithm. Therefore, the choice of the flow routing algorithm should be considered carefully when calculating TWIs. MFD algorithms should be preferred over SFD algorithms when the TWIs are used to match the humidity value of forest communities.

The weighting of the TWI with yearly precipitation data showed no clear improvement with regards to matching the TWI values with the humidity value of the forest communities. While for some resolutions and flow routing algorithms the weighting posed a slight amelioration, the opposite was observed for other resolutions and algorithms. Consequently, weighting the TWI with mean yearly precipitation data does not pay off with regards to a better differentiation between forest communities based on humidity values.

The Random Forest models showed high AUC values ranging from 0.80 to 0.87. This suggests that Random Forest is a useful tool to explain the distribution of different forest community types using elevation and DTM derivatives. Therefore, future work that involves classifying forest communities based on topographic variables should consider also using Random Forest. Besides its satisfactory results, the algorithm is easy to use and computation time reasonable.

The sampling design was set to a proportional stratified regular sampling with the goal of achieving a spatially balanced sampling design. The proportional sampling lead to a highly unbalanced data set, as the area fractions of the forest communities differ immensely. Consequently, a disproportional sampling scheme might be more favourable to use for future studies that use decision-tree based machine learning algorithms like Random Forest.

This study shows the potential of using topographic variables to differentiate between forest communities. Overall, the topographic variables evaluated in this thesis showed promising results with regards to distinguishing between forest communities. With further improvement of the methodological approach applied in this study and the inclusion of additional variables, certain forest communities could be mapped remotely, especially those found at extremes with regards to elevation, soil humidity or soil acidity. This might be useful for forest practitioners already as the costs of mapping forest communities found at high elevations are high and requires a lot of time. Where the topographical characteristics of forest communities are too similar to conduct the mapping remotely, field mapping would still be necessary. Nevertheless, topographic variables could still be useful to plan a more efficient field mapping. The facilitated mapping of forest communities could lead to an increased fraction of mapped forests in Switzerland and, therefore, potentially ensure more site-adapted silvicultural measures. This could, in turn, help improve the protective function of forests against gravitational natural hazards such as rockfall, avalanches and shallow landslides.

Future studies aiming to distinguish between forest communities should consider including edaphic parameters to account for the preferences of different tree species with regards to soil acidity. Additionally, further research is needed to determine the optimal DTM resolution to classify forest communities. Furthermore, the Random Forest model parameters need to be calibrated to the optimal settings. Finally, the sampling scheme should be adapted accordingly when using decision tree-based algorithms like random forest to ensure to data set is balanced.

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A Appendix

A.1 Forest community types in AR

TABLE A.1: Number, German and Latin name of forest community types found in the canton of AR

Forest community number	German name	Scientific name
1	Typischer Hainsimsen-Buchenwald	Luzulo-Fagetum typicum
2	Hainsimsen-Buchenwald mit Weissmoos	Luzulo-Fagetum leucobryetosum
1h	Artenarmer Simsen-Tannen-Buchenwald	Luzulo-Abieto-Fagetum, Artenarme Variante
6	Waldmeister-Buchenwald mit Hainsimse	Galio-Fagetum luzuletosum
7a	Typischer Waldmeister-Buchenwald	Galio-Fagetum typicum
7e	Waldmeister-Buchenwald mit Hornstrauch	Galio-Fagetum cornetosum
7f	Waldmeister-Buchenwald mit Bingelkraut	Galio-Fagetum mercurialetosum
7S	Waldmeister-Buchenwald mit Waldziest	Galio-Fagetum stachyletosum
7g	Waldmeister-Buchenwald mit Bärlauch	Galio-Fagetum allietosum
8a	Typischer Waldhirsen-Buchenwald	Milio-Fagetum typicum
8ak	Typischer Waldhirsen-Buchenwald, Ausbildung mit anstehendem Gestein	Milio-Fagetum typicum

Table A.1 continued from previous page

8b	Waldhirsen-Buchenwald mit Lockerähriger Segge	Milio-Fagetum caricetosum remotae
8c	Artenarmer Waldhirsen-Buchenwald	Milio-Fagetum, artenarme Ausbildung
8d	Waldhirsen-Buchenwald mit Hainsimse	Milio-Fagetum luzuletosum
8dk	Waldhirsen-Buchenwald mit Hainsimse, Aisbildung mit angstehendem Gestein	Milio-Fagetum luzuletosum
8e	Waldhirsen-Buchenwald mit Hornstrauch	Milio-Fagetum cornetosum
8f	Waldhirsen-Buchenwald mit Bingelkraut	Milio-Fagetum mercurialietosum
8S	Waldhirsen-Buchenwald mit Waldziest	Milio-Fagetum stachyletosum
8g	Waldhirsen-Buchenwald mit Bärlauch	Milio-Fagetum allietosum
8*	Waldhirsen-Buchenwald mit Rippenfarn	Milio-Fagetum blechnetosum
9	Typischer Platterbsen-Buchenwald	Lathyro-Fagetum typicum
10	Platterbsen-Buchenwald mit Weisssegge	Lathyro-Fagetum caricetosum albae
10w	Platterbsen-Buchenwald mit Schlaffer Segge	Lathyro-Fagetum caricetosum flaccae
11	Aronstab-Buchenwald	Aro-Fagetum
12	Typischer Bingelkraut-Buchenwald	Mercurialidi-Fagetum typicum
12C	Bingelkraut-Buchenwald mit Kitaibels Zahnwurz	Mercurialidi-Fagetum cardaminetosum kitaibelii
12e	Bingelkraut-Buchenwald mit Weisssegge	Mercurialidi-Fagetum caricetosum albae
12g	Bingelkraut-Buchenwald mit Bärlauch	Mercurialidi-Fagetum allietosum
12k	Typischer Bingelkraut-Buchenwald, Ausbildung mit anstehendem Gestein	Mercurialidi-Fagetum typicum

Table A.1 continued from previous page

12S	Bingelkraut-Buchenwald mit Waldziest	Mercurialidi-Fagetum stachyetosum
12w	Bingelkraut-Buchenwald mit Schlaffer Segge	Mercurialidi-Fagetum caricetosum flaccae
13	Typischer Linden-Buchenwald	Tilio-Fagetum typicum
13h	Typischer Alpendost-Buchenwald	Adenostylo-Fagetum typicum
14	Seggen-Buchenwald mit Weisssegge	Carici albae-Fagetum typicum
14w	Seggen-Buchenwald mit Schlaffer Segge	Carici albae-Fagetum caricetosum flaccae
15	Seggen-Buchenwald mit Bergsegge	Carici-Fagetum caricetosum montanae
16	Blaugras-Buchenwald	Seslerio-Fagetum
17	Steilhang-Buchenwald mit Buntreitgras	Seslerio-Fagetum calamagrostietosum variae
17T	Eiben-Buchenwald	Taxo-Fagetum
18	Waldschwingel-Tannen-Buchenwald	Festuco-Abieti-Fagetum
18M	Typischer Karbonat-Tannen-Buchenwald	Adenostylo-Abieti-Fagetum typicum
18*	Karbonat-Tannen-Buchenwald mit Weisssegge	Adenostylo-Abieti-Fagetum caricetosum albae
18k	Waldschwingel-Tannen-Buchenwald, Ausbildung mit anstehendem Gestein	Festuco-Abieti-Fagetum
18v	Buntreisgras-Tannen-Buchenwald mit Rostsegge	Adenostylo glabrae-Abieti-Fagetum calam. variae, Ausb. m. Cx. ferr.
18w	Typischer Buntreitgras-Tannen-Buchenwald	Adenostylo glabrae-Abieti-Fagetum calamagrostietosum variae
19	Typischer Waldsimsen-Tannen-Buchenwald	Luzulo-Abieti-Fagetum typicum
19f	Waldsimsen-Tannen-Buchenwald mit Waldschachtelhalm	Luzulo-Abieti-Fagetum equisetetosum sylvatici

Table A.1 continued from previous page

19k	Typischer Waldsimsen-Tannenbuchenwald, Ausbildung mit anstehendem Gestein	Luzulo-Abieti-Fagetum typicum
20	Typischer Hochstauden Tannen-Buchenwald	Adenostylo alliariae Abieti-Fagetum typicum
20C	Hochstauden-Tannen-Buchenwald mit Kitaibels Zahnwurz	Adenostylo alliariae-Abieti-Fagetum cardaminetosum kitaibelii
20E	Waldgersten-Tannen-Buchenwald	Adenostylo alliariae-Abieti-Fagetum hordelymetosum
20g	Hochstauden-Tannen-Buchenwald mit Bärlauch	Adenostylo alliariae-Abieti-Fagetum allietosum
20k	Typischer Hochstauden Tannen-Buchenwald, Ausbildung mit anstehendem Gestein	Adenostylo alliariae Abieti-Fagetum typicum
22	Hirschzungen-Ahornwald	Phyllitido-Aceretum
22k	Hirschzungen-Ahornwald, Ausbildung mit anstehendem Gestein	Phyllitido-Aceretum
24+	Ulmen-Ahornwald mit Bingelkraut	Ulmo-Aceretum mercurialietosum
26	Typischer Ahorn-Eschenwald	Aceri-Fagetum typicum
26e	Ahorn-Eschenwald mit Weisssegge	Aceri-Fagetum caricetosum albae
26h	Ahorn-Eschenwald, Höhenausbildung	Aceri-Fagetum, Höhenausbildung
27a	Typischer Bach-Eschenwald	Carici-remotae-Fraxinetum typicum
27f	Bach-Eschenwald mit Riesenschachtelhalm	Carici-remotae-Fraxinetum equisetetosum telmateiae
27h	Bach-Eschenwald, Höhenausbildung	Carici remotae-Fraxinetum Ausbildung mit Petasites albu
27*	Hochstauden-Weisserlen-Ahornwald	Adenostylo-Alnetum incanae
28	Ulmen-Eschen-Auenwald mit Winterschachtelhalm	Ulmo-Fraxinetum equisetetosum hyemale
29	Typischer Ulmen-Eschen-Auenwald	Ulmo-Fraxinetum typicum

Table A.1 continued from previous page

29C	Ulmen-Eschen-Auenwald mit Weisssegge	Ulmo-Fraxinetum tcaricetosum albae
29m	Typischer Ulmen-Eschen-Muldenwald	Ulmo-Fraxinetum typicum, Muldenausbildung
29mh	Ulmen-Eschen-Muldenwald mit Waldschachtelhalm	Ulmo-Fraxinetum equisetetosum hyemale
30	Schwarzerlen-Eschenwald	Pruno-Fraxinetum
32C	Grauerlenwald mit Hornstrauch	Alnetum incanaue cornetosum
46	Typischer Heidelbeer-Tannen-Fichtenwald	Vaccinio myrtilli-Abieti-Piceetum typicum
46*	Heidelbeer-Tannen-Fichtenwald mit Torfmoos	Vaccinio myrtilli-Abieti-Piceetum sphagnetosum
48	Blockschutt-Tannen-Fichtenwald	Asplenio-Abieti-Piceetum
49	Schachtelhalm-Tannen-Fichtenwald	Equiseto-Abieti-Fagetum typicum
50	Typischen Hochstauden-Tannen-Fichtenwald	Adenostylo alliariae-Abieti-Piceetum typicum
50*	Karbonat-Tannen-Fichtenwald mit Kahlem Alpendost	Adenostylo glabrae-Abieti-Piceetum typicum
53	Zwergbuchs-Fichtenwald	Polygalo chamaebuxi-Piceetum
56	Moorrand-Fichtenwald	Sphagno-Piceetum
60*	Buntreisgras-Fichtenwald	Calamagrostio variae-Piceetum
61	Pfeifengras-Föhrenwald	Molinio-Pinetum
62	Orchideen-Föhrenwald	Cephalanthero-Pinetum
65	Erika-Föhrenwald	Erico-Pinetum
71	Torfmoos-Bergföhrenwald	Sphagno-Pinetum montanae
u	unbestockt	unstocked

A.2 Fractions of forest communities in AR

TABLE A.2: Area fraction, total area, number of polygons and mean area per polygon of all the different forest community types in the canton of AR.

Forest community	Area fraction [%]	Total area [m^2]	Number of polygons	Mean area per polygon [m^2]
19	15.4883	7142730.6	1954	3655.4
20	8.1891	3776563.4	1150	3284.0
8a	7.7908	3592891.4	1124	3196.5
18	7.7830	3589254.0	1087	3302.0
8d	6.9208	3191648.7	1042	3063.0
19f	6.8137	3142261.2	553	5682.2
20E	4.7709	2200190.8	587	3748.2
8S	4.2632	1966046.5	832	2363.0
12	3.9358	1815085.1	696	2607.9
18M	3.3017	1522651.1	497	3063.7
12S	2.3644	1090368.7	566	1926.4
8f	2.2062	1017408.3	201	5061.7
12w	1.9055	878768.7	426	2062.8
18w	1.7587	811063.2	401	2022.6
26	1.4431	665515.0	579	1149.4
17	1.2197	562490.1	201	2798.5
46	1.2032	554882.8	226	2455.2
8c	1.1761	542362.6	119	4557.7
49	1.0235	472025.0	268	1761.3
8*	0.9902	456628.8	107	4267.6
20g	0.8839	407621.0	168	2426.3
26h	0.6653	306815.0	302	1015.9
17T	0.5374	247854.8	132	1877.7
8e	0.4903	226129.5	134	1687.5
12g	0.4109	189503.6	131	1446.6
15	0.3579	165055.8	130	1269.7
27h	0.3271	150859.1	279	540.7
27f	0.3078	141940.4	181	784.2
18v	0.3000	138342.9	62	2231.3
12e	0.2587	119292.7	81	1472.7
6	0.2322	107061.3	33	3244.3

7a	0.2294	105807.6	18	5878.2
1	0.2152	99226.7	85	1167.4
56	0.1552	71558.3	34	2104.7
8g	0.1349	62196.2	47	1323.3
1h	0.1348	62166.7	35	1776.2
46*	0.1174	54147.9	28	1933.9
20C	0.1173	54104.7	11	4918.6
7f	0.1083	49929.2	5	9985.8
18*	0.1040	47960.3	71	675.5
11	0.0889	41006.1	22	1863.9
8fk	0.0865	39881.6	4	9970.4
29	0.0860	39661.8	51	777.7
27a	0.0834	38455.8	56	686.7
14w	0.0738	34046.8	17	2002.8
10w	0.0727	33530.2	10	3353.0
13h	0.0553	25499.6	17	1500.0
71	0.0503	23209.6	5	4641.9
12C	0.0450	20768.5	5	4153.7
7g	0.0430	19823.4	1	19823.4
53	0.0377	17372.5	7	2481.8
60*	0.0316	14583.7	7	2083.4
7e	0.0316	14564.7	12	1213.7
9	0.0308	14217.1	16	888.6
16	0.0298	13752.9	23	598.0
10	0.0287	13226.6	2	6613.3
26e	0.0283	13029.3	18	723.8
18k	0.0241	11127.6	13	856.0
8ak	0.0223	10269.0	6	1711.5
13	0.0208	9593.7	20	479.7
22	0.0207	9539.8	21	454.3
29m	0.0188	8668.0	5	1733.6
14	0.0169	7788.8	12	649.1
7S	0.0157	7234.2	9	803.8
8b	0.0150	6915.4	4	1728.8
29mh	0.0138	6368.5	5	1273.7
50*	0.0109	5034.7	4	1258.7
12k	0.0104	4817.5	11	438.0

29C	0.0055	2553.0	3	851.0
2	0.0054	2507.3	5	501.5
61	0.0050	2312.8	2	1156.4
24+	0.0048	2213.2	8	276.7
62	0.0048	2198.9	4	549.7
28	0.0041	1904.7	2	952.4
65	0.0041	1881.5	1	1881.5
8dk	0.0019	856.8	1	856.8
30	0.0018	826.3	1	826.3
32C	0.0017	767.6	5	153.5
27*	0.0010	446.5	2	223.2
19k	0.0007	331.1	1	331.1
20k	0.0007	313.9	1	313.9
22k	0.0003	115.9	1	115.9
50	0.0002	85.1	1	85.1
u	8.2295	3795170.2	378	10040.1

A.3 Sample points

TABLE A.3: Number of sample points extracted for each forest community type

	Number of sample points		
Forest community	5 m resolution	2 m resolution	0.5 m resolution
1	1330	1324	1317
2	33	32	37
1h	823	839	834
6	1425	1435	1440
7a	1409	1403	1405
7e	195	194	194
7f	668	665	665
7S	100	102	97
7g	262	264	264
8a	47925	47924	47982
8ak	137	136	136
8b	97	93	96
8c	7243	7247	7235
8d	42557	42475	42688
8dk	11	11	10
8e	3020	3009	3027
8f	13535	13581	13561
8fk	527	533	530
8S	26106	26208	26290
8g	822	833	834
8*	6081	6050	6092
9	187	185	186
10	181	176	178
10w	453	456	438
11	558	547	553
12	24235	24168	24215
12C	277	271	281
12e	1595	1584	1583
12g	2515	2535	2521
12k	64	63	65
12S	14594	14570	14522

Table A.3 continued from previous page

12w	11761	11702	11722
13	133	129	128
13h	341	339	340
14	104	105	100
14w	459	450	458
15	2190	2208	2187
16	178	178	192
17	7520	7511	7454
17T	3294	3284	3290
18	47789	47854	47854
18M	20295	20288	20293
18*	659	644	645
18k	154	147	140
18v	1821	1847	1823
18w	10770	10797	10866
19	95178	95332	95201
19f	41900	41925	41878
19k	4	3	5
20	50420	50408	50407
20C	722	718	733
20E	29326	29378	29364
20g	5438	5425	5426
20k	3	4	5
22	124	128	126
22k	1	1	1
24+	30	28	27
26	8843	8859	8883
26e	182	178	176
26h	4075	4094	4120
27a	529	503	504
27f	1886	1903	1883
27h	2031	2002	1996
27*	4	6	3
28	25	24	20
29	530	537	524
29C	34	35	32
29m	116	117	114

Table A.3 continued from previous page

29mh	85	85	83
30	10	11	12
32C	12	9	9
46	7394	7397	7419
46*	708	708	712
49	6286	6292	6318
50	1	2	1
50*	69	63	68
53	234	229	234
56	955	951	953
60*	198	196	190
61	28	31	32
62	31	28	30
65	22	26	28
71	310	308	311
u	50581	50570	50561

A.4 Elevation, aspect and slope values

A.4.1 Elevation values

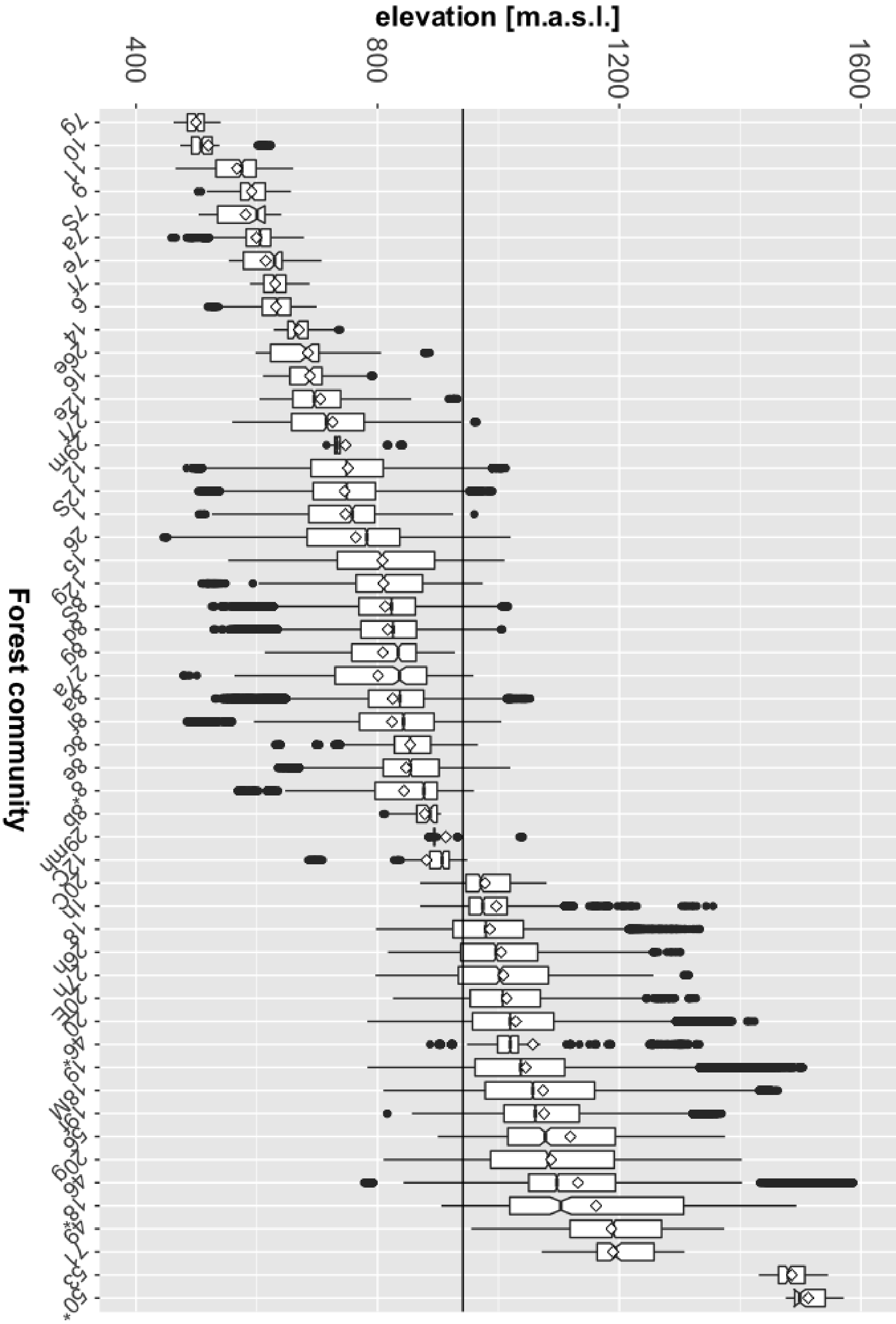


FIGURE A.1: Elevation of all different forest community types. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median elevation value. The values were extracted from the 5 m resolution DTM.

A.4.2 Aspect values

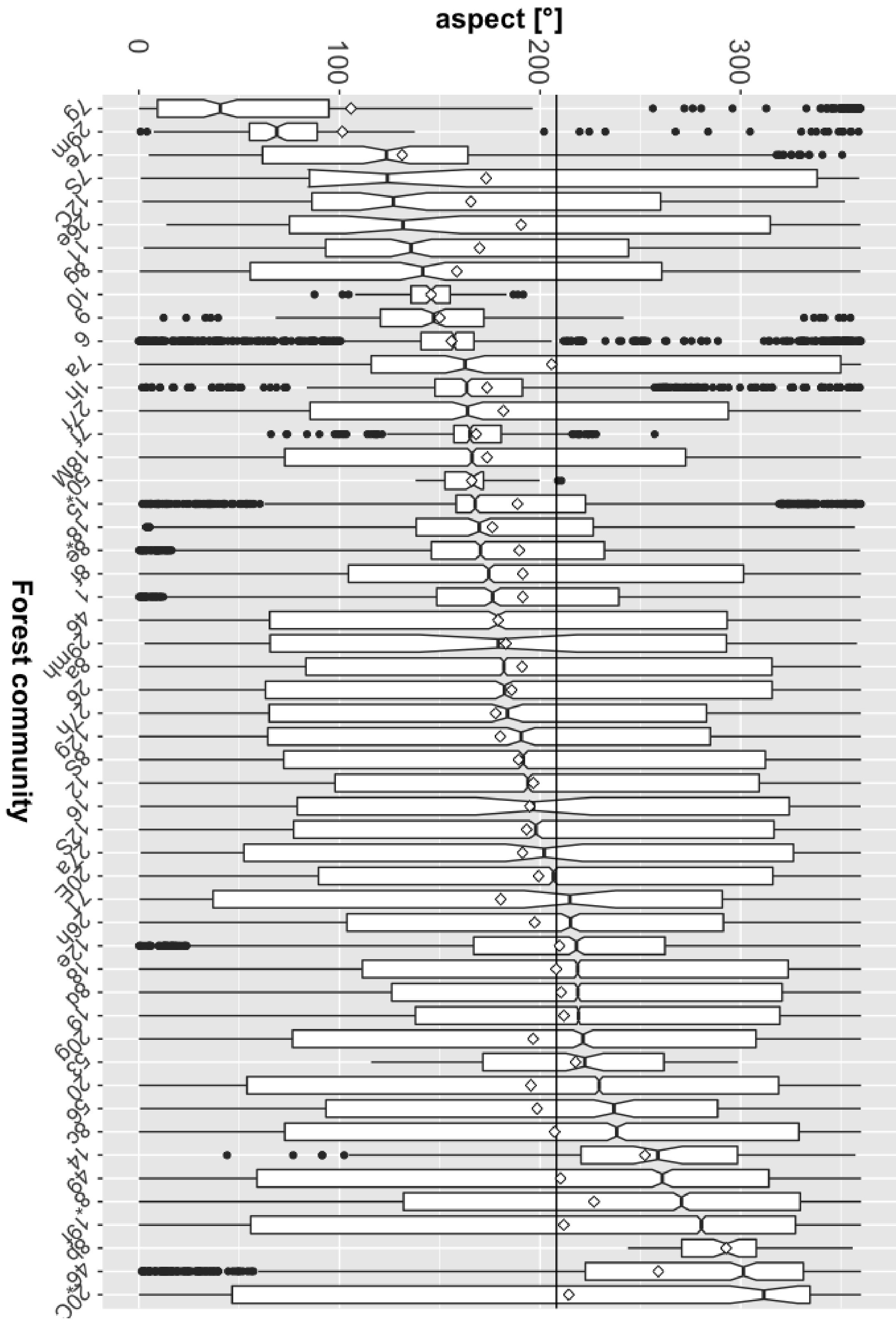


FIGURE A.2: Aspect of all different forest community types. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median aspect value. The values were extracted from the 5 m resolution DTM.

A.4.3 Slope values

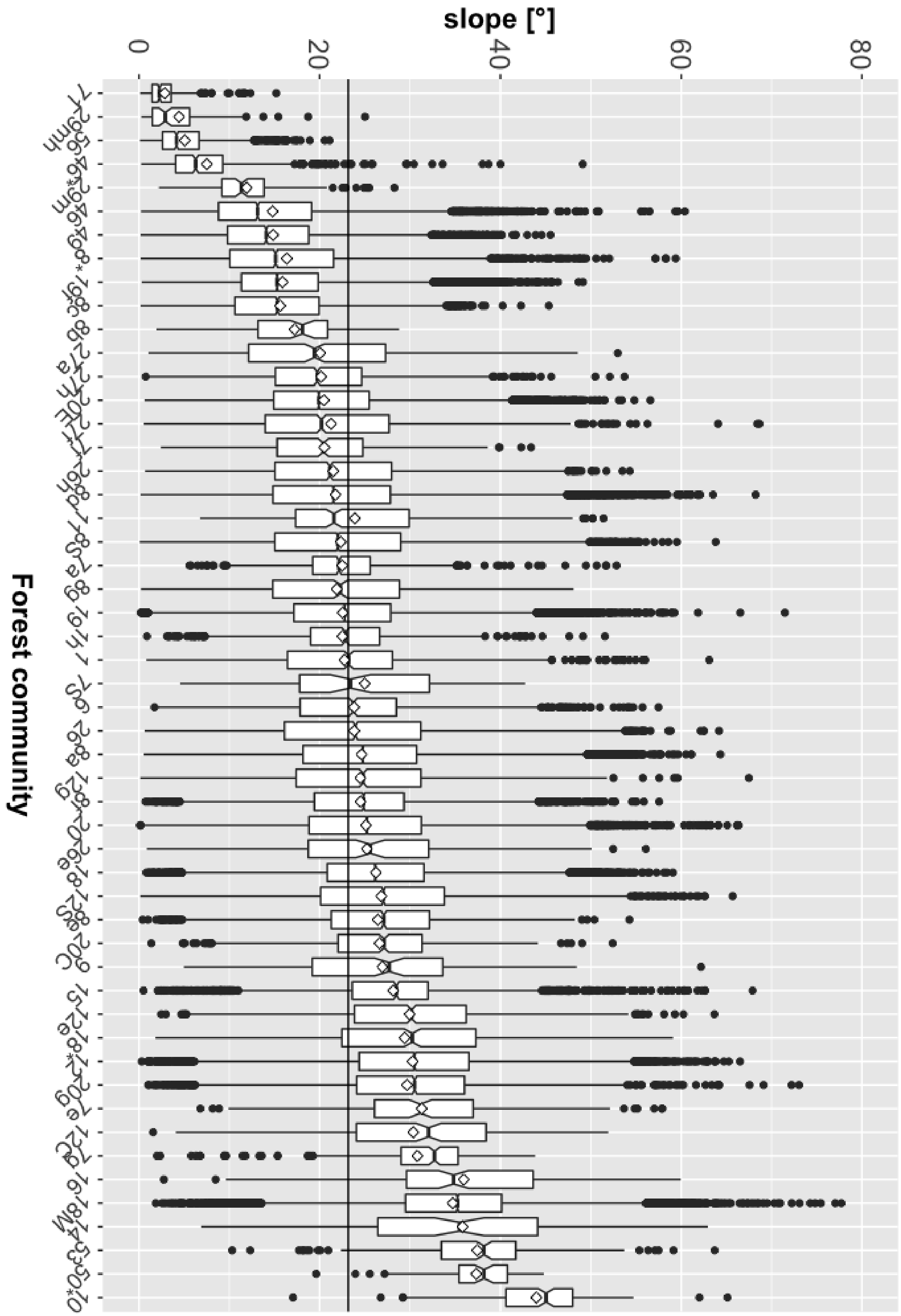
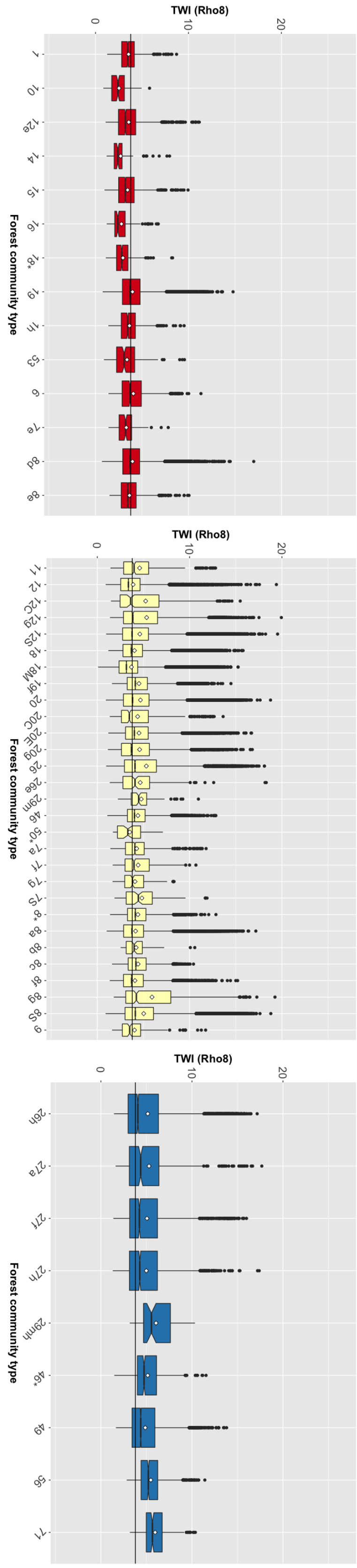


FIGURE A.3: Slope of all different forest community types. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median slope value. The values were extracted from the 5 m resolution DTM.

A.5 TWI values

A.5.1 5 m resolution

Rho8 algorithm (5 m resolution)



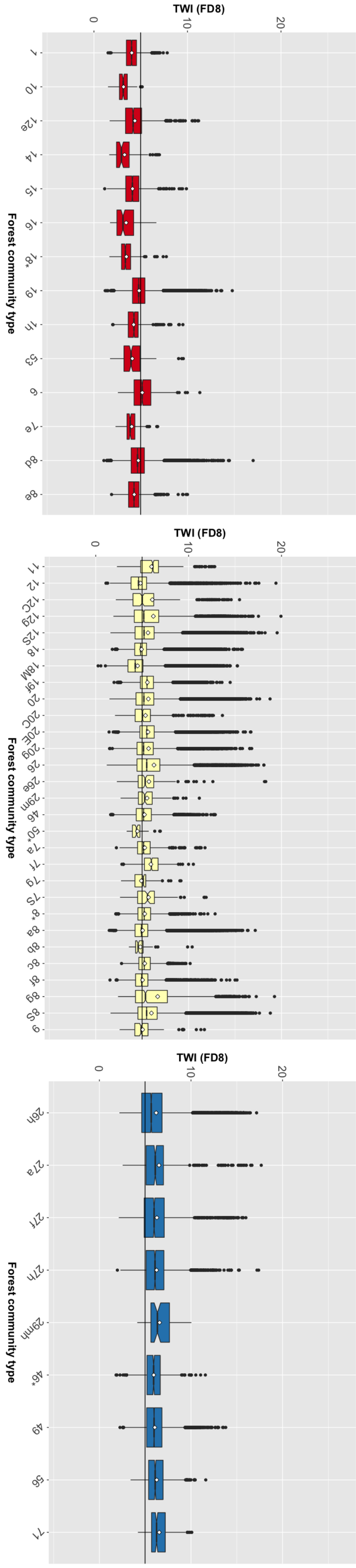
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.4: TWI (Rho8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

FD8 algorithm (5 m resolution)



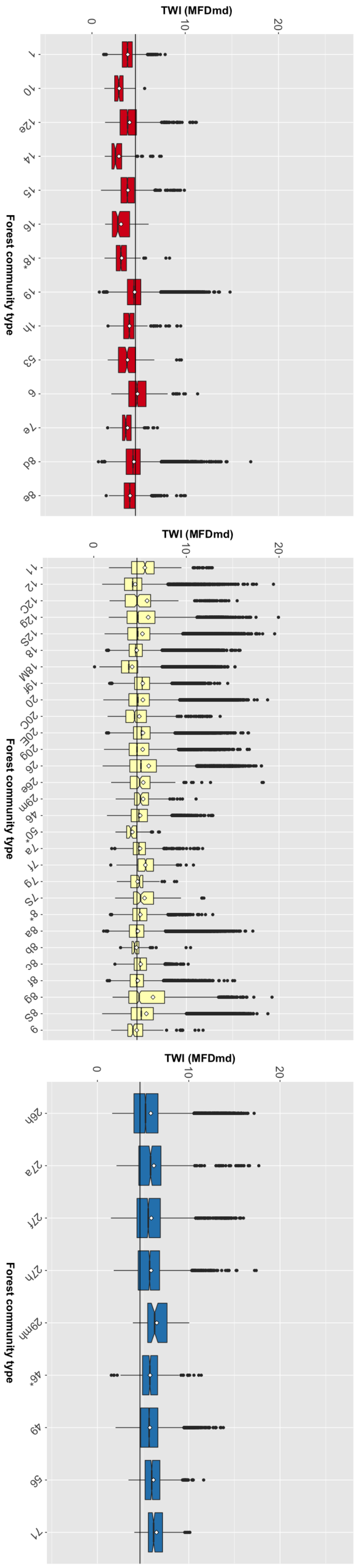
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.5: TWI (FD8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

MFD-md algorithm (5 m resolution)



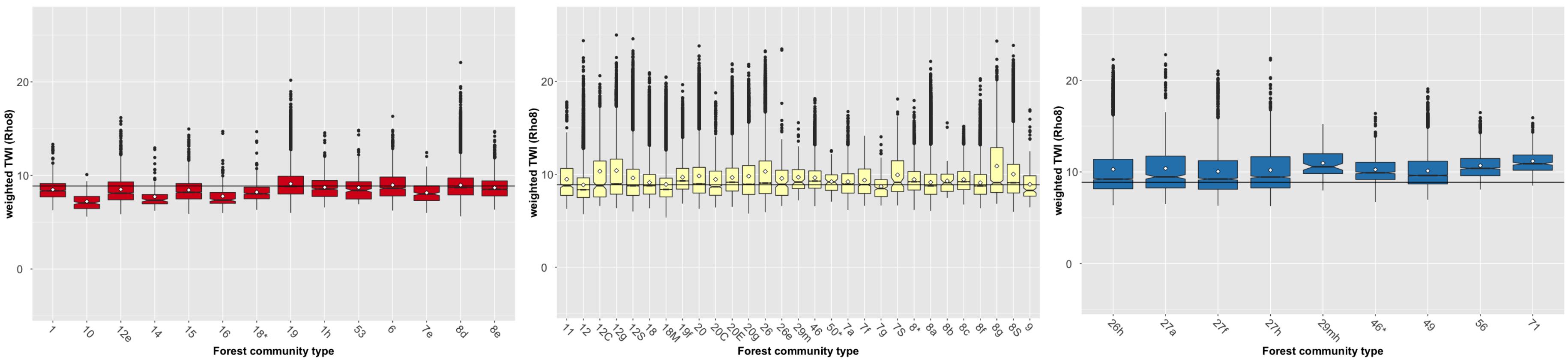
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.6: TWI (MFD-md) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

weighted Rho8 algorithm (5 m resolution)



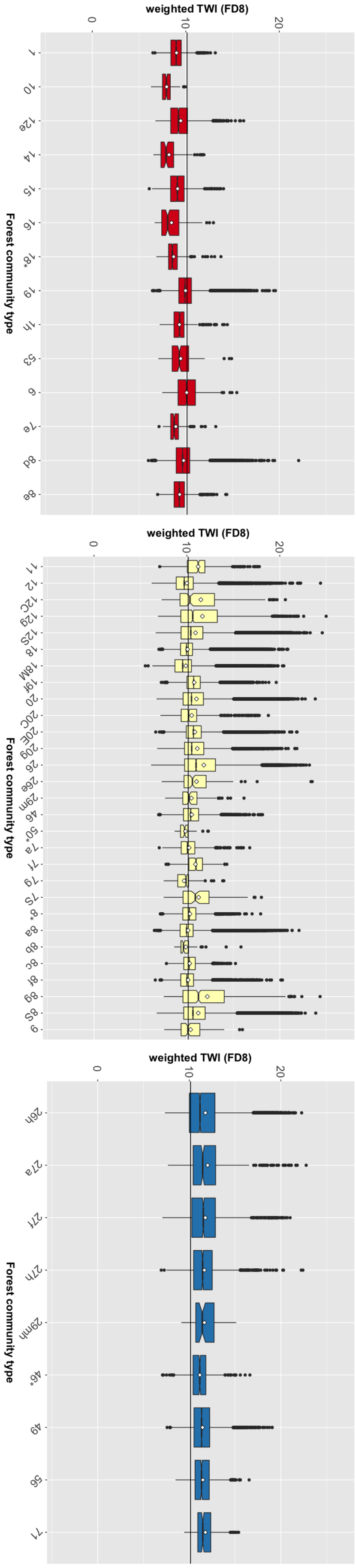
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.7: weighted TWI (Rho8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

weighted FD8 algorithm (5 m resolution)



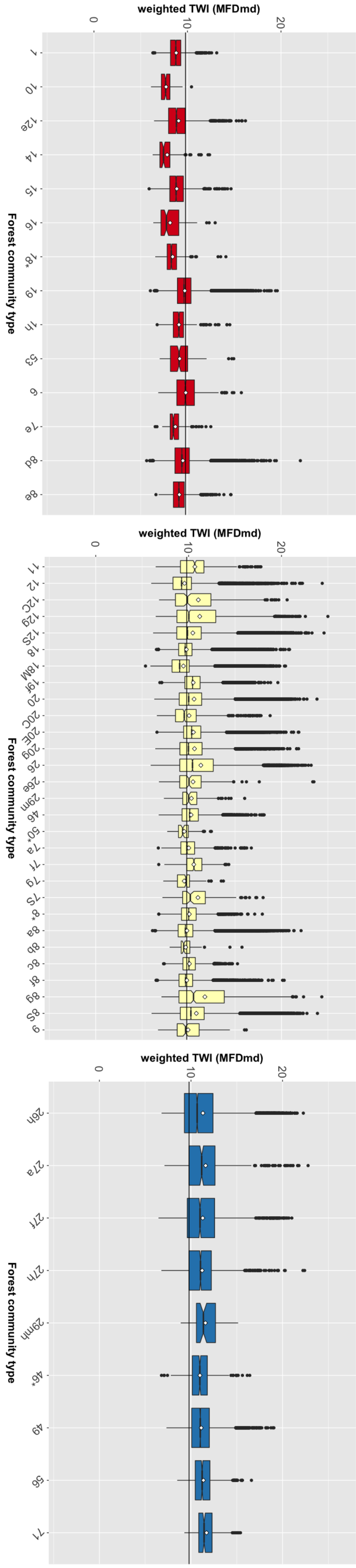
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.8: weighted TWI (FD8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

weighted MFD-md algorithm (5 m resolution)



(a) dry forest communities

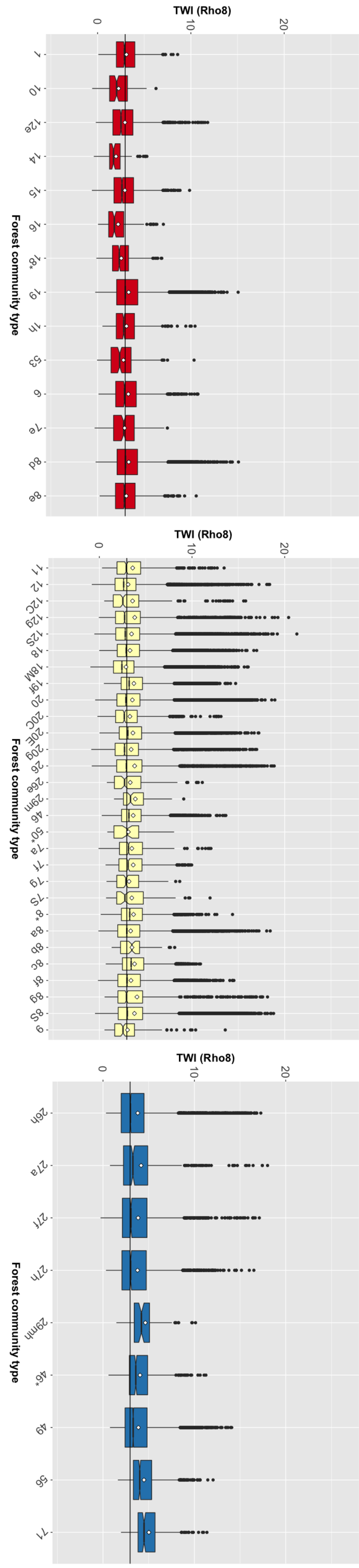
(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.9: weighted TWI (MFD-md) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

A.5.2 2 m resolution

Rho8 algorithm (2 m resolution)



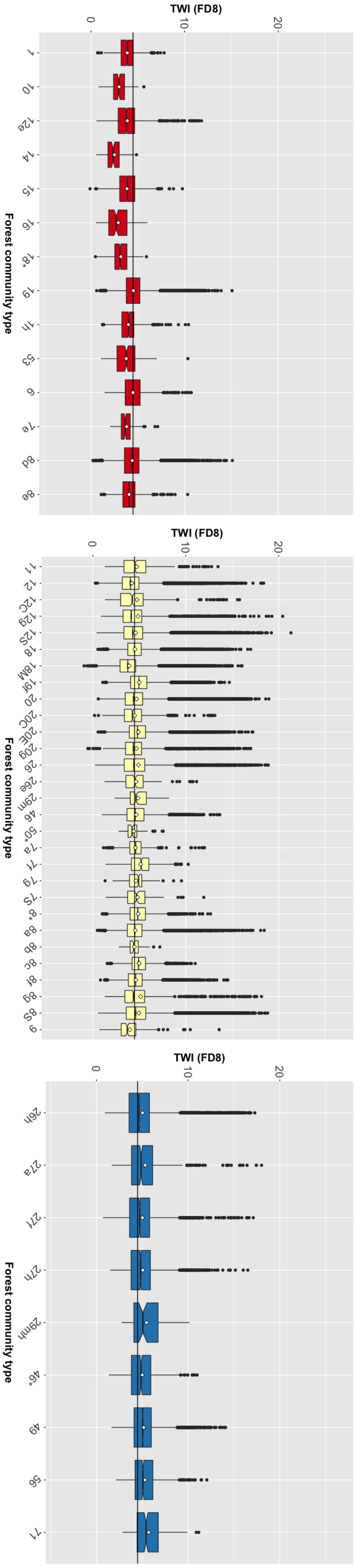
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.10: TWI (Rho8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

FD8 algorithm (2 m resolution)



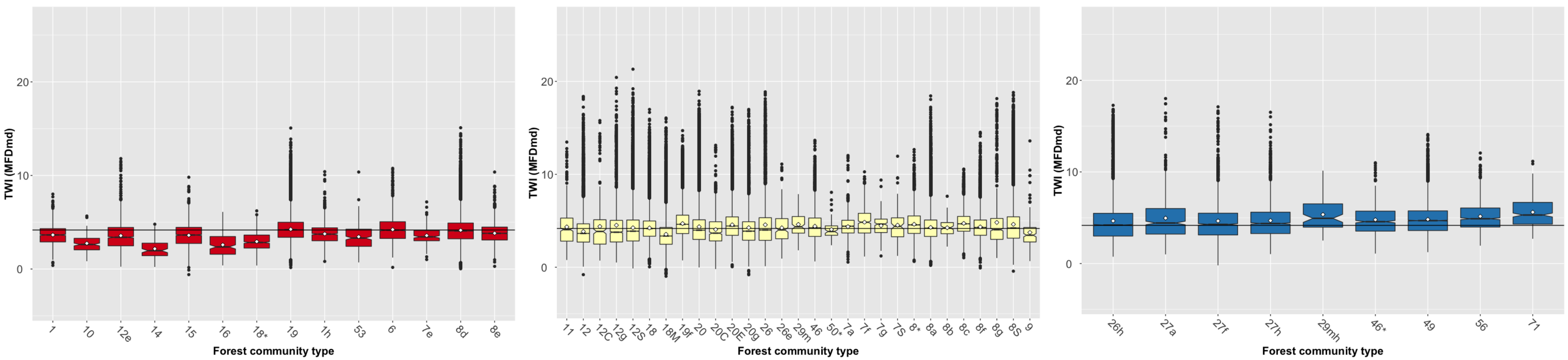
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.11: TWI (FD8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

MFD-md algorithm (2 m resolution)



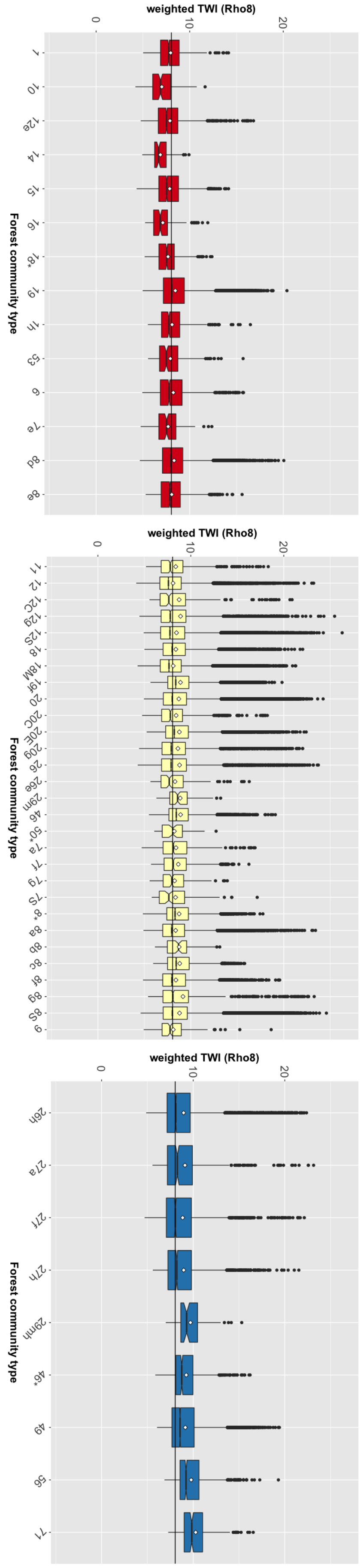
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.12: TWI (MFD-md) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

weighted Rho8 algorithm (2 m resolution)



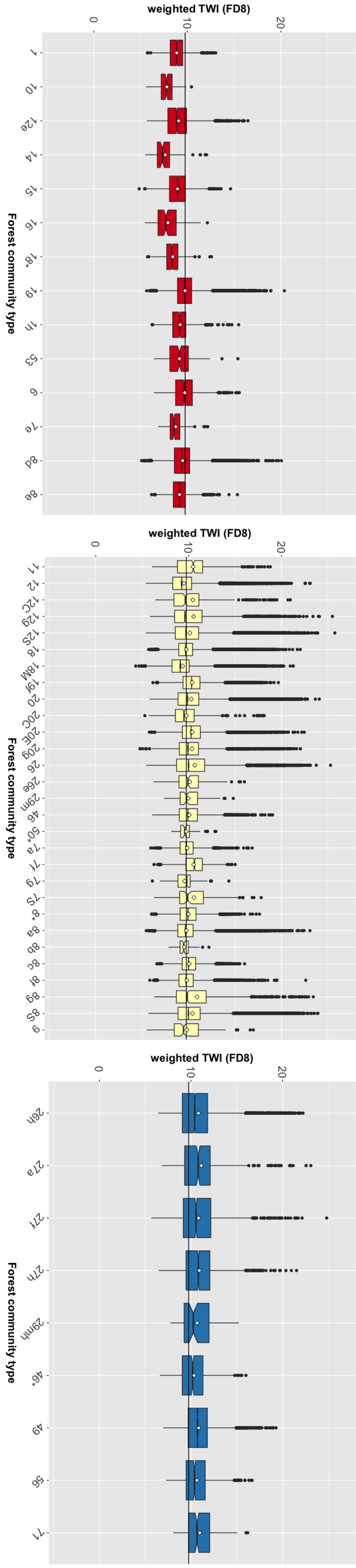
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.13: weighted TWI (Rho8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

weighted FD8 algorithm (2 m resolution)



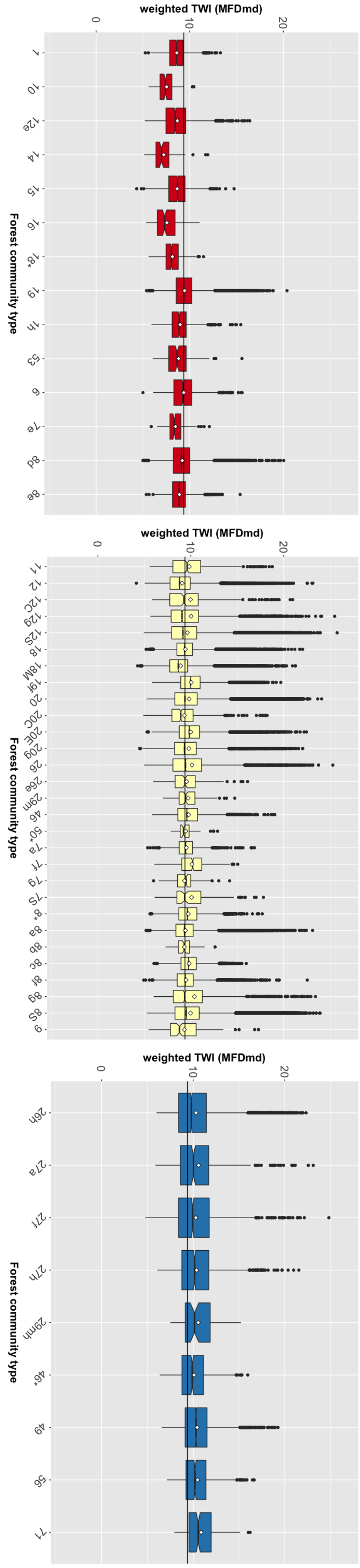
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.14: weighted TWI (FD8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

weighted MFD-md algorithm (2 m resolution)



(a) dry forest communities

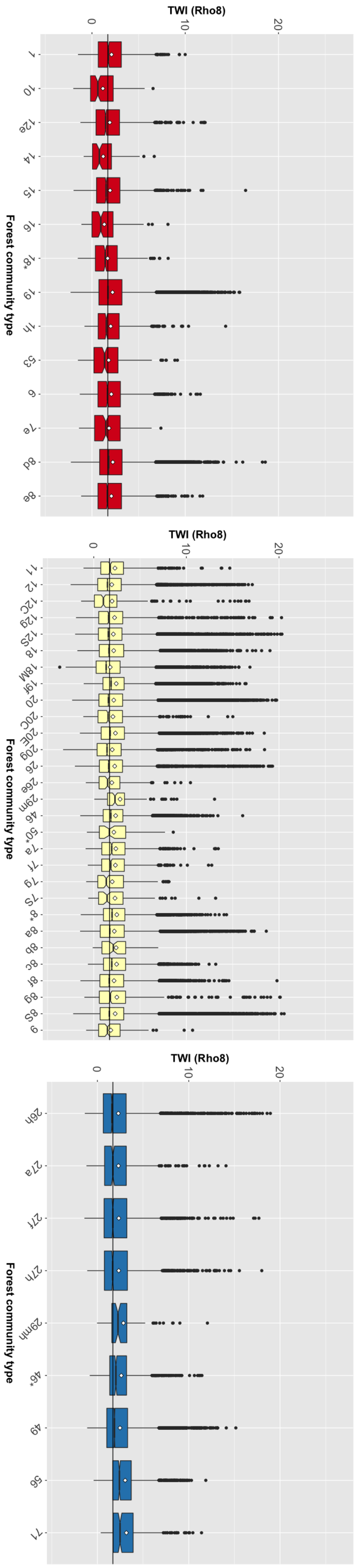
(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.15: weighted TWI (MFD-md) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

A.5.3 0.5 m resolution

Rho8 algorithm (0.5 m resolution)



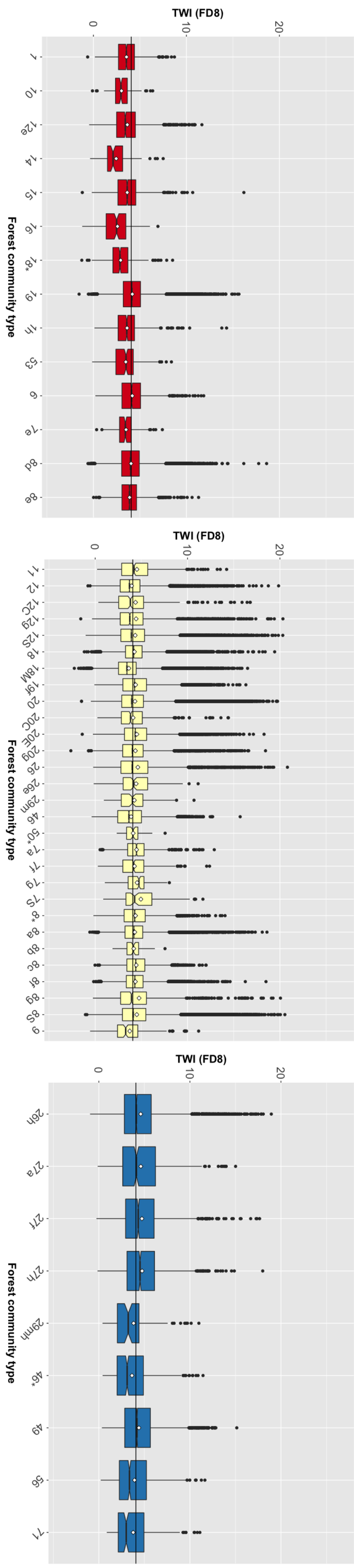
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.16: TWI (Rho8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

FD8 algorithm (0.5 m resolution)



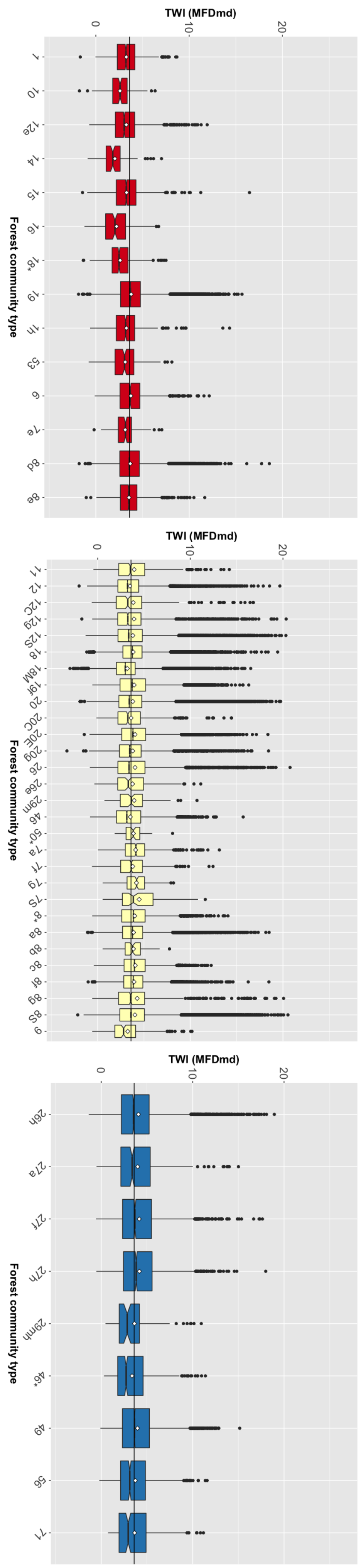
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.17: TWI (FD8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

MFD-md algorithm (0.5 m resolution)



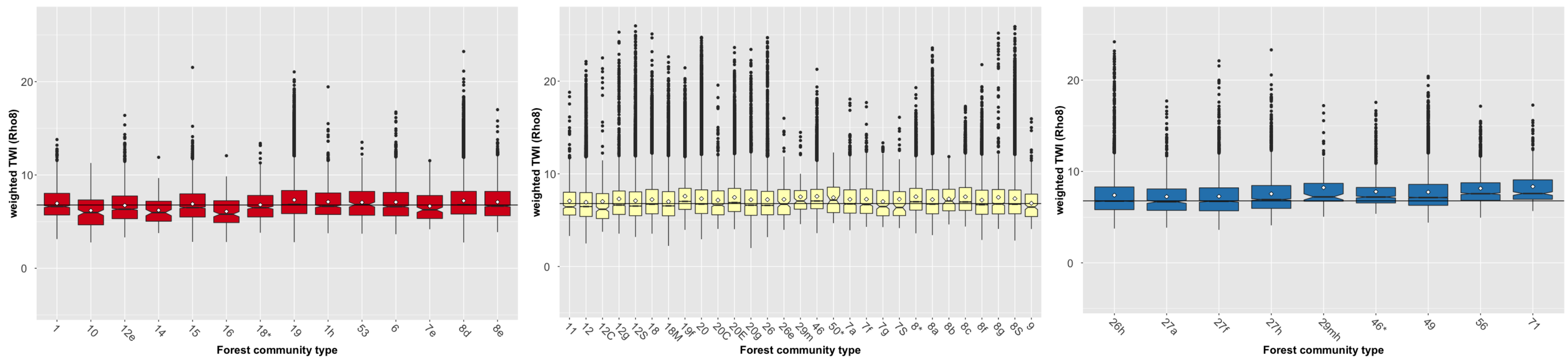
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.18: TWI (MFD-md) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

weighted Rho8 algorithm (0.5 m resolution)



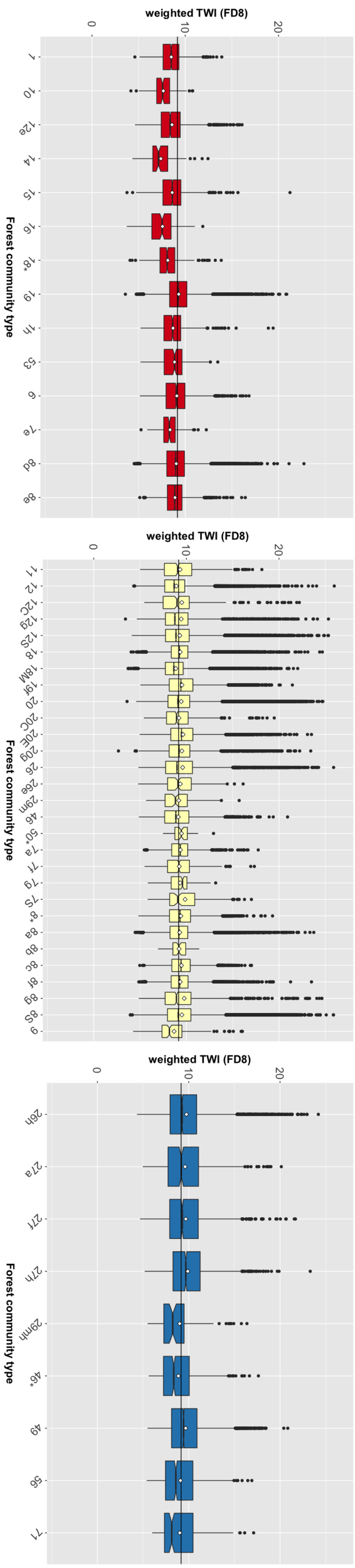
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.19: weighted TWI (Rho8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

weighted FD8 algorithm (0.5 m resolution)



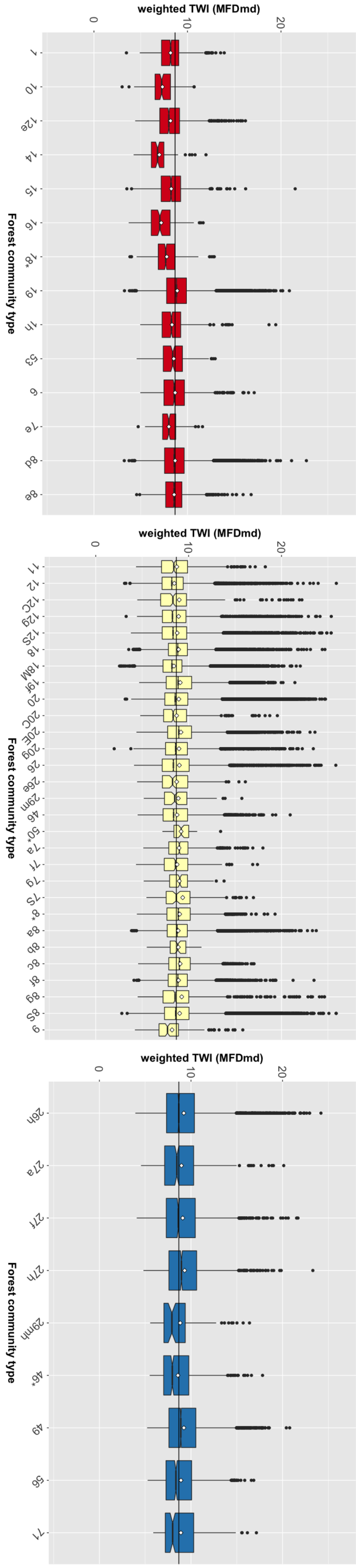
(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.20: weighted TWI (FD8) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

weighted MFD-md algorithm (0.5 m resolution)



(a) dry forest communities

(b) fresh-moist forest communities

(c) wet forest communities

FIGURE A.21: weighted TWI (MFD-md) values of the different forest community types in the canton of AR. The forest community types were grouped into (a) dry (b) fresh-moist and (c) wet according to their position in the ecograms. The numbers on the x-axis refer to the German/Latin name of the forest communities as listed in Table A.1. The black horizontal line indicates the total median TWI value of the corresponding resolution and algorithm.

A.6 Ecograms of the forest community types

A.6.1 *Hochmontane* elevational zone

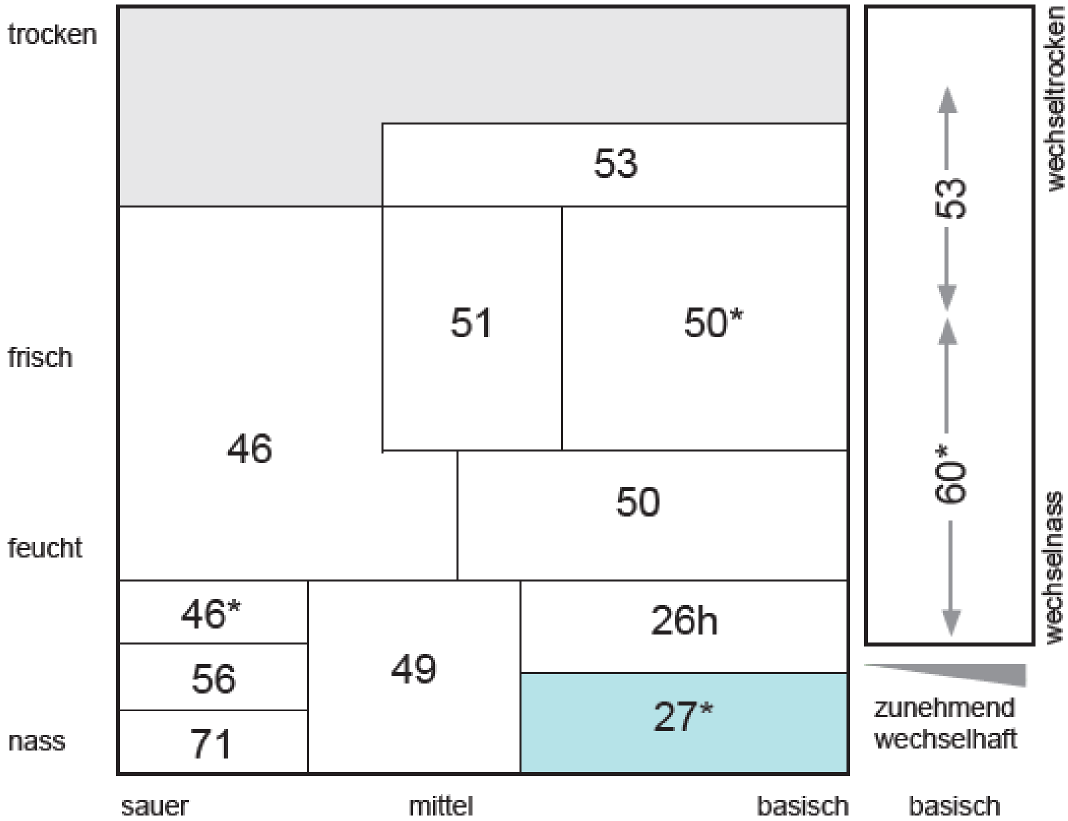


FIGURE A.22: Ecogram of the *Hochmontane* elevational zone in the canton of AR. The forest community types are classified according to soil moisture and soil acidity.

A.6.2 *Obermontane* elevational zone

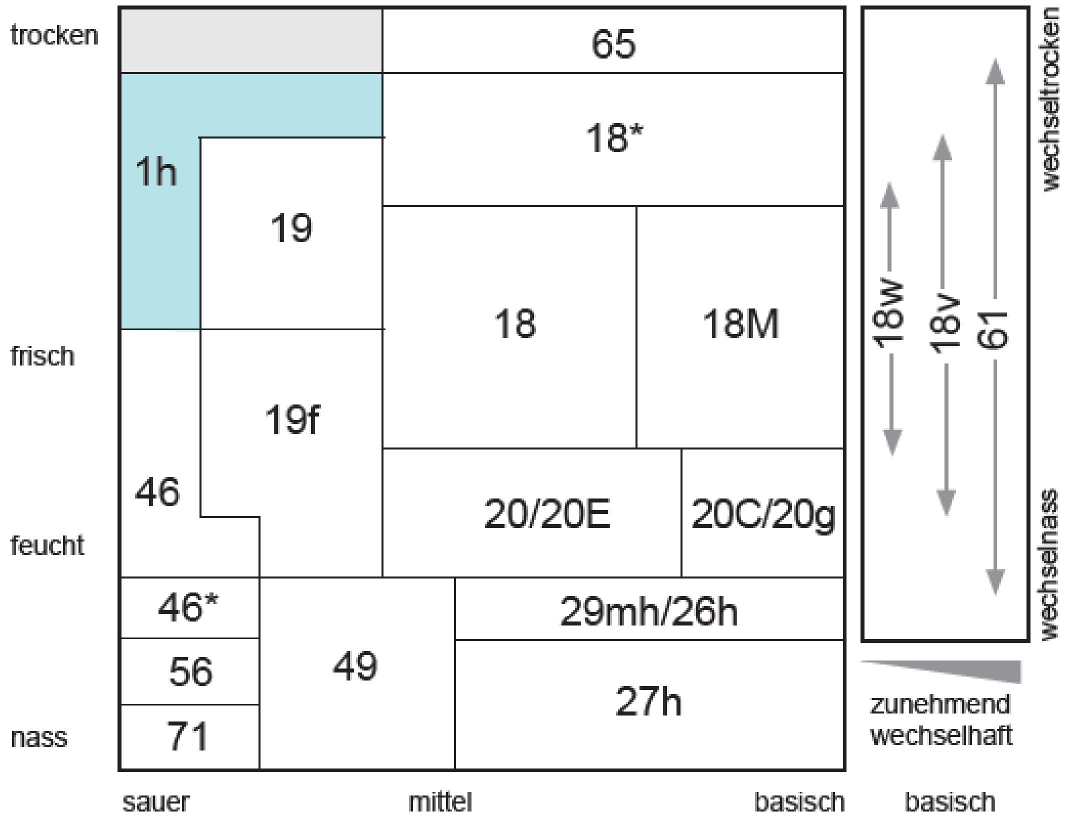


FIGURE A.23: Ecogram of the *Obermontane* elevational zone in the canton of AR. The forest community types are classified according to soil moisture and soil acidity. The numbers refer to the German/Latin name of the forest communities as listed in Table A.1.

A.6.3 *Untermontane* elevational zone

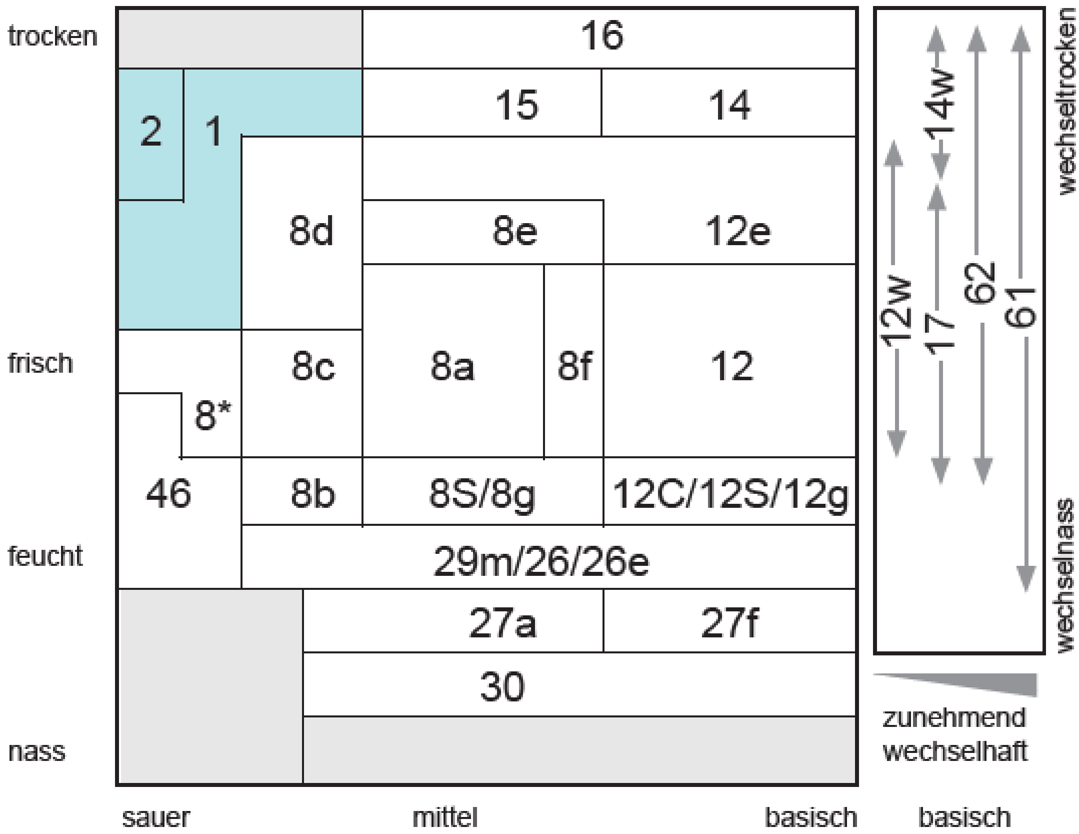


FIGURE A.24: Ecogram of the *Untermontane* elevational zone in the canton of AR. The forest community types are classified according to soil moisture and soil acidity. The numbers refer to the German/Latin name of the forest communities as listed in Table A.1.

A.6.4 *Submontane* elevational zone

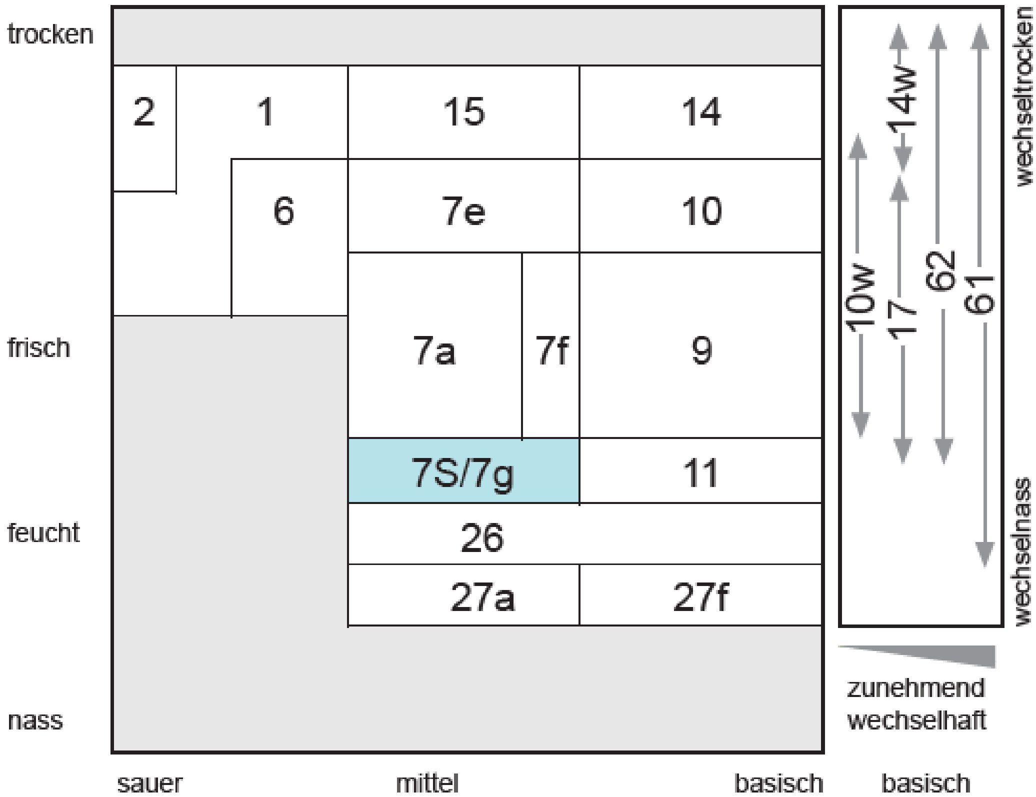


FIGURE A.25: Ecogram of the *Submontane* elevational zone in the canton of AR. The forest community types are classified according to soil moisture and soil acidity. The numbers refer to the German/Latin name of the forest communities as listed in Table A.1.

A.7 Declaration of originality

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Declaration of originality

The signed declaration of originality is a component of every semester paper, Bachelor's thesis, Master's thesis and any other degree paper undertaken during the course of studies, including the respective electronic versions.

Lecturers may also require a declaration of originality for other written papers compiled for their courses.

I hereby confirm that I am the sole author of the written work here enclosed and that I have compiled it in my own words. Parts excepted are corrections of form and content by the supervisor.

Title of work (in block letters):

Possibilities of differentiating between forest community types with topographic variables in the canton of Appenzell Ausserrhoden

Authored by (in block letters):
For papers written by groups the names of all authors are required.

Name(s):	First name(s):
Simmler	Kevin

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Place, date	Signature(s)
Bubikon, 4.5.20	K. Simmler

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