INTEGRATION OF SENTINEL-1, SENTINEL-2 AND ANCILLARY DATA SOURCES FOE MAPPING MIRES IN BAVARIA AND SUMAVA NATIONAL PARKS

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Enschede, The Netherlands, [02, 2017]

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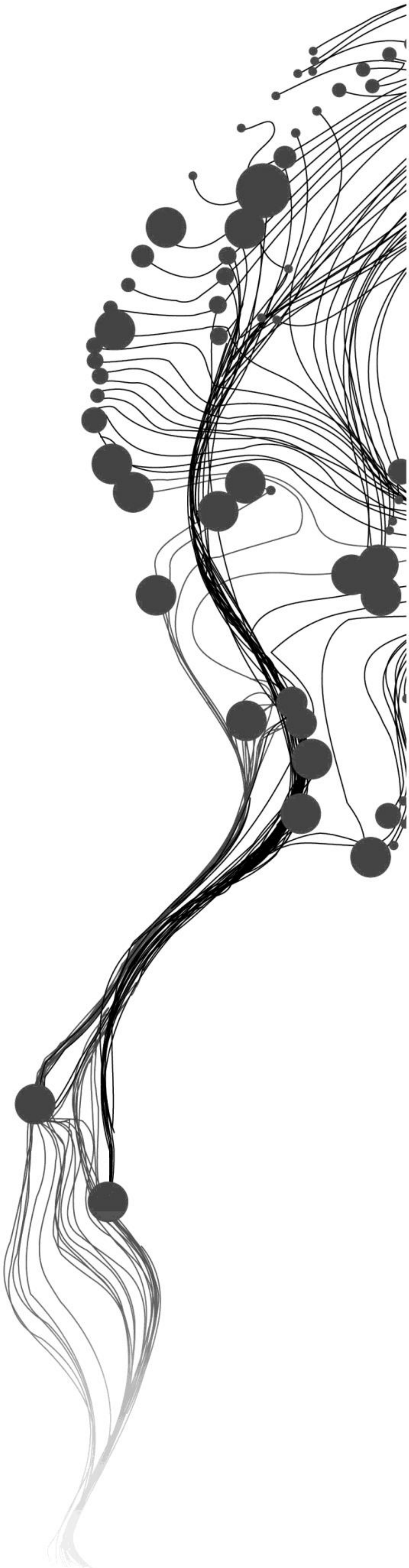

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Enschede, The Netherlands, [02, 2017]

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
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ABSTRACT

Mire is the most precious also most sensitive biotype of the Bavarian and the Šumava National Parks. In the past, most of the mires were drained for forestry, agriculture and peat extraction. To conserve mires, the spatial distribution of mires needs to be identified. Using field survey method is time and money consuming. With the development of remote sensing techniques, optical images become more efficient compared to field survey. However, the quality of optical images would influenced by clouds. The information under vegetation canopy cannot be detected use optical image only. Thus weather-independent and day-and-night SAR data were considered useful in mapping mires. Ancillary data source like topographic data and soil type information plays a key role in the formation of mires which was also recognised of vital importance in mapping mires. The aim of this research is to map mires in the Bavarian Forest National Park and Šumava National Park using random forest classifier based on Sentinel-1 SAR data, Sentinel-2 multi-spectral images, topographic information and soil type information. The results indicated that the classifier was not able to discriminate mire and non-mire classes using Sentinel-1 SAR data alone, Sentinel-2 multi-spectral image or combination of Sentinel-1 SAR data and Sentinel-2 multi-spectral data. However, the accuracy was significantly improved when incorporating topographic data with Sentinel-1 & Sentinel-2 data with overall accuracy in the Bavarian Forest National Park and Šumava National Park increased to 90.63% and 88.46%, respectively. Integration of Semtimle-1, Sentinel-2, topographic and soil type information can further improved the overall accuracy and peaked at 93.75%.in the Bavarian Forest National Park and 92.31% in the Šumava National Park, respectively. The most important variable for differential mire and non-mire classes were slope and soil type information. This research concluded that the pixel-based RF classification using integration of Sentinel-1 SAR data, Sentinle-2 multi-spectral images, topographic information and soil type information improved the mapping accuracy of mires and provide a feasible approach to differentiate mire from other land cover types in a forest landscape.

Key words: mire, mapping, Sentinel-1, Sentinel-2, topographic, soil type, Random Forest

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1. INTRODUCTION

1.1. Background

"Mire represents a general term that embraces all peat-forming wetlands" (Johnson & Gerbeaux, 2004). The importance of mires has been widely recognized. As the natural habitats of many endemic and rare species, mires make contribution to protecting biodiversity (Joosten & Salathe, 2001). The accumulation of peat in mires overtime make it capable to conserve information for antiquated vegetation, maintain prehistoric ecological status as well as record the evolution process (Svobodová et al., 2002).

The Bohemian Forest is the area that forms one of the most important mire regions in Central Europe, where mires cover more than 15% (Svobodová et al., 2002). The Bavarian Forest National Park and the Šumava National Park were established 1970 and 1991, respectively (Čížková et al., 2011). These two parks protect an area of 92,284 ha in the Bohemian Forest (Čížková et al., 2011). The mire is the most precious also most sensitive biotype of the Bavarian and the Šumava National Parks. To conserve mires effectively and better manage mire resources, the spatial distribution and accurate borders of mires need to be identified. This is difficult because mires are often in remote regions, covering a large spatial extent and holding a featureless nature with blurry boundaries (Brown et al , 2007).

Figure 1 Open raised bog in the Bavarian Forest National Park (Křenová, 2011)

Mapping mires using traditional ground survey methods faced with great challenges. On the one hand, mires inherit the complex characteristic of wetland habitats that is poorly defined boundaries because of its special world between dry land and water (Brown et al., 2007). On the other hand, accurate ground truth information is always limited due to inaccessibility to mire. Studies have been successfully implemented through using remote sensing data.

Remote sensing imagery used in mires mapping mainly include aerial photograph and optical images (Connolly et al., 2007; Krankina et al., 2008; Poulin et al., 2002; Romshoo, 2004). In the past, researchers usually combine the aerial photograph and fieldwork to map the mire (Harris et al., 2006; Mcmorrow et al., 2004). As the size of study area increase, these methods become time and money consuming. Afterwards, satellite imagery was used. Satellite imagery can cover lager area and the cost of per unit imaged is less (Fonji & Taff, 2014). Some researchers used multi-spectral data Landsat TM images and SPOT images and combined visible with near-infrared bands to extract unique reflectance characteristics of mires (McGovern et al., 2000). However, the disadvantage of optical images to map mire is obvious since information under cloud and vegetation canopy can't be detected.

Compared to optical remotely sensed data, high-resolution, day-and-night and weather-independent images can be provided by SAR data. When monitoring widespread mires, use of SAR data can avoid time and climate limitations (Moreira et al., 2013). In addition, SAR data is sensitive to soil moisture, vegetation water content and geometry features thus can offer precise response to different mire types (Moreira et al., 2013). What's more, the ability of microwave to penetrate forest vegetation can give more information about the upper layer of mires hidden by forests (Nursyamsi, Noor, & Maftu'ah, 2016). Hence, SAR data is appropriate for mapping mires.

Incorporating optical images with SAR data therefore gives a more promising opportunity for mire mapping. Li and Chen (2005) used a rule-based decision tree to assess the ability of Landsat-7 ETM+, Radarsat-1 C band and Digital Elevation Model (DEM) data in classifying wetland in Canada. The results showed that the wetland classification accuracy significantly improved using combination of optical images, SAR, and DEM data compared to using the data individually.

Mire typically developed in flat regions or gentle incline with poor drainage capacity. The nature of mire makes it impossible to exist in steep slope. Thus topographic information (i.e., slope) which can be extracted from DEM is considered as useful information layer in mapping mires. Some researchers assumed that mires formed in gently sloping area where the slopes are no more than 5° (Li et al., 2014; Niu et al., 2009). While Connolly et al. (2007) adopted the criteria that mires cannot be developed where the slopes area greater than 25 degrees.

Because most of the mires in the Bavarian Forest and Šumava National Parks are covered by bog forest with a density canopy which cause difficulties for mire mapping use both optical images and SAR data. There is a need to collect remotely sensed data during leaf-off conditions.

1.2. Problem Statement

In the past, about 70% of the mires in the Bavarian Forest National Park and the Šumava National Park were drained for forestry, agriculture and peat extraction, therefore, caused degradation in mire ecology and structure (Bufková et al., 2010). Recently, some of the mires have been restored according to a long term project "Šumava Mountain Mire Restoration Programme" implemented since 1999 (Bufková et al., 2010). To protect the mires, firstly, the location of the mires should be identified. However, field data acquisition and visual interpretation is labor intensive, time-consuming and costly. The use of ground survey method is very limited and cannot be widely applied in other remote and large regions which require plentiful time and financial support. What's more, the inefficiency of ground survey makes it difficult to update the information about mires distribution over time.

Many studies have been carried out on the mapping of mires using either SAR data or multi-spectral satellite images (Brown et al., 2007; Krankina et al., 2008; Li et al., 2014; Torbick et al., 2012). But it is rare to find researches about mapping mires through combining SAR data with multi-spectral images, not to mention adding additional topographic factors as well as soil type information to mire mapping. Moreover, spatial resolution of the remotely sensed data (i.e., Sentinel-1SAR data and Sentinel-2) to be used in this study is relatively high, which is more appropriate for mire mapping in a forest landscape where small mires are common which cannot be captured by the coarse resolution satellite images (Krankina et al., 2008). Thus, the synergistic use of Sentinel-1 SAR data, Sentinel-2 multi-spectral imagery would be more likely to offer a more promising approach in mapping mires in a forest landscape.

1.3. Research Objectives

This study aims to assess the accuracy of mire maps derived from either separate or combination use of multi-sensor remote sensing data (i.e., Sentinel-1 SAR and Sentinel-2 multi-spectral) and ancillary geographical data (i.e., topographic and soil type information). The specific objectives of this research are as follows:

- To map the mires in Bavarian Forest National Park and Šumava National Parks using Sentinel-1 SAR data and Sentine-2 multi-spectral data, respectively.
- To map the mires in Bavarian Forest National Park and Šumava National Parks using the combination of Sentinel-1 SAR data and Sentinel-2 multi-spectral data, respectively.
- To map the mires in Bavarian Forest National Park and Šumava National Parks using the combination of Sentinel-1 SAR data, Sentinel-2 multi-spectral data, topographic data and soil type information, respectively.

1.4. Research Questions

- What are the differences in mire mapping accuracies between the use of Sentinel-1 SAR data and Sentinel-2 multi-spectral images?
- Does the combination of Sentinel-1 SAR data and Sentinel-2 multi-spectral images significantly improve the mire mapping accuracy?
- Does adding topographic or soil type information significantly improve the mire mapping accuracy?
- What are the most important variables which contributed most to the accuracy of mire mapping?

1.5. Hypotheses

<u>Hypothesis 1</u>

H_0: There is no statistically significant difference in mire mapping accuracies between the use of the Sentinel-1 SAR and the Sentinel-2 multispectral images.

H_1: The mire mapping accuracy derived from the Sentinel-1 SAR data is significantly higher than the one derived from the Sentinel-2 multispectral images.

<u>Hypothesis 2</u>

H_0: There is no statistically significant difference in mire mapping accuracies between the use of the Sentinel-1 data (or Sentinel-2 data) and integration of Sentinel-1 with Sentinel-2 data.

H_1: Integration of Sentinel-1 SAR data with Sentinel-2 multispectral images can significantly improve the mire mapping accuracy.

Hypothesis 3

H_0: There is no statistically significant difference in mires mapping accuracies between the integration of Sentinel-1 with Sentinel-2 data and the integration of multi-sensor remote sensing data (i.e., Sentinel-1 and Sentinel-2 data) with ancillary geographical data (i.e., topographic and soil type information).

H_1: Adding topographic and soil type information can significantly improve the mire mapping accuracy.

2. MATERIALS AND METHODS

2.1. Study Area

The Bavarian Forest and Šumava National Parks are located in the Bohemian Forest, a mountain ridge astride the frontier with the Czech Republic and Germany in the heart of Europe (Láha et al., 2012). The total area is 92,284 ha and falls within 48°42' N to 49 °11'N in latitude and 13°29' E to 14°13' E in longitude. The altitude is between 750 and 1453m above sea level (a.s.l). Mires in this area are spread between 650 and 1350 m a.s.l (Svobodová et al.,2002). The highest peaks of BF & ŠNP are reached to 1,453m (in Mt. Rachel) and 1,379m (in Plechý), respectively (Křenová & Kiener, 2007). At lower elevation, the densely wooded landscape is mainly including crystal clear mountain streams, unspoilt marshlands, bogs and bog woodlands while at higher elevation is more abandoned mountain pastures (Láha et al., 2012). The prevalent climate of this region is relatively humid, characterized by a long and harsh winter. The mean annual temperature is 6.2 °C. Average annual precipitation is 760 mm (Bufková et al., 2010). The mires in this area range from bogs which are only supplied by precipitation to fens which obtain nutrients and water from mainly from soil, rocks and groundwater (Svobodová et al., 2002).

Because of the different quality of ground truth data and ancillary soil type information in the Bavarian Forest National Park and the Šumava National Park, the analyze in the two parks are discussed separately as two parts.

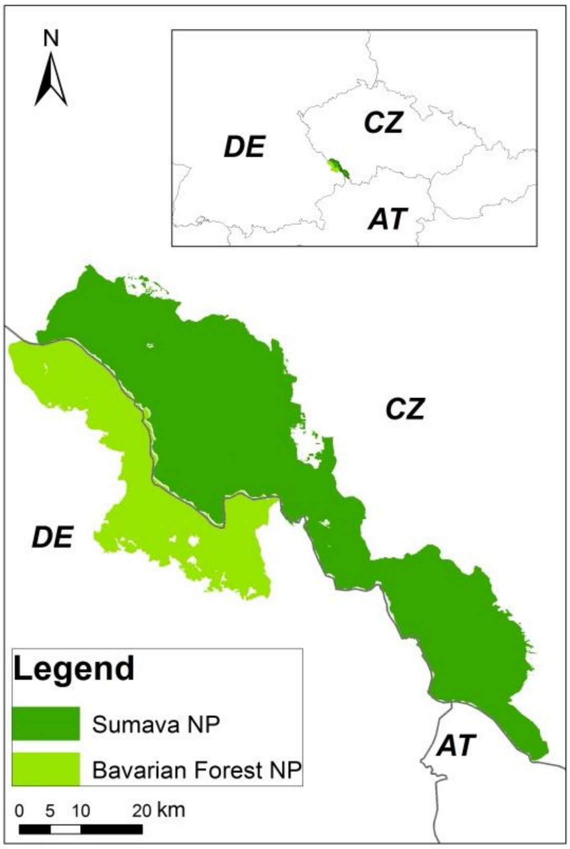

Figure 2 Location of the the Bavarian Forest National Park in Germany and the Šumava National Park in Czech Republic

2.2. Data Preparing and Processing

2.2.1. Setinel-1 data and pre-processing

The Sentinel-1 mission developed by the European Space Agency (ESA) is composed of a constellation of two identical near-polar orbiting satellites. Sentinel-1A and Sentinel-1B was launched in 2014 and 2016, respectively. Sentinel-1 carries a single C-band Synthetic Aperture Radar (SAR) instrument operating at a center frequency of 5.405GHz to measure radar backscatter and supports the operation in dual polarization (HH+HV, VV+VH). There are four imaging modes in Sentinel-1 including: Stripmap (SM), Interferometric Wide swath (IW), Extra Wide Swath (EW) and Wave Mode (WM). And the Sentinel-1 SAR data can be acquired under 3 levels: Level 0, Level 1 and Level 2.

In this study, the Standard Level 1 product of GRDH (ground-range detected, high resolution) collected in the IW mode was selected with two alternating polarization modes VV (vertical transmit, vertical receive) and VH (vertical transmit, horizontal receive). This image was obtained on 6 December 2015 (Scene ID= S1A_IW_GRDH_1SDV_20151206T051734_20151206T051759_008917_00CC33_B229) without calibration. Through using the Sentinel Toolbox (SNAP) developed by ESA, the images can be transferred from DN values (amplitude) to sigma backscatter images expressed in dB scale. The specific calibrated processes are as follows: 1) Radiometric correction. Radiometric errors always exist in the level-1 images in which the radiometric were uncalibrated. Using the Radar-Radiometric-Calibrate tool in SNAP, backscatters σ_0 can be achieved. 2) Speckle filtering. The SAR can transmit interference electromagnetic pulses to detect the target. The coherent superposition of the reflected pulses, making the SAR images appear random distribution of black and white pixels, called speckle noise (Torres et al., 2012). In order to diminish the influence of speckles on image interpretation and improve the quality of the image, the SNAP-Radar-Speckle Filtering-Single Product Speckle Filtering tool was used through the radiation calibration. The Refind Lee method with a 3*3 pixel window was chosen to apply as it can smooth the images meanwhile conserving the edges. 3) Geometric correction. Due to the fact that SAR images have side-view imaging characteristics, SAR image geometric distortions (overlapping, shadow) may appear in relief displacement. In SNAP, the Radar-Geometric-Terrain Correction tool was chosen to apply Range Doppler method for image registration. After that, the image was converted to dB value and projected to the Universal Traverse Mercator coordinate system (UTM zone 33, WGS 84). VV and VH bands were resampled to 20 meters spatial resolution using nearest neighborhood method. Some research argued that C-band SAR data was available in classification, texture features would help to improve the mapping accuracy (Waske & Braun, 2009). Thus Gray level co-occurrence matrix (GLCM) texture variables (mean, variance, homogeneity, contrast, dissimilarity, angular second moment, entropy and correlation) (Ouma & Tateishi, 2006) was chose to use in this study, which can be calculated from the GRDH product within a moving window of 5*5 pixel size based on ENVI 4.8 software. The characteristics of the collected Sentinel-1 IW data are displayed in Table1.

Table 1 Characteristics of Sentinel-1 Interferometric Wide swath mode (Torres et al., 2012)

Parameter	Interferometric Wide swath mode (IW)
Polarization	Dual VV+VH
Azimuth resolution	<20 m
Ground range resolution	<5 m
Azimuth and range looks	Single
Swath	>250 km
Maximum NESZ	-22 dB
Radiometric stability	0.5 dB
Radiometric accuracy	1 dB
Phase error	5°

2.2.2. Setinel-2 data and pre-processing

The Sentinel-2 mission developed by the European Space Agency (ESA) comprises two satellites (Sentinel-2A and Sentinel-2B) operating in the same orbit (786 km) launched in 2015 and planned to be launched in 2017, respectively. A revisit time of 5 days for each satellite can be achieved. Sentinel-2 satellites provide high resolution (10m, 20m and 60m) multi-spectral imagery (13 spectral bands in visible, near infrared and shortwave infrared domains) with the swath width of 290 km. Spectral bands with a spatial resolution of 60 m are mainly used for evaluating atmospheric condition (Feilhauer et al., 2014). Therefore, the data with a spatial resolution of 10 m and 20 m were chosen to be applied in this research. Table 2 shows the 13 spectral bands of Sentinel-2 ranging from visible (VIS) band to short-wave infrared (SWIR) band.

Table 2 Characteristics of Sentinel-2 (Drusch et al., 2012)

Bands	Wavelength (μm)	Resolution (m)	Description
Band 1	0.433	60	Ultra blue
Band 2	0.49	10	Blue
Band 3	0.56	10	Green
Band 4	0.665	10	Red
Band 5	0.705	20	Visible and Near Infrared (VNIR)
Band 6	0.74	20	Visible and Near Infrared (VNIR)
Band 7	0.775	20	Visible and Near Infrared (VNIR)
Band 8	0.842	10	Visible and Near Infrared (VNIR)
Band 8A	0.865	20	Visible and Near Infrared (VNIR)
Band 9	0.94	60	Short Wave Infrared (SWIR)
Band 10	1.375	60	Short Wave Infrared (SWIR)
Band 11	1.61	20	Short Wave Infrared (SWIR)
Band 12	2.19	20	Short Wave Infrared (SWIR)

The multi-spectral image used in this research was acquired on 31 December 2015 (Scene ID= S2A_OPER_PRD_MSIL1C_PDMC_20151231T175836_R022_V20151231T102248_20151231T102248) with a UTM projection (UTM zone 33, WGS 84). All chosen bands were then resampled to 20 meters spatial resolution using nearest neighborhood method .

2.2.3. Topographic information

Topographic information, including slope, aspect, elevation and terrain position (i.e., peak, ridge, pass, plane, channel and pit), can be extracted from 30m SRTM Digital Elevation Model (DEM). The DEM have been geo-referenced with the Sentinel-2 multi-spectral images. Topographic modeling tool in ENVI (version 5.3) software has been used to generate elevation and slope from DEM data. Six terrain position classes were calculated using the Topographic features tool in ENVI (version 5.3) software.

2.2.4. Soil type information

Soil type in the Bavarian Forest National Park and the Šumava National Park mainly includes: lithosol, ranker, distric cambisol at medium altitude, distric cambisol at higher altitude, canbic podzol, podzol, dystric planosol, stagno-gleyic plansol, fluvisol, gleysol and histosol (Milan, 1996). The gleysol and histosol often occurs in mires while other soil types may occur on steep slopes, agriculture lands and floodplains (Milan, 1996). Soil type information for different habitat type can be extracted from the soil map which is provided by the management organization in the Bavarian Forest National Park. While in the Šumava National Park, the soil type information were classified using maximum likelihood classification method based on a geocoded scanned soil map of Czech Republic download from European Soil Data Center (ESDAC).

2.2.5. Ground truth data

The mire ground truth data for training and validating in the Bavarian National Park were based on the irregularly distributed permanent plots setting in 2006 within the Park. And most of the mires were concentrated in a few locations because of the inaccessibility and the natural distribution of the mires. The GPS position of these sites was collected in 2016 by the staff in the Bavarian Forest National Park. To obtain independent data set and reduce the influence of the spatial autocorrelation, a minimum 50 meters separate distance was set through the mire points. After that, a 500 meters buffer was created around the points of mires. The non-mire ground truth data were randomly generated in the non-buffer area, and it was double checked with the Ariel photographs. There are totally 48 points for mires and 48 points for non-mire. 2/3 of the mire and non-mire ground truth data was randomly selected for training and the remaining 1/3 was selected for validation. The distribution of the training and validation data was shown in Figure 3.

In the Šumava National Park, only 5 points for mires were available. Therefore most of the mire points were generated through the interpretation of the very high resolution ariel photographs implemented by the staff in the national park with a minimum separate distance of 50 m. The same sampling strategy was applied as the Bavarian Forest National Park to generate non-mire ground truth data. There are totally 36 mire points and 36 non-mire points. 2/3 of the mire and non-mire ground truth data was randomly selected for training and the remaining 1/3 was selected for validation. The distribution of the training and validation data was shown in Figure 4.

Because of the different quality of the ground truth data in the two national parks, it is necessary to consider them as two different study areas. The analysis in the two parks later should be separate.

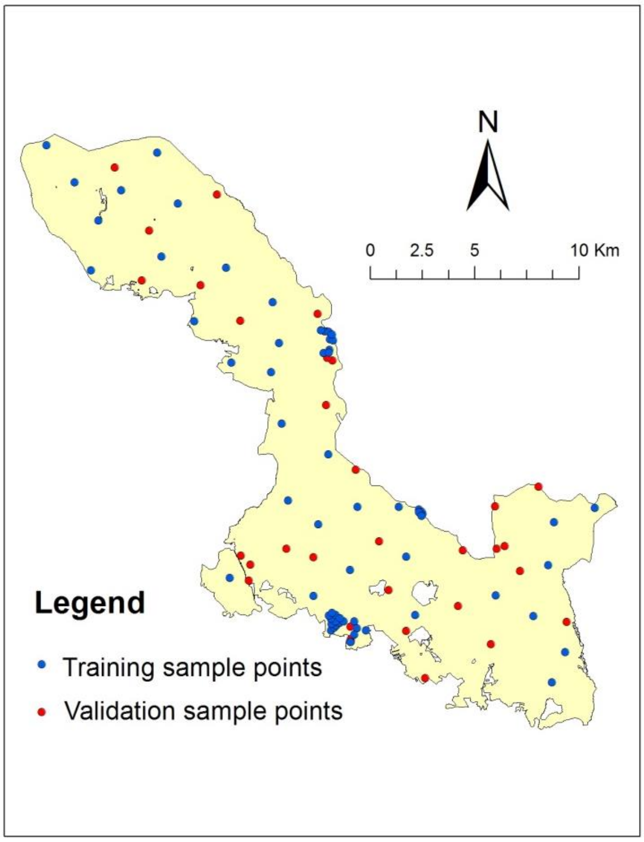

Figure 3 Sample points of mire and non-mire classes in the Bavarian Forest National Park

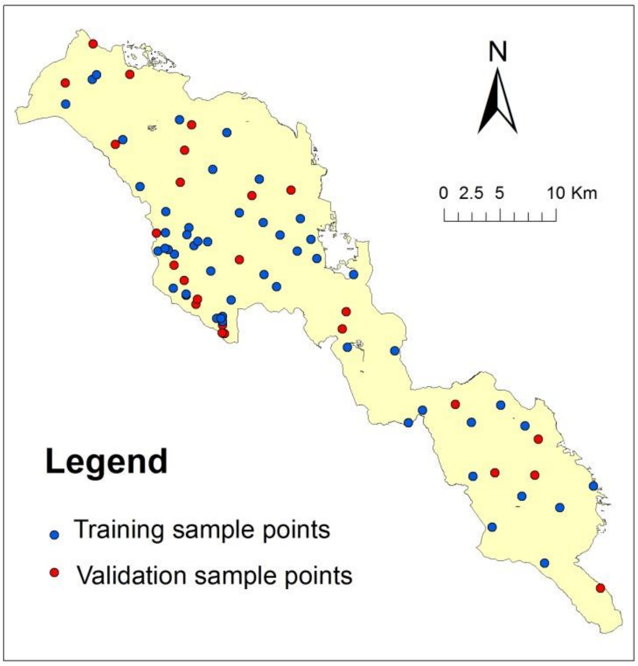

Figure 4 Sample points of mire and non-mire classes in the Šumava National Park

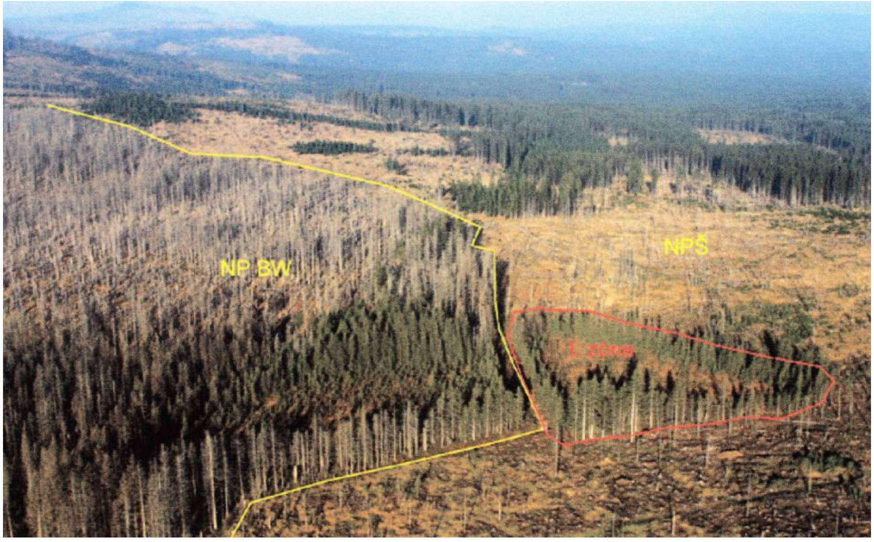

Figure 5 The raised bogs with its vegetation in the Bavarian National Park (Křenová, 2011)

2.3. Methods

Land cover in this study was classified into two categories of mires and non-mires using Random Forest algorithm based on Sentinel-1 SAR data, Sentinel-2 multi-spectral imagery, topographic data and soil type information. Reference data for training and validation were obtained from the Bavarian and Šumava National Parks. The main process of this study can be divided into two parts: Random Forest classification and accuracy assessment.

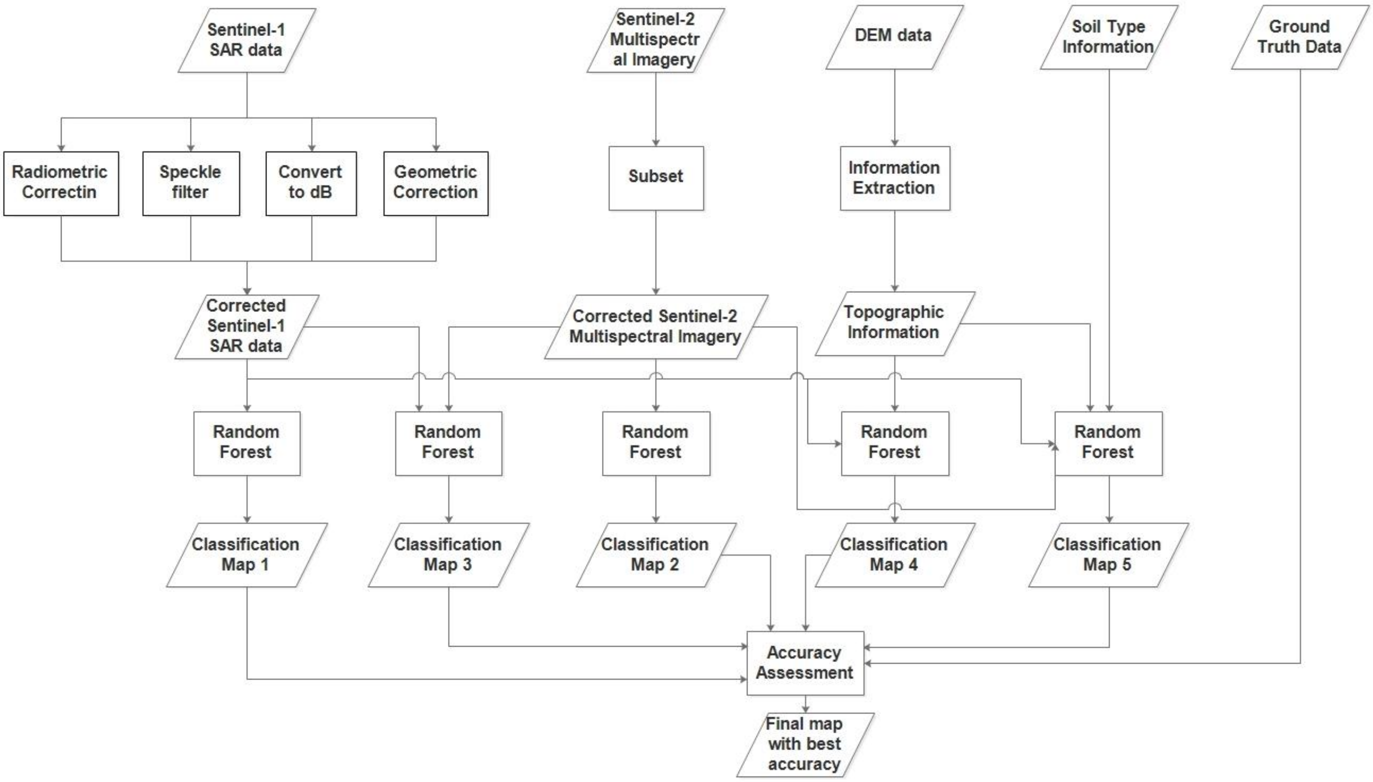

Figure 6 Methodology Flowchart

2.3.1. Random Forest Algorithm

Random Forest (RF) algorithm is widely used in diverse remote sensing image classification and showed to be powerful (Torbick et al., 2012). Random Forest algorithm maintain three main advantages: non-parametric operating capacity , high classification accuracy and ability to extract best input variable with highest contribution (Rodriguez et al., 2012). Compared to parametric classification method (i.e. Maximum likelihood) which is used to estimate normally distributed data, RF algorithm offer a possibility to incorporating multi-sensor remotely sensed data with adjuvant data since multidimensional and non-parameter distributed data can be processed using this technique (Millard & Richardson, 2015). Furthermore, this method is less sensitive to training sample size and performs well even with small sample size and without any feature reduction (Rodriguez et al., 2012; Waske & Braun, 2009). Waske & Braun (2009) indicated RF outperforms other methods like support vector machine (SVM) and maximum likelihood in terms of classification accuracy. Pal (2005) made a comparison between SVM and Random Forest and concluded that user-defined parameters required by RF is easier to define and have less number.

The Random Forest classifier operates by constructing a combination of tree classifiers. Each tree is independently built on the basis of a bootstrapped sample of the training dataset. Since the input variables are randomly selected, each tree holds various separating criteria. The routine procedure mainly contains three steps. First, through using bootstrapping sample strategy to get independent subset from the training data, a number of trees will be grown(Pal, 2005). At each node, the tree will be split using a reduced number of input variables. Some studies indicated that the number of features at each node should be the square root of the total number of features (Nan et al.,2015). Then, each tree will vote for the best input variable using the bootstrapped samples (Millard & Richardson, 2013). Finally, the forest cast the votes and chooses the classification with the majority votes (Millard & Richardson, 2013). In each tree, one third of all training data was keep to calculate Out of Bog (OOB) error using the bootstrapping strategy as an alternative of cross-validation (Millard & Richardson, 2013). A smaller value of OOB error indicates higer OOB accuracy as well as higher classification accuracy in RF classification. Although OOB error proved to be useful in some research (Kellndorfer et al., 2014), Millard and Richardson (2013) find that independent accuracy assessment is still necessary to avoid inflation of the mapping accuracy.

In this study, RF classification will be applied using predictive variables including Sentinel-1 data, Sentinel-2 data, topographic information and soil type information in R Statistics open-source statistical software. The randomForest (Liaw & Wiener, 2002), rgdal (Bivand, Keitt, & Rowlingson, 2014) and raster (Hijmans, 2014) packages in the software will be used to generate all classifications. The specific predictive variables included Sentinel-1 VV&VH bands, Sentinel-2 band (2-8A, 11, 12), slope, aspect, elevation, slope position and Sentinel-1 textual features. When running the RF model in R software, there are two important parameters that need to be defined: the number of decision tress (ntree) and the number of split variables in each node (mtry). The default ntree in the software is 500 while the default mtry equals to the square root of all input variables (Na et al., 2015). As the number of features increase, using the default parameter may achieve higher OOB error. In this research, 1000 decision trees were generated based on the experience that increases or reduces the number of ntree cannot obtain any improvement in mapping accuracy (Millard & Richardson, 2013, 2015). The mtry were set to square root of all input variables ranged from 3 to 6 based on the different number of input variables.

2.3.2. Accuracy Assessment

The performance of different mire maps derived from either separate or combination use of multi-sensor remote sensing data (i.e., Sentinel-1 SAR and Sentinel-2 multi-spectral) and ancillary geographical data (i.e., topographic and soil type information) will be evaluated based on confusion matrix, overall accuracy and kappa coefficient. Although the overall accuracy can be utilized to evaluate the classification accuracy, but it highly depends on the number of categories in the classification and contains chance agreement thus sometimes not stringency enough (Jiang, 2011).

To accommodate for the limitation of chance agreement in overall accuracy, chance-corrected measures like Cohen's kappa coefficient (Cohen, 1960) are proposed. Cohen's kappa can measure the agreement between actual land cover classes and classified classes without chance agreement thus provide a better index for accuracy assessment (Li & Chen, 2005). The range of kappa coefficient can be -1 to 1, but usually falls from 0 to 1. A value of 0 indicates no change-independent agreement exists while a value of 1 indicates perfect agreement. The level of kappa has been classified in different ways (Tang et al., 2015). Landis and Koch (1977) proposed that the model's performance can be assessed as: poor (kappa<0), slight (kappa: 0-0.2), fair (kappa: 0.21-0.40), moderate (kappa: 0.41-0.60), substantial (kappa: 0.61-0.80) and almost perfect (kappa: 0.81-1). The kappa coefficient of different mires maps will be compared for the significant difference by pairwise comparison of Z-statistics (Congalton, 1991). The result is considered to be statistically different when z value lager or equal to 1.96, which also indicates a 95% confidence interval.

3. RESULTS

In this chapter, pixel based Random Forest classification method was applied to map mires in the Bavarian Forest National Park and Sumava National Park, respectively. The ground truth data quality as well as soil type information has huge difference in the two national parks. Thus, it's necessary to show the mapping result in two parts. The first part is the classified map for mire distribution in the Bavarian Forest National Park; the second part is about the mire distribution map in the Sumava National Park.

3.1. Mapping mires in the Bavarian Forest National Park

Multi-source data was used to mapping mires in the Bavarian Forest National Park. There are totally five different combinations of the input data sources. First, only use the Sentinel-1 SAR image to do the classification. The input variables include SAR VV& VH bands, and texture features. Second, only use the Sentinel-2 multi-spectral image to do the classification. The input variables include band2-band 8A, Band 11 and band 12. After that, use the combination of Sentinel-1 and Sentinel-2 data. Then, adding ancillary topographic information (elevation, slope, aspect and terrain position) into the input variables to do the classification. Finally, involve soil type information into the model and make classification use all the variables.

3.1.1. Mapping mires using Sentinel-1 SAR images

3.1.1.1. Random forest classification

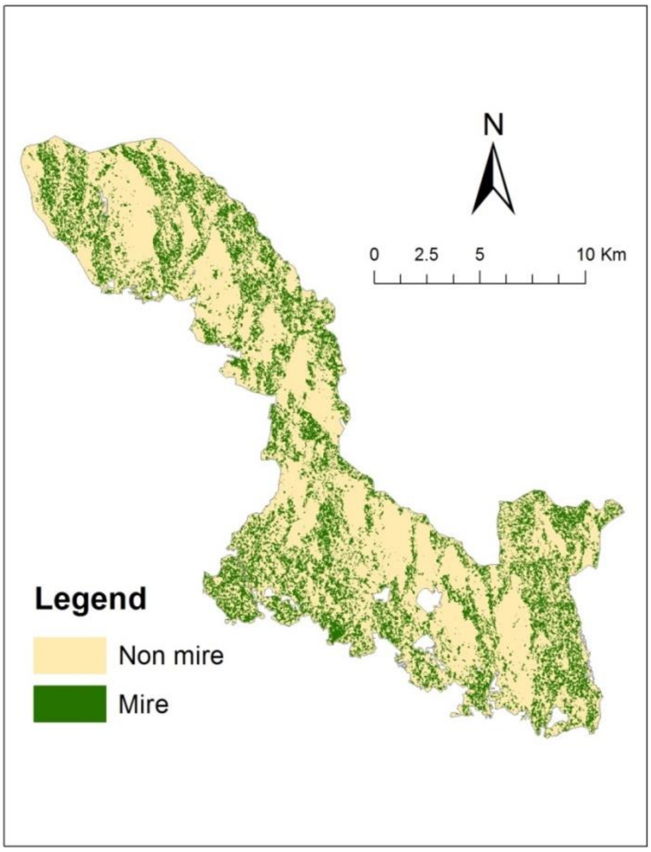

Figure 7 Classification result in the Bavarian Forest National Park using single Sentinel-1 SAR image

Figure 7 shows the classification result of mire or non-mire use the Sentinel-1 SAR image only. The classified map illustrates mire for green colour and non-mire for yellow colour. From the map, through interpretation, the mire covers almost half of the study area. It's difficult to distinguish the distribution pattern of mires. Map appears noisy throughout the whole area thus the lower accuracy can be anticipated.

3.1.1.2. Accuracy assessment

According to the confusion matrix, the overall accuracy was 62.5% and Kappa coefficient was 0.25. The result for Kappa coefficient was fair based on the model performance proposed by Landis and Koch (1977). Therefore it was difficult to discriminate mire and non-mire classes using SAR data alone.

Table 3 Error matrix of classification result in the Bavarian Forest National Park using single Sentinel-1 SAR image

Referenced data				
Classified Data	Mire	Non mire	Total	User accuracy
Mire	12	8	20	60.00%
Non mire	4	8	12	66.67%
Total	16	16	32	
Producer Accuracy	75.00%	50.00%		
				Overall Accuracy = 62.5%
				Kappa Statistics = 0.25

3.1.2. Mapping mires using Sentinel-2 Multi-spectral images

3.1.2.1. Random forest classification

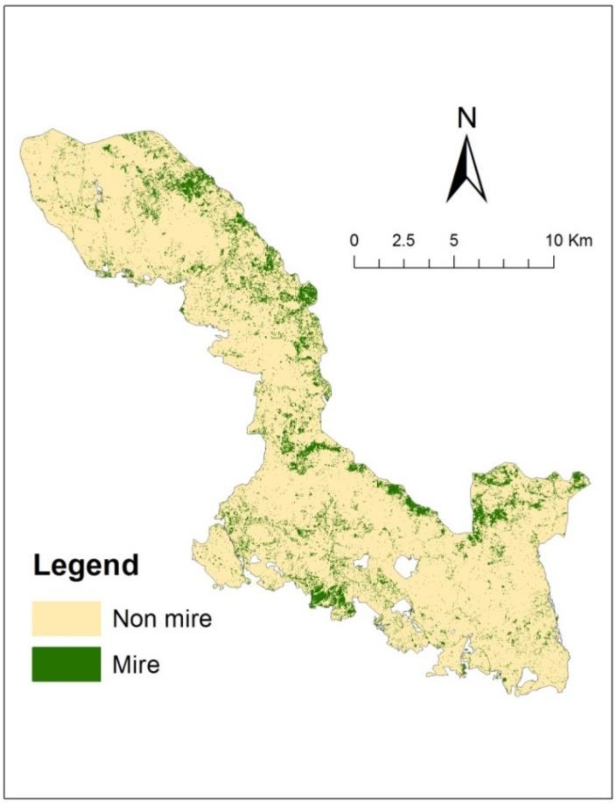

Figure 8 Classification result in the Bavarian Forest National Park using single Sentinel-2 Multi-spectral image

Figure 8 shows the classification result of mire or non-mire use the single Sentinel-2 multi-spectral image in the Bavarian Forest National Park. The yellow colour represents non-mire class while green colour represents mire class. Compared to the classified map (Figure 7) only use Sentinel-1 SAR data, the area of mires decrease a lot when use Sentinel-2 multi-spectral images only make classification. Most of the mires with large patches were distributed along the edge of the study area. Small fragments can be found in the middle of the national park.

3.1.2.2. Accuracy assessment

The confusion matrix demonstrated that the overall accuracy and Kappa coefficient was 59.38% and 0.19, respectively. The result for Kappa coefficient was slight based on the model performance proposed by Landis and Koch (1977). Therefore using Sentinel-2 image only to differential mire and non-mire is not acceptable.

Table 4 Error matrix of classification result in the Bavarian Forest National Park using single Sentinel-2 Multi-spectral image

Referenced data				
Classified Data	Mire	Non mire	Total	User accuracy
Mire	11	8	19	57.89%
Non mire	5	8	13	61.54%
Total	16	16	32	
Producer Accuracy	68.75%	50.00%		
				Overall Accuracy = 59.38%
				Kappa Statistics = 0.19

3.1.3. Mapping mires using combination of Sentinel-1 and Sentinel-2 images

3.1.3.1. Random forest classification

Using Random Forest method, classified map for mire and non-mire resulted from combination of Sentinel-1 SAR data and Sentinel-2 multi-spectral images were attained. The distribution pattern of mires in this map was similar to the classified map only using Sentinel-2 data. Influenced by speckle noise of the SAR image, this map is full of fragments.

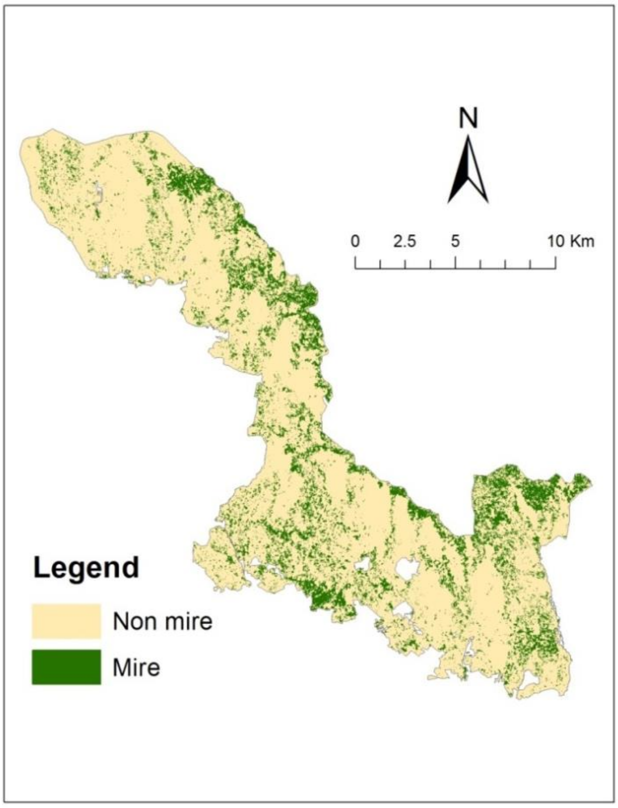

Figure 9 Classification result in the Bavarian Forest National Park using combination of Sentinel-1 SAR image and Sentinel-2 Multi-spectral image

3.1.3.2. Accuracy assessment

Based on the confusion matrix, the overall accuracy was 68.75% and Kappa coefficient was 0.38. The result for Kappa coefficient was fair according to the model performance proposed by Landis and Koch (1977). Integration of Sentinel-1 and Sentinel-2 image didn't perform very well in mire mapping.

Table 5 Error matrix of classification result in the Bavarian Forest National Park using combination of Sentinel-1 SAR image and Sentinel-2 Multi-spectral image

Referenced data				
Classified Data	Mire	Non mire	Total	User accuracy
Mire	13	7	20	65.00%
Non mire	3	9	12	75.00%
Total	16	16	32	
Producer Accuracy	81.25%	56.25%		
				Overall Accuracy = 68.75%
				Kappa Statistics = 0.38

3.1.4. Mapping mires using Sentinel-1, Sentinel 2 and topographic information

3.1.4.1. Random forest classification

Figure 10 shows the classification result of mire and non-mire classes through incorporating multi-sensor remotely sensed data (Sentinel-1 and Sentinel data) with ancillary topographic information (elevation, slope , aspect and terrain position). This classified map has better performance compared to the map generated before as we expected. The distribution area of mires were more concentrated in the southwest part and the fragments of mires have a sharply decrease. Most of the mires were distributed along the side of the rivers.

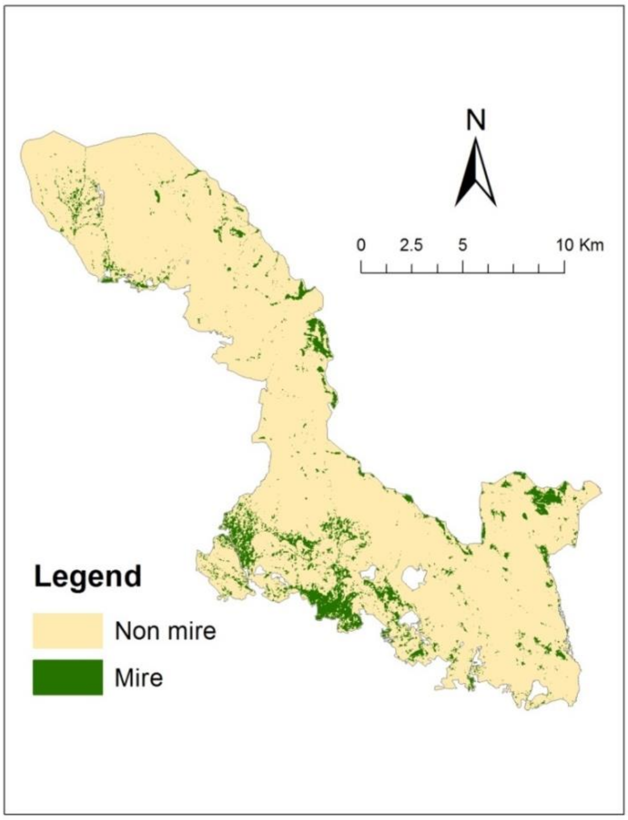

Figure 10 Classification result in the Bavarian Forest National Park using integration of Sentinel-1 SAR image, Sentinel-2 Multi-spectral image and topographic information

3.1.4.2. Accuracy assessment

The confusion matrix shows that the overall accuracy was 93.75% and Kappa coefficient was equal to 0.81. The result for Kappa coefficient was almost perfect based on the model performance proposed by Landis and Koch (1977). Therefor the mires were well mapped through incorporating Sentinel-1, sentinel-2 with adjuvant topographic information.

Table 6 Error matrix of classification result in the Bavarian Forest National Park using integration of Sentinel-1 SAR image, Sentinel-2 Multi-spectral image and topographic information

Referenced data				
Classified Data	Mire	Non mire	Total	User accuracy
Mire	15	2	17	88.24%
Non mire	1	14	15	93.33%
Total	16	16	32	
Producer Accuracy	93.75%	83.75%		

Overall Accuracy = 90.63%
Kappa Statistics = 0.81

3.1.5. Mapping mires using Sentinel-1, Sentinel -2, topographic and soil type information

3.1.5.1. Random forest classification

The classification result of mire mapping using integration of Sentinel-1, Sentinel-2 topographic and soil type information was shown in Figure 11. Obviously, this map performs better than single SAR images or optical images, or combination of SAR and optical images. Most of the mires were distributed along the rivers or valleys in low slopes. Boundary of mires class were more clearly and well defined with fragments reduced rapidly.

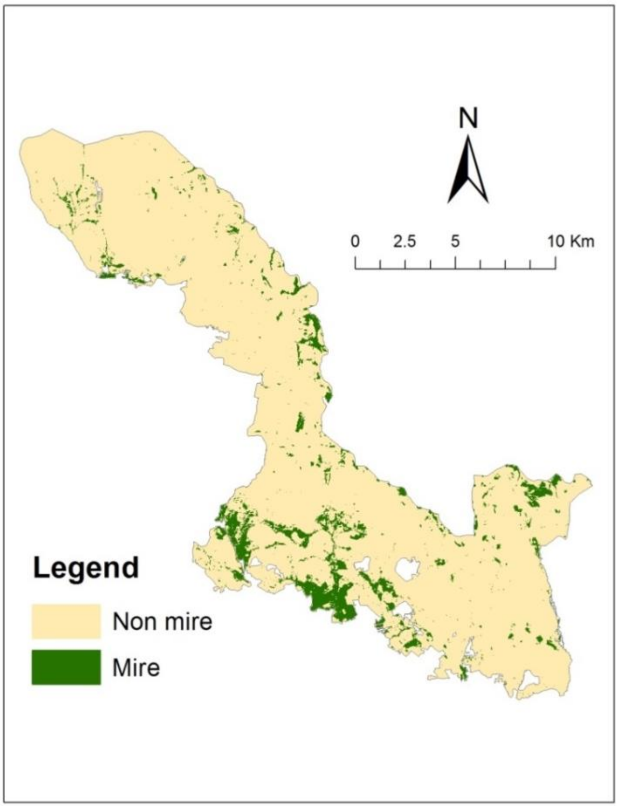

Figure 11 Classification result in the Bavarian Forest National Park using integration of Sentinel-1 SAR image, Sentinel-2 Multi-spectral, topographic data and soil type information

3.1.5.2. Accuracy assessment

The confusion matrix demonstrated that ehe overall accuracy was 93.75% and Kappa coefficient was 0.88. The result for Kappa coefficient was …based on the model performance proposed by Landis and Koch (1977), which indicates that good predictive performance could be achieved through involving topographic and soil type information.

Table 7 Error matrix of Classification result in the Bavarian Forest National Park using integration of Sentinel-1 SAR image, Sentinel-2 Multi-spectral image, topographic and soil type information

	Referenced data			
Classified Data	Mire	Non mire	Total	User accuracy
Mire	14	0	14	100.00%
Non mire	2	16	18	88.89%
Total	16	16	32	
Producer Accuracy	87.50%	100.00%		
				Overall Accuracy = 93.75%
				Kappa Statistics = 0.88

3.1.6. Accuracy comparison and Test of significance

Differences between the OOB accuracy and independent accuracy can be seen in the Figure 12 below. In general, OOB accuracies provides more pessimistic accuracy than the independent accuracies and the differences range from 4.69% to 28.12% Different combination of data sources yield various mapping accuracy. Figure 12 shows that as the OOB accuracy increase, there is an improvement in the independent classification accuracy. OOB accuracy represents an alternative of cross-validation and independent accuracy is required to valid mapping accuracy (Bricher et al., 2013). Therefore in this research, the independent overall accuracy was used to evaluate the mapping accuracy.

OOB accuracy, independent accuracy and Kappa coefficients for all classifications using RF classifier were displayed in table 8. The single SAR variables (VH, VV and texture features) didn't perform well to produce classification map (overall accuracy =62.5%, kappa=0.25). Also, use optical bands only cannot generate acceptable mire map (overall accuracy =59.38%, kappa =0.19). When combining SAR data and optical images, there is a slightly increase in the mapping accuracy (overall accuracy = 68.75%, kappa=0.38). Adding additional topographic information improves the overall accuracy sharply from 68.75% to 90.63%. The integration of Sentinel-1, Sentinel-2, topographic and soil type information can achieve the highest overall accuracy (93.75%) and Kappa coefficient (0.88).

The table 9 shows the Kappa z-test for pairwise comparison among all classifications. Overall, these three classifications resulted in similar mapping accuracy: 1) Sentinel-1 SAR images only (overall accuracy =62.5%, kappa=0.25), 2) Sentinel-2 multi-spectral image only (overall accuracy =59.38%, kappa=0.19), 3) combination of Sentinel and Sentinel-2 data (overall accuracy 68.75%, kappa=0.38). The significant improvement in the accuracy was gained by adding ancillary topographic information (z value = 4.69, $p<0.01$). The integration of Sentinel-1, Sentinel-2, topographic and soil type information can also significantly improve the mapping accuracy compared to use the combination of Seneinel-1 and Sentinel-2 data (z value = 5.62, $p<0.01$).

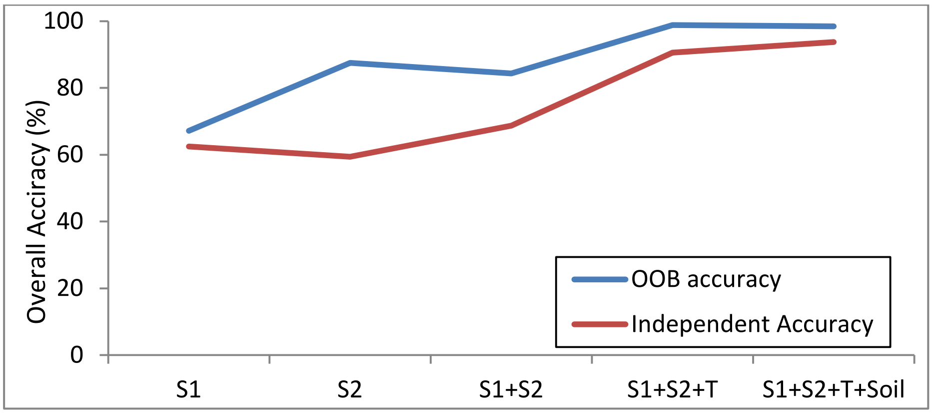

Figure 12 OOB versus independent accuracy of all classifications in the Bavarian Forest National Park

Table 8 Overall classification accuracy in the Bavarian Forest National Park

Data Sources	OOB Error	OOB accuracy	OA	Kappa
S1	32.81	67.19	62.50	0.25
S2	12.50	87.50	59.38	0.19
S1+S2	15.62	84.38	68.75	0.38
S1+S2+T	1.12	98.88	90.63	0.81
S1+S2+T+Soil	1.56	98.44	93.75	0.88

Table 9 The z-statistic comparison of selected classifications for mire mapping in the Bavarian Forest National Park. Significantly different accuracies with 95% confidence interval are indicated by *

Data Sources	S1	S2	S1+S2	S1+S2+T	S1+S2+T+Soil
S1	——				
S2		——			
S1+S2			——		
S1+S2+T	5.93*	6.49*	4.69*	——	
S1+S2+T+Soil	6.90*	7.48*	5.62*		——

3.1.7. Variables importance

The Gini index shown in the Figures below indicates the variables importance for all classifications with different combination of data sources. Only the top 10 important variables were selected to display in the figure.

It can be identified that not all of the variables performs equally in the classification result. Figure 13 illustrates that, when only use Sentinel-1 SAR data to map mires, VV is the most important variable for the result. Based on the variables importance in Figure 14, Band 4 was found to be relatively important among all multi-spectral variables. When combining the Sentinel-1 SAR data and Sentinel-2 multi-spectral images, SAR intensities and texture features were found to be more effective than optical bands. Figure 16 demonstrates the performance of the variables when adding additional topographic information in the classification. Slope provides most significant contribution to the result with value equivalent to 10.04. As can be seen, after involve soil type information into the model and run the model using all variables, the soil type information and the slope make most contribution to the classification with value equal to 9.33 and 8.24 respectively. The following important variables are optical band4 and VV mean. On the contrast, except for VV mean and VH mean, other texture variables were not shown to be very useful in the classification.

Some of the top 10 important variables were repeated occurred in in different classifications, such as VV, VV mean, VH, VH mean, Sentinel-2 band3 and Sentinel-2 band4. Among all 5 classifications, the Gini indices for the same variable were different while the order of importance was almost the same.

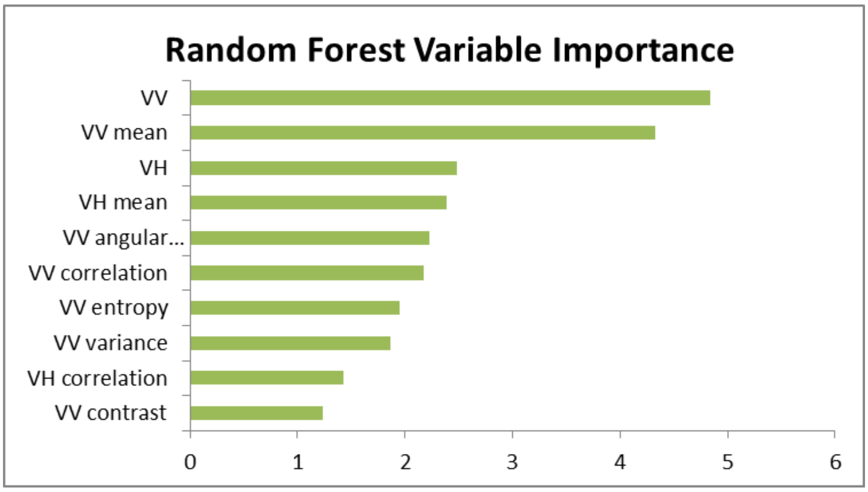

Figure 13 Variable Importance Plot of classification result using single Sentinel-1 SAR image in the Bavarian Forest National Park based on the Gini index

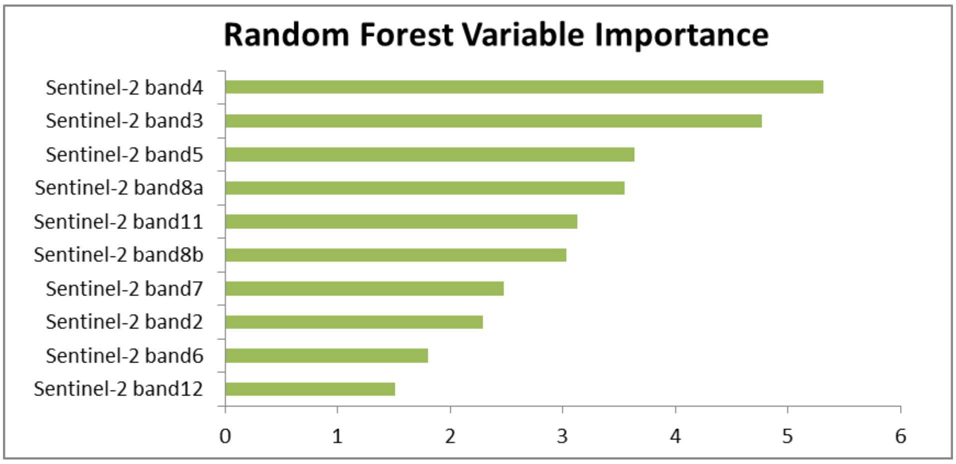

Figure 14 Variable Importance Plot of classification result using single Sentinel-2 multi-spectral image in the Bavarian Forest National Park based on the Gini index

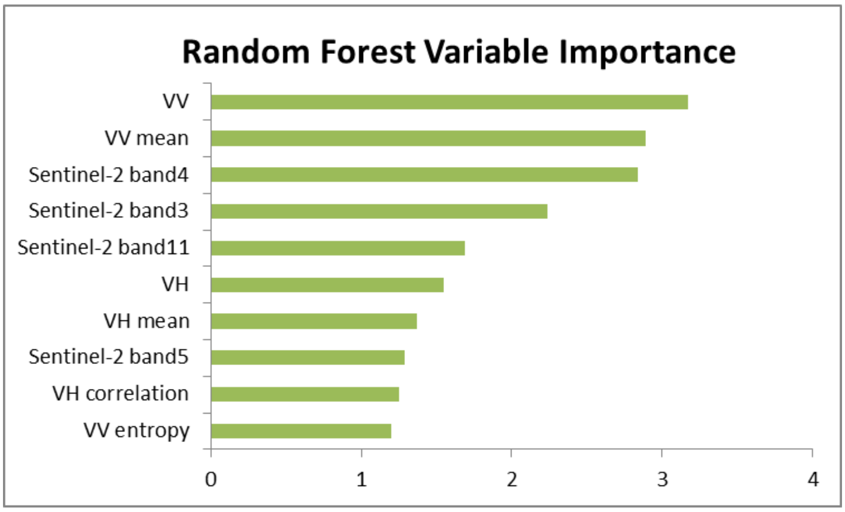

Figure 15 Variable Importance Plot of classification result using combination of Sentinel-1 SAR image and Sentinel-2 multi-spectral image in the Bavarian Forest National Park based on the Gini index

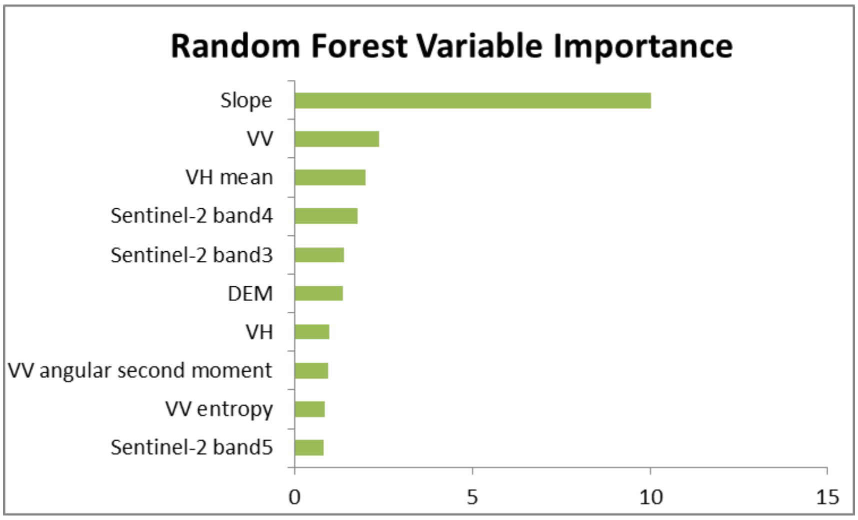

Figure 16 Variable Importance Plot of classification result using integration of Sentinel-1 SAR image, Sentinel-2 multi-spectral image and topographic information in the Bavarian Forest National Park based on the Gini index

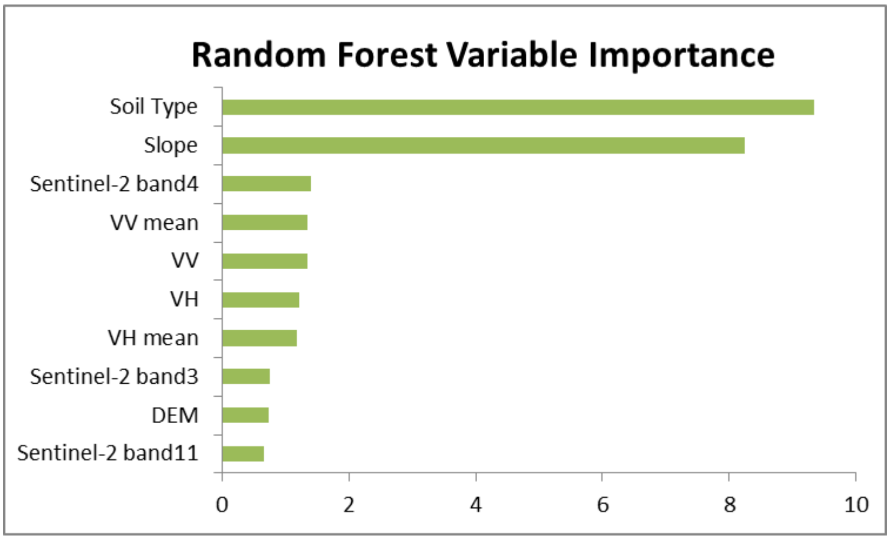

Figure 17 Variable Importance Plot of classification result using integration of Sentinel-1 SAR image, Sentinel-2 multi-spectral image, topographic data and soil type information in the Bavarian Forest National Park based on the Gini index

3.2. Šumava Forest National Park

Multi-source was applied to mapping mires in the Bavarian Forest National Park. There are totally five different combinations of the input data sources. First, use the single Sentinel-1 SAR image to map mires. The input variables include SAR VV& VH bands, and texture features. Second, use single Sentinel-2 multi-spectral image to map mires. The input variables include band2-band 8A, Band 11 and band 12. After that, use the combination of Sentinel-1 and Sentinel-2 data. Then, include ancillary topographic information (elevation, slope, aspect and terrain position) to map mires. Finally, involve soil type information into the model and make classification use all the variables.

3.2.1. Mapping mires using Sentinel-1 SAR images

3.2.1.1. Random forest classification

Figure 18 shows the result of mire mapping only use the Sentinel SAR intensives and texture features. The whole study area was covered by mires based on the classification result. Thus, it can be anticipated that the accuracy should be low since most of the areas considered to be forests.

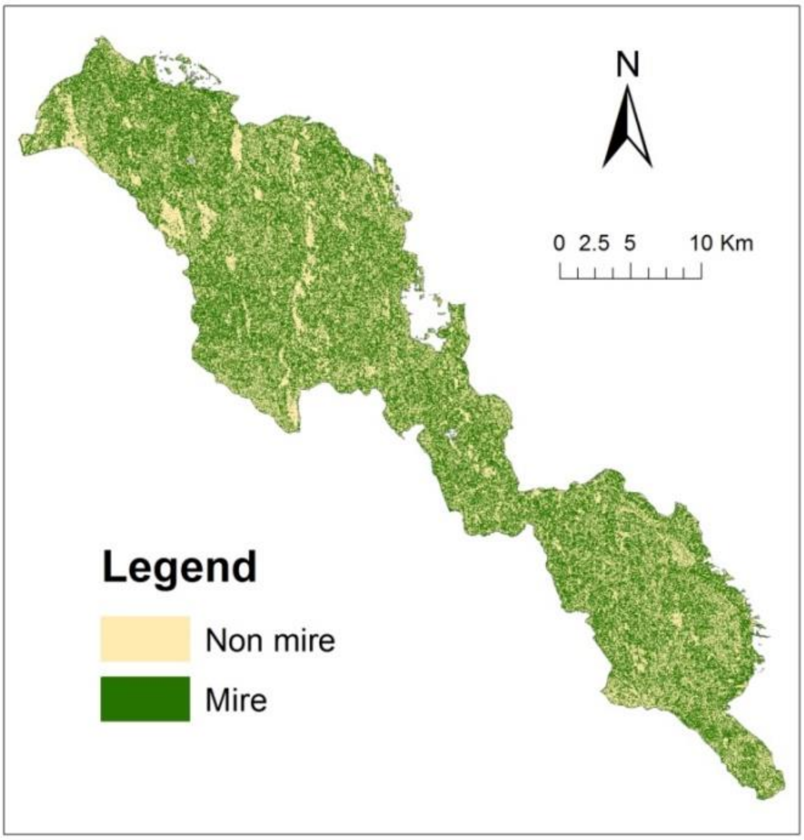

Figure 18 Classification result in the the Šumava National Park using single Sentinel-1 SAR image

3.2.1.2. Accuracy assessment

As can be seen, the overall accuracy was 50% and Kappa coefficient was equivalent to 0. The result for Kappa coefficient was slight according to the model performance proposed by Landis and Koch (1977). Thus mire cannot be well mapped use SAR intensity only. Single C-band SAR image performs poor in differential mire and non-mire area in a forest landscape.

Table 10 Error matrix of classification result in the the Šumava National Park using single Sentinel-1 SAR image

	Referenced data			
Classified Data	Mire	Non mire	Total	User accuracy
Mire	5	5	10	50.00%
Non mire	8	8	16	50.00%
Total	13	13	26	
Producer Accuracy	38.46%	61.54%		
Overall Accuracy = 50.00%				
Kappa Statistics = 0				

3.2.2. Mapping mires using Sentinel-2 Multi-spectral images

3.2.2.1. Random forest classification

Figure 19 shows the classification result of mire or non-mire use the Sentinle-2 multi-spectral image only. It can be found that almost half of the study area was covered by mires. Compared to the classified map use single SAR image, the mires distribution area reduced rapidly. Focus on the noise in the map, there still some misclassification between mire and non-mire classes.

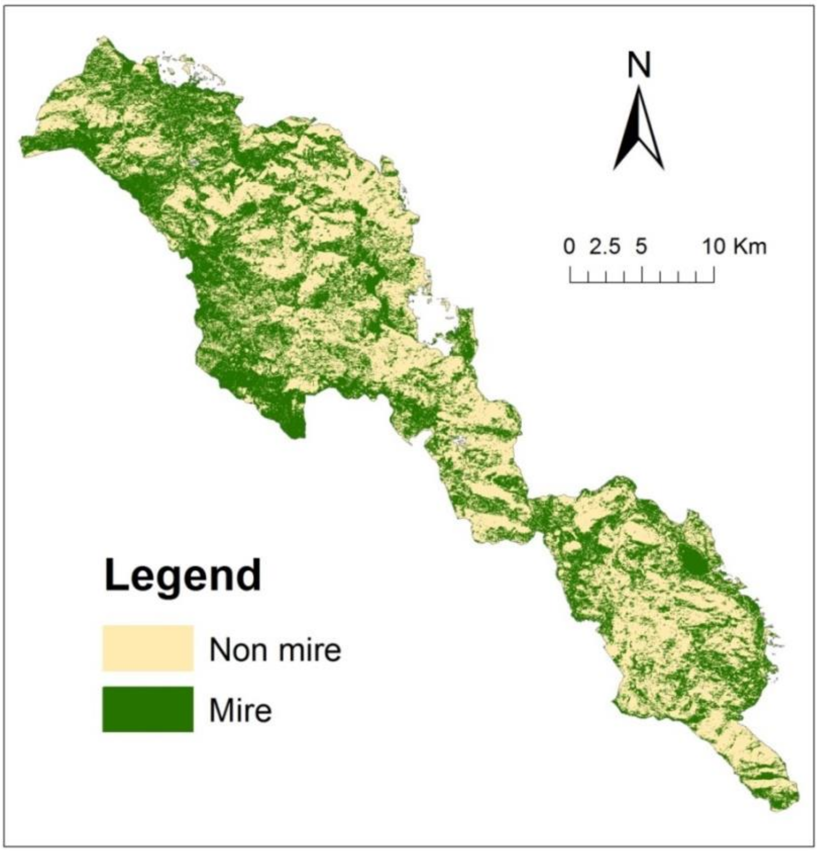

Figure 19 Classification result in the Šumava National Park using single Sentinel-2 Multi-spectral image

3.2.2.2. Accuracy assessment

According to the confusion matrix, the overall accuracy was 73.08% and Kappa coefficient was 0.46. The result for Kappa coefficient was moderate based on the model performance proposed by Landis and Koch (1977). The user accuracy for mire was 87.5% while for non-mire was only 66.76%. It means that more non-mire area was misclassified to mire area. Thus the mire area was over estimated. Use single Sentinel-2 optical image cannot map mire properly.

Table 11 Error matrix of classification result in the Šumava National Park using single Sentinel-2 Multi-spectral image

	Referenced data			
Classified Data	Mire	Non mire	Total	User accuracy
Mire	7	1	8	87.50%
Non mire	6	12	18	66.67%
Total	13	13	26	
Producer Accuracy	53.85%	93.21%		
Overall Accuracy = 73.08%				
Kappa Statistics = 0.46				

3.2.3. Mapping mires using combination of Sentinel-1 and Sentinel-2 images

3.2.3.1. Random forest classification

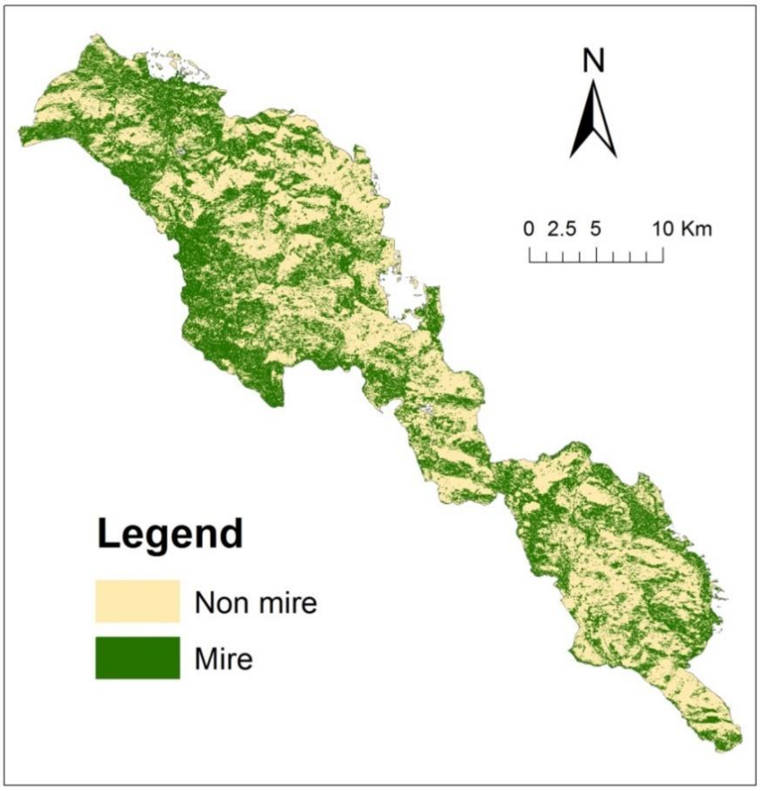

Figure 20 Classification result in the Šumava National Park using combination of Sentinel-1 SAR image and Sentinel-2 Multi-spectral image

Figure 20 shows the classification result of mire or non-mire use the combination of Sentinel-1 SAR and Sentinel-2 multi-spectral image. The classified map with similar to the mire map use optical image only. Mire spread through the whole study area and concentrated in the northwest part.

3.2.3.2. Accuracy assessment

The confusion matrix shows that the overall accuracy was 57.69% and Kappa coefficient was 0.15. The result for Kappa coefficient was slight according to the model performance proposed by Landis and Koch (1977). Thus incorporating SAR data with multi-spectral image cannot map mires properly.

Table 12 Error matrix of classification result in the Šumava National Park using combination of Sentinel-1 SAR image and Sentinel-2 Multi-spectral image

	Referenced data			
Classified Data	Mire	Non mire	Total	User accuracy
Mire	6	4	10	60.00%
Non mire	7	9	16	56.25%
Total	13	13	26	
Producer Accuracy	46.15%	69.23%		
Overall Accuracy = 57.69%				
Kappa Statistics = 0.15				

3.2.4. Mapping mires using Sentinel-1, Sentinel 2 and topographic information

3.2.4.1. Random forest classification

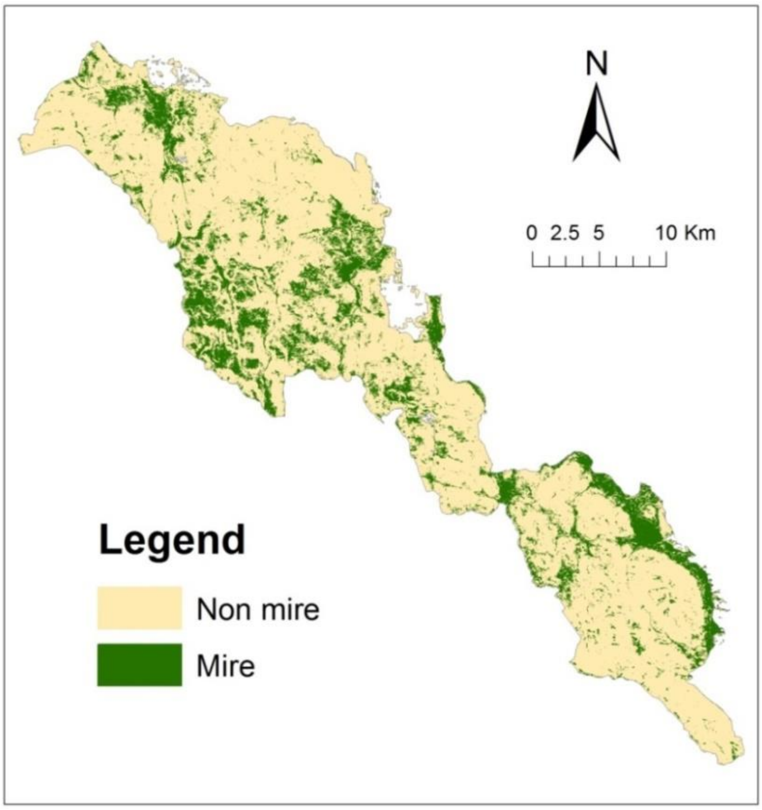

Figure 21 Classification result in the Šumava National Park using integration of Sentinel-1 SAR image, Sentinel-2 Multi-spectral image and topographic information

Figure 21 shows the classification result of mire or non-mire when adding topographic information. The area of mires decreased a lot compared with the map without topographic information. The mires were more concentrated and distributed along rivers, lakes and valleys. Boundaries of mire became more clearly while fragmentations still exist in the northeast part and the south part.

3.2.4.2. Accuracy assessment

According to the confusion matrix, the overall accuracy was 88.46% and Kappa coefficient was 0.77. The result for Kappa coefficient was substantial based on the model performance proposed by Landis and Koch (1977) which indicates a good performance in the classification. Incorporating topographic information with SAR data and optical images thus provide a proper way to map mires.

Table 13 Error matrix of classification result in the Šumava National Park using integration of Sentinel-1 SAR image, Sentinel-2 Multi-spectral image and topographic information

	Referenced data			
Classified Data	Mire	Non mire	Total	User accuracy
Mire	12	2	14	85.71%
Non mire	1	11	12	91.67%
Total	13	13	26	
Producer Accuracy	92.31%	84.62%		
Overall Accuracy = 88.46%				
Kappa Statistics = 0.77				

3.2.5. Mapping mires using Sentinel-1, Sentinel -2, topographic and soil type information

3.2.5.1. Random forest classification

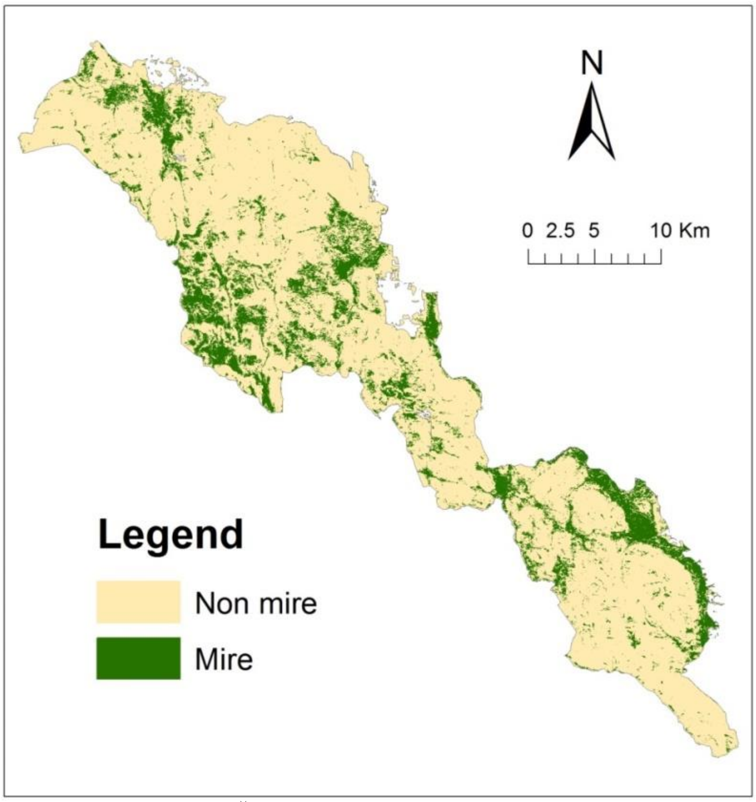

Figure 22 Classification result in the Šumava National Park using integration of Sentinel-1 SAR image, Sentinel-2 Multi-spectral image, topographic and soil type information

Figure 22 shows the classification result of mire or non-mire use the integration of Sentinel-1, Sentinel-2, topographic and soil type information. From the map, the distribution pattern of mires can be distinguished. Mires were concentrated beside the river or along the valleys with low slopes. The boundary between mire and non-mire appears more explicitly thus relatively higher mapping accuracy can be anticipated.

3.2.5.2. Accuracy assessment

The confusion matrix displays that the overall accuracy was 92.31 and Kappa coefficient was 0.85. The result for Kappa coefficient was almost perfect based on the model performance proposed by Landis and Koch (1977). The mires were well mapped through f Sentinel-1, Sentinel-2, topographic and soil type information.

Table 14 Error matrix of classification result in the Šumava National Park using integration of Sentinel-1 SAR image, Sentinel-2 Multi-spectral image, topographic and soil type information

	Referenced data			
Classified Data	Mire	Non mire	Total	User accuracy
Mire	12	1	13	92.31%
Non mire	1	12	13	92.31%
Total	13	13	26	
Producer Accuracy	92.31%	92.31%		
Overall Accuracy = 92.31%				
Kappa Statistics = 0.85				

3.2.6. Accuracy comparison and Test of significance

Differences between the OOB accuracy and independent accuracy can be seen in the Figure 23 below. The OOB and the independent accuracies are almost the same. The improvement of the OOB accuracy can also lead to the increase of the overall accuracy. Various mapping accuracy can be found using different combination of data sources. In this research, overall accuracy and Kappa coefficients was used to evaluate the mapping accuracy.

Table 15 shows the OOB accuracy, independent accuracy and Kappa coefficients for all classifications using RF classifier. Using the SAR images only cannot generate available mire maps (overall accuracy =50%, kappa=0). The same situation occurs when use optical bands alone to produce mire map (overall accuracy =73.08%, kappa=0.46). The combination of SAR data and optical images even reduce the overall accuracy from 73.08%.to 57.69%. High overall accuracy can be achieved by adding additional topographic information or use the integration of Sentinel-1, Sentinel-2, topographic and soil type information. The overall accuracy of these two classifications reaches to 88.46% and 92.31%, respectively.

From the pairwise Kappa z-test showing in the Table 16, it can be found that single Sentinel-2 mapping accuracy is significantly higher than the single SAR data mapping accuracy at a 95% confidence level. The combination of Sentinel-1 and Sentinel-2 image cannot improve the mapping accuracy compared to single Sentinel-2 optical image classification, while its performance in mapping is significantly higher than single SAR classification(z=2.52). Adding ancillary topographic information can achieve significant improvement in the mapping accuracy compared to use single Sentinel-1 or Sentinel-2 image or the combination of Sentinel-1 and Sentinel-2 image. When additional soil type information was involved, there is no significance difference. The integration of Sentinel-1, Sentinel-2, topographic and soil type information can significantly improve the mapping accuracy compared to use single SAR or optical image or the combination of Seneinel-1 and Sentinel-2 data and obtained the highest accuracy (overall accuracy =92.31%, kappa=0.85).

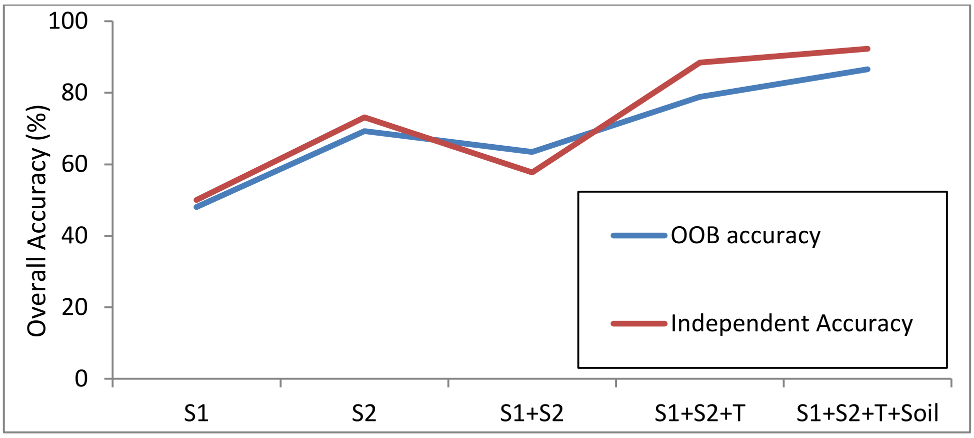

Figure 23 OOB versus independent accuracy of all classifications in the Šumava National Park

Table 15 Overall classification accuracy in the Šumava National Park

Data Sources	S1	S2	S1+S2	S1+S2+T	S1+S2+T+Soil
S1	——				
S2	3.81*	——			
S1+S2	2.52*		——		
S1+S2+T	7.10*	2.99*	5.62*	——	
S1+S2+T+Soil	8.21*	3.96*	6.65*		——

Table 16 The z-statistic comparison of selected classifications for mire mapping in the Bavarian Forest National Park. Significantly different accuracies with 95% confidence interval are indicated by *

Data Sources	OOB Error	OOB accuracy	OA	Kappa
S1	51.92	48.08	50.00	0.00
S2	30.77	69.23	73.08	0.46
S1+S2	36.54	63.46	57.69	0.15
S1+S2+T	21.15	78.85	88.46	0.77
S1+S2+T+Soil	13.46	86.54	92.31	0.85

3.2.7. Random forest importance

Based on the Gini index shown in the figures below, the variables importance in classification result can be illustrated.

Figure 24 displays that VV is the most important variable for the result when applying RF classification only use Sentinel-1 SAR data. As it can be seen in figure 25, band 12 was found to be more important than other optical bands. Figure 26 demonstrates the performance of the variables when combining

Sentinel-1 SAR data and Sentinel-2 multi-spectral in the classification and band 12 provides most significant contribution to the classification. Optical bands outperform VV and texture features in general. The combination of the Sentinel-1 SAR data , Sentinel-2 multi-spectral images and topographic information demonstrate that topographic information were more effective in mire mapping compared to SAR data or multi-spectral images. Slope is the most important variable in the topographic information. Elevation also has relatively high contribution to the classification result. When adding ancillary soil type, the order of the importance remains the sane and the slope was again found to be most useful in the classification. Soil type information was the following second important variable. SAR bands and texture features yield poor performance in all classifications. Overall, slope, soil type information, elevation and some optical bands were of vital importance to discriminate mire and non-mire in a forest landscape while SAR data didn't show good performance.

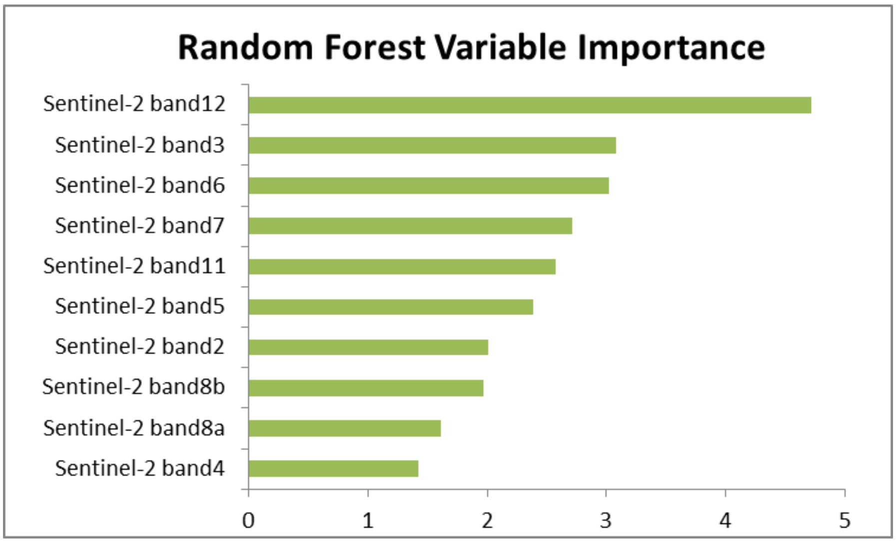

Figure 24 Variable Importance Plot of classification result using single Sentinel-1 SAR image in the Šumava National Park based on the Gini index

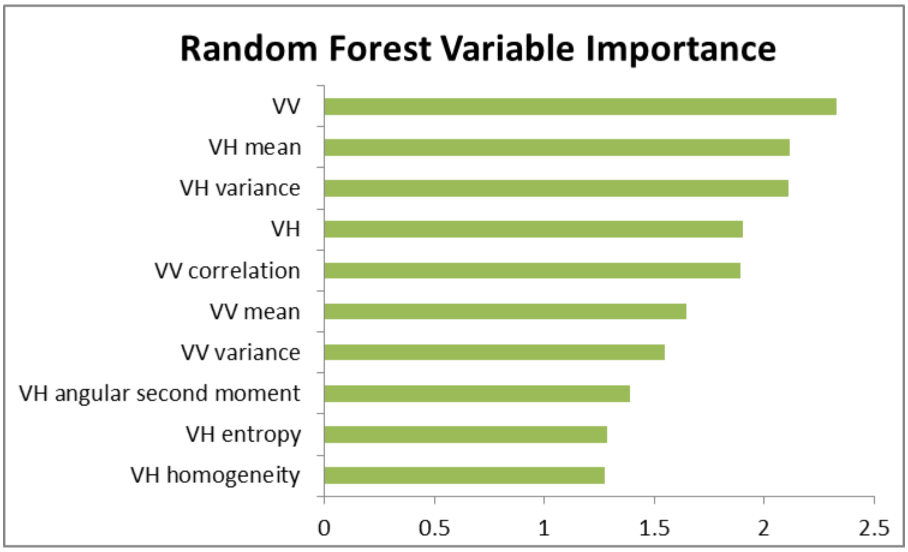

Figure 25 Variable Importance Plot of classification result using single Sentinel-2 multi-spectral image in the Šumava National Park based on the Gini index

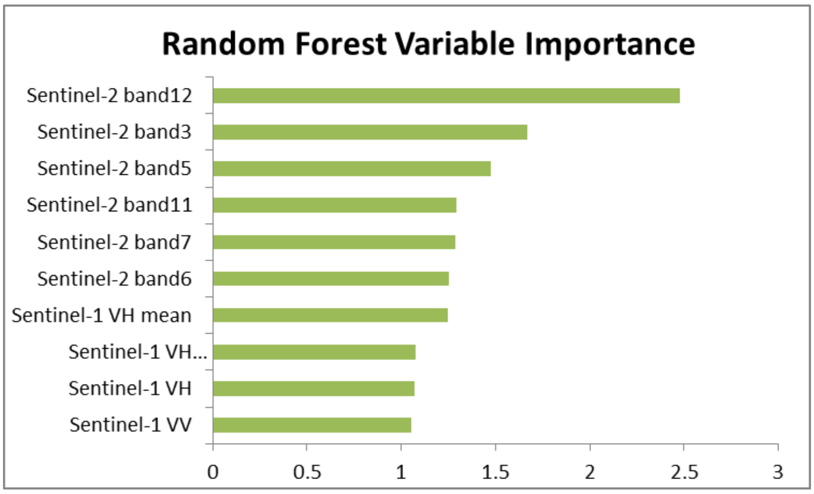

Figure 26 Variable Importance Plot of classification result using combination of Sentinel-1 SAR image and Sentinel-2 multi-spectral image in the Šumava National Park based on the Gini index

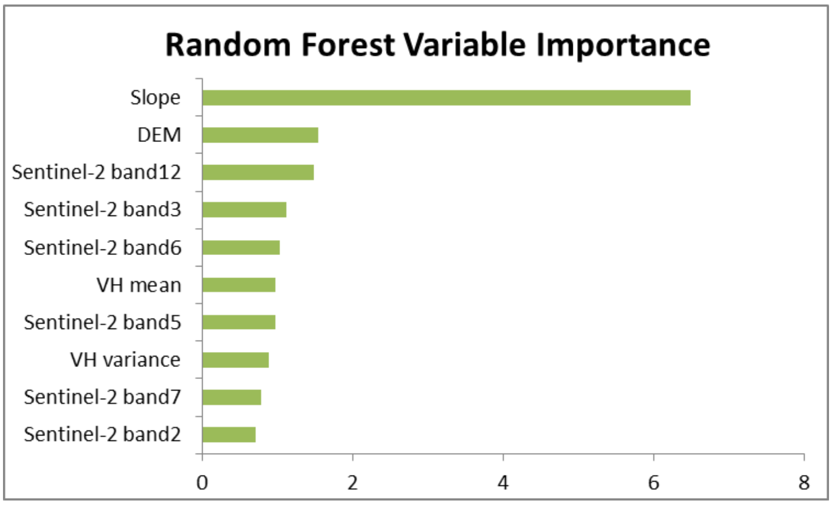

Figure 27 Variable Importance Plot of classification result using integration of Sentinel-1 SAR image, Sentinel-2 multi-spectral image and topographic information in the Šumava National Park based on the Gini index

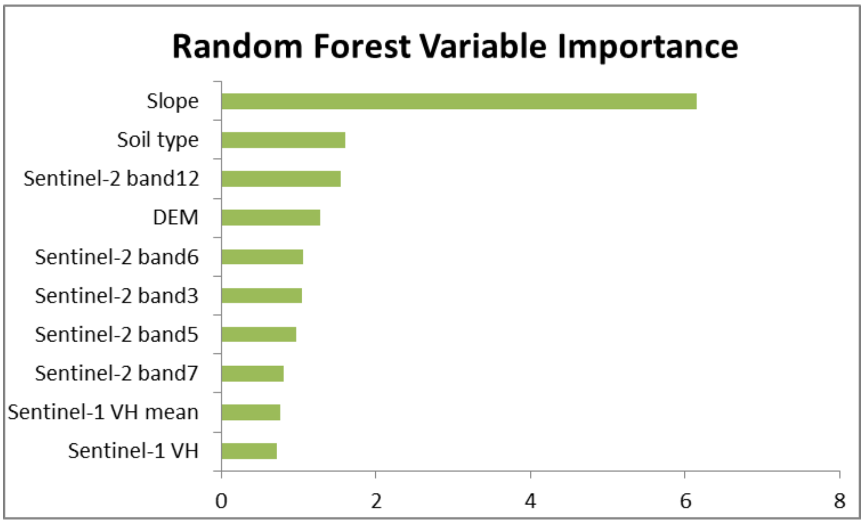

Figure 28 Variable Importance Plot of classification result using integration of Sentinel-1 SAR image, Sentinel-2 multi-spectral image, topographic data and soil type information in the Šumava National Park based on the Gini index

4. DISCUSSION

4.1. Mapping mires using Sentinel-1 SAR data and Sentinel-2 multi-spectral images

Due to the fact that C-band VV polarization can be used to monitoring forested wetlands only during leaf-off seasons but not for entire year (Lang & Kasischke, 2008). The Sentinel-1 SAR data used in this research were obtained under leaf-off conditions. To make the mapping result between SAR data and optical images more comparable, the optical image was also collected during leaf-off seasons in the same year. Since the ground truth data in the Bavarian Forest National Park were collected in the field thus more reliable than that in the Šumava National Park which was selected based on interpretation, the result was discussed in two parts in terms of the two parks.

This study supposed to take advantage of both SAR data and optical images, while the mapping results were not as good as we expected. In the Bavarian Forest National Park, The mire cannot be perfectly mapped use either single SAR or optical image, or combination of SAR data and optical image with their overall accuracy was 68.75%, 59.38% and 62.50%, respectively. Also, from the result Kappa z-test, it can be found that there is no significantly difference among the mapping accuracy resulted from either single SAR or optical images or integration of SAR and optical images. The reason may be as follows. The Sentinel-1 SAR data is C band radar which cannot penetrate the forest canopy thus only reflect the backscattering coefficients on the top of the forest layer (Balzter et.al, 2015). Although in some research, it has been proved that during leaf-off seasons, C band have the ability to detect wetlands in a forest landscape (Lang & Kasischke, 2008). The speckle noise which is a particular effect holds by radar could still reduce the ability to differential mire and non-mire classes. It was caused by the interference of multiple scatters reflecting from the surface within a resolution cell. To reduce the speckle-related uncertainty and increase the mapping efficiency, speckle filter has been applied (Balzter et al., 2015; Inglada et al., 2016; Ou et al., 2016; Paloscia et al., 2013). But the speckles still exist after trying several filter methods. It brought great variance to the training samples. In addition, although the C band SAR data have been proved to be highly suitable to detect mires (J. Li & Chen, 2005), the backscatter values of mires in forest landscape and forest vegetation may overlap each other thus make it difficult to discriminate the two classes. Consequently, salt and pepper noise appear in the classified map and the mapping accuracy is relatively low (overall accuracy=62.5%, kappa=0.25).

When only use optical image as the input to mapping mires, the spectral characteristics between forest vegetation and mires in forest landscape were almost the same, therefore many mire pixels were misclassified as non-mires. What's more, per-pixel method was widely used in the mire classification according to its ability of dealing with multi-source data. But it could still difficult for pixel based method to figure out the within-class variability in optical image and speckle noise in SAR data(Na et al., 2015). It can be imagine that the combination of SAR data and optical images performs poor in the mire classification.

As can be seen, in the Šumava Forest National Park, the Kappa z-test for mapping accuracy of SAR data and optical images was a bit difference compared to the result in the Bavarian Forest National Park. The mapping accuracy using single Sentinel-2 multi-spectral image is significantly higher than using single Sentinel-1 SAR data in the Šumava Forest National Park While in the Bavarian, it has been proved that there is no significant difference between the two images. It was mainly caused by the quality of ground truth data. The ground truth data in the Bavarian Forest National Park was obtained in the field while in Š umava, it was based on visual interpretation in high resolution Ariel photograph, error may exists during the interpretation process. What's more, the Šumava National Park covers a larger area and contains more mire. But the sample size was only 36 fore mires and 36 for non-mire class. Some research indicated that the training sample size would influence the mapping accuracy. After testing the influence of various training sample size in peatland mapping, Millard & Richardson (2015) concluded that significant improvement of mapping accuracy can be observed through the increasing of training samples size. A smaller training sample size would lead to underestimated OOB accuracy as well as independent overall accuracy (Millard & Richardson, 2015). Based on the analysis above, the mapping accuracy could also be influenced.

4.2. Mapping mires adding ancillary topographic information

The mires cannot be distinguished through the use of Sentinel-1 SAR data and Sentinel-2 multi-spectral images. Slope is of crucial importance to enhance the detectability of topographic information in the mire forming process, since majority of mires was grown in the area where slope < 8° (Lang et.al, 2008). The reason behind this was that the formation of mires requires a relatively high water table (Corcoran et al., 2011). The slope of the landscape had an impact on the flow rate of water which indirectly influences the accumulation of water in the soil (Corcoran et al., 2011). What's more, the peat accumulation on mineral soil and mire expansion were also affected by the slope (McRae et.al, 2008). The increase of the slope would lead to less peat accumulation (Aitkenhead, 2016). Consequently, the slope was related to the development of mires thus make great contribution to identifying mires. The result in this study showed that when topographic features (elevation, slope, aspect and terrain position) was considered into the model, the accuracy was significantly improved with overall accuracy increased to 90.63% and Kappa increased to 0.81 in the Bavarian Forest National Park, overall accuracy increased to 88.46% and Kappa increased to 0.77 in the Šumava National Park. Thus the integration of SAR, optical and topographic information could be an ideal tool to map mires even in a forest landscape where mire is hard to detect through remote sensing techniques only.

4.3. Mapping mires when adding soil type information

After adding soil type information, the highest classification accuracy was achieved both in the Bvarian Forest National Park and the Šumava National Park. The formation of mires requires high organic matters as well as high water table in the soil (Aitkenhead, 2016; Campos, Silva, & Vidal-Torrado, 2012). The Histosol contains more organic matter and has high water holding capacity (Campos et al., 2012). Thus there is a more possibility for mire to develop in this soil type. While for the sandy soil, a lack of organic matter and water content makes it difficult for the grown of mire (Aitkenhead, 2016).

Most of the speckles in the Bavrian Forest National Park were eliminated after including the soil type information. In the Šumava National park, some fragments and speckles still existed in the classified map. And misclassification still existed between mire and non-mire classes. This could be overcome through considering object-based method. Compared to pixel oriented classification method, object-based classification (OBM) was more labor and money consuming (Na et al., 2015). But the main advantage of OBM is that it could group the pixels with spatially homogeneous values into segments, thus the segments can be assigned to classes according to spectral, texture and contextual features (Dengsheng Lua et.al, 2012). In this way, the speckle noise could be reduced thus a higher accuracy can be achieved.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conculusions

The specific conclusions as answers to the research questions are showing as follows.

Question1: What are the differences in mire mapping accuracies between the use of Sentinel-1 SAR data and Sentinel-2 multi-spectral images?

- The mapping accuracies of Sentinel-1 SAR data (overall accuracy 62.50%, kappa 0.25) and Sentinel-2 multi-spectral images data (overall accuracy 59.38%, kappa 0.19) in the Bavarian Forest National Parks are relatively low. There are no significantly differences between the two data to map mires in the Bavarian Forest National Park. The mapping accuracy of Sentinel-2 (overall accuracy 50%, kappa 0) is significantly higher than the Sentinel-1 SAR data (overall accuracy 73.09%, kappa 0.46) in the Šumava National Park. Using single SAR or optical images was not able to discriminate mire and non-mire classes in a forest landscape.

Question2: Does the combination of Sentinel-1 SAR data and Sentinel-2 multi-spectral images significantly improve the mire mapping accuracy?

- There is no significant improvement in the mapping accuracy in the Bavarian Forest National Park. The overall accuracy was 68.75% and the Kappa statistics was 0.38. The mapping accuracy using combination of Sentinel-1 and Sentinel-2 image was significantly higher than use single Sentinel-1 SAR image, while was similar to use Sentinel-2 multi-spectral image only in the Šumava National Park. The overall accuracy was 57.69% and the Kappa coefficient was 0.15. Using combination of Sentinel-1 and Sentinel-2 image was not able to differential mire and non-mire classes in a forest landscape.

Question3: Does adding topographic or soil type information significantly improve the mire mapping accuracy?

- Adding ancillary topographic and soil type information can significantly improve the mapping accuracy both in the Bavarian Forest National Park and the Šumava National Park. Thus the pixel-based RF classification using integration of Sentinel-1 SAR data, Sentinle-2 multi-spectral images, topographic information and soil type information improved the mapping accuracy of mires and provide a feasible approach to differentiate mire from other land cover types in a forest landscape.

Question4: What are the most important variables which contributed most to the accuracy of mire mapping?

- Comparing the variable importance based on the Gini inedx, it can be concluded that the most important variables for mire mapping in a forest landscape were soil type information and slope.

5.2. Recommendations

In this research, limited number of training and validation data for mire and non-mire classes was obtained in the Bavarian Forest National Park and the Šumava National Park, which cause more uncertainty in the classification result. The size of training samples would influence the mapping accuracy. An increase of the training samples could help to improve mapping accuracy. For further research, the field work should be organized in advance and more time should be set for field to acquire enough observations of mire and non-mire classes.

Using Sentinel-1 and Sentuinel-2 data only was not able to differential mire and non-mire classes. After including the topographic and soil type information, the mire was well mapped. For further analyse, topographic and soil type information should be considered to be important input layers. It is also suggested to use object-based classification method in further research to reduce the fragmentations in the classification result.

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