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# Identification of wet areas in forest using remote sensing data

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**Abstract.** Aim of this study is to evaluate different remote sensing indices to detect spatial distribution of wet soils using GIS based algorithms. Area of this study represents different soil types on various quaternary deposits as well as different forest types. We analyzed 25 sites with the area of 1 $km^2$ each in central and western part of Latvia. Data about soil characteristics like thickness of peat layer and presence of reductimorphic colors in soil was collected during field surveys in 228 random points within study sites. ANOVA test for comparing means of different soil wetness classes and binary logistic regression analysis for evaluating the accuracy of different remote sensing indices to model spatial distribution of wet areas are used for analysis. Main conclusion of this study is that for different quaternary deposits and soil texture classes different algorithms for soil wetness prediction should be used. Data layers for predicting soil wetness in this study are various modifications and resolutions of digital elevation model like depressions, slope and SAGA wetness index as well as Sentinel-2 multispectral satellite imagery. Accuracy of soil wetness classification of soils on moraine, fluvial and eolian sediments exceeds 94%, whereas on the clayey sediments it is close to 80%.

**Key words:** DEM, satellite imagery, quaternary deposits.

## INTRODUCTION

Surface topography and potential energy of gravity of the Earth are main aspects that determines water flow direction and accumulation (Zinko et al., 2005). Infiltration rate on different soil types and underlying sediments may vary because of different hydraulic parameters and therefore surface water and groundwater may infiltrate or accumulate in depressions (Wang et al., 2015). Poorly drained and wet soils are important for biodiversity, water exchange, chemical and other processes, but may be a challenge in forestry, agriculture and similar fields (Detenbeck et al., 1999; McNabb et al., 2001).

Soil disturbance, like rutting and soil compaction is a consequence of timber harvesting operations, but its impact is variable and can be reduced through improved planning of forest management operations (Ares et al., 2005). The level of soil damage resulting from forestry operations depends on factors like machine-applied pressure, soil texture, soil organic matter and water content (Ampoorter et al., 2010). Degraded soil leads to reduced soil bearing capacity, release of sediments and pollutants to surface water, damages aesthetics, unsafe working conditions and increasingly negative public opinion (Campbell et al., 2013). Soil wetness maps can be combined with other data, such as soil type or soil bearing capacity, in order to contribute to decision making tools in forest operation planning (Mohtashami et al., 2017), therefore associated environmental and financial costs can be limited (Christensen et al., 1996).

Large scale LiDAR (*Light Detecting and* Ranging) surveys have provided scientists with precise topographical data which can be used in soil moisture predicting. Various topographical indices can be used in order to predict spatial distribution of wet soils such as topographical wetness index (TWI) and depth to water (DTW) mapping (Ågren et al., 2014). Topographical information in wet areas can be combined with multispectral satellite imagery, because distribution of plant species and timing and progression of plant development may provide information about plants and their environment like soil moisture, soil temperature, illumination and other aspects (Reed et al., 1994).

The focus of the article is to evaluate different remote sensing indices in modeling of spatial distribution of wet soils. The indices evaluated in the article are based on local depression detecting, slope analysis, Saga wetness index analysis and Sentinel-2 multispectral imagery analysis (Böhner et al., 2002; Wang & Liu, 2006).

## MATERIALS AND METHODS

### Study area

Study area consists of 25 objects, which are made to represent various forest types on dry mineral soils and drained mineral soils (Fig. 1) and different quaternary sediment types (moraine, clayey, fluvial and eolian sediments). The size of each site is 1 x 1 km$^2$ and consists from up to 10 randomly generated point sample plots. Because of relatively large area of each study object, various forest types can be represented in each of them. In total 228 sample plots was generated and surveyed during field measurements to collect data which is relevant for study but can't be measured by remote sensing methods. Collected data consists of soil texture for depth up to 1 m, depth of peat layer and depth, thickness and severity of reductimorphic horizon.

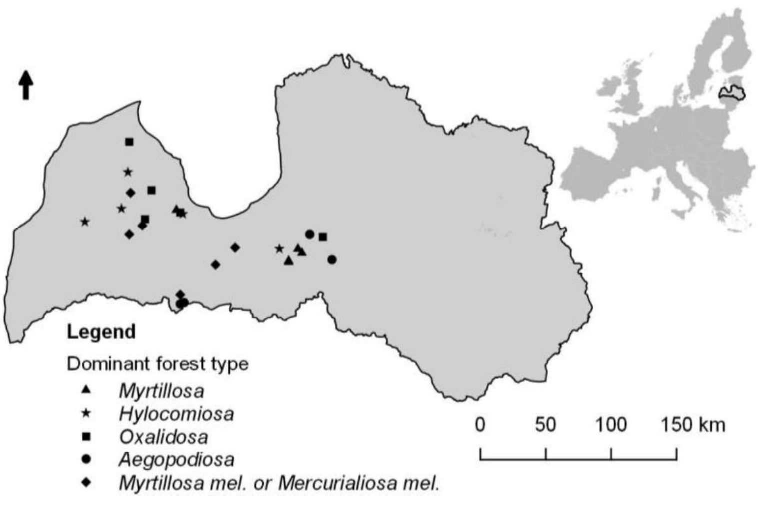


**Figure 1.** Study area.

**Remote sensing data**

Remote sensing data for this study is obtained from Latvian Geospatial Information Agency (LiDAR) and European Space Agency (Multispectral satellite imagery). Since 2013, Latvian Geospatial Information Agency is gathering high resolution elevation and vegetation cover scans using LiDAR technology for all of Latvia with a point density of at least 1.5 points per $m^2$, an average horizontal point error of 0.36 m and vertical accuracy of 0.12 m.

Bare ground digital elevation models (DEM) for all 25 study sites were created. The area of each DEM is 9 $km^2$ (3 x 3 km) and contains study site together with 8 neighboring 1 $km^2$ cells. Neighboring cells are added for hydrological runoff modeling for central cell. DEM's are created in various resolutions e.g. 1, 2 and 5 m. This was done in Global Mapper v.15 software through triangulated irregular network (TIN). Resulting DEM's are hydrographically corrected by automatically branching road artifacts at stream crossings. All further DEM processing was carried out with Grass GIS 7.2 and QGIS 2.18.15 modeling tools. DEM's were used to derive fallowing raster datasets in various resolutions: depressions, slope and Saga wetness index. Depressions raster map is generated by extracting original DEM from filled DEM, slope and Saga wetness index raster maps are generate by using designated GIS tools.

Satellite imagery is used to obtain data about forest canopy light reflection spectrum within the study objects. There is significant difference between coniferous and deciduous trees in near infrared spectrum, so red and near infrared spectral bands with 10 m resolution are used in this study. Normalized Difference Vegetation Index (NDVI) is calculated mathematically,

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)} \quad (1)$$

where NIR – near infrared spectral band; VIS – visible red spectral band.

**Field measurements**

Soil wetness was determined and divided into four classes during field surveys according to soil properties and water regime in sample plots. The criteria of separating various wetness classes are occurrence and depth of peat layer and occurrence and intensity of reductimorphic colors in upper soil horizons (0–1 m). The division of soil wetness is as follows:

1 – dry mineral soil with no peat layer and upper soil layer is having no reductimorphic colors; 2 – No peat and upper soil layer is having < 20% of reductimorphic colors; 3 – peat layer is < 30 cm thick and upper soil layer is having 20–50% reductimorphic color; 4 – Peat layer is thicker than 30 cm and/or reductimorphic color is dominant in upper soil layer.

Soil samples from diagnostic horizons were analyzed by feel (Brady & Weil, 2002) and as Vos et al. (2016) points out, it is sufficient to estimate soil particle size distribution using this method instead of conducting expensive and time-consuming laboratory analysis. Soil texture was used to determine sediment type. Soil texture is important parameter which determines the drainage level of soil and rate of infiltration into soil and can be used to better understand distribution of soil wetness. Field works were carried out from July till October and synchronization with satellite imagery were not carried out.

**Data analysis**

To combine field data with information from raster layers, previously generated random point layer was converted to polygon layer with radius of 10 m. QGIS tool *Raster statistics for polygons* was used to add mean values of remote sensing indices to newly generated polygon layer.

Example of data sampling is shown in Fig. 2. Study plots that represent wet soils are shown as points and dry soils as triangles. There is visible trend that wet soils tends to be in depressions, in areas with low slope gradient and in areas with high Saga wetness index.

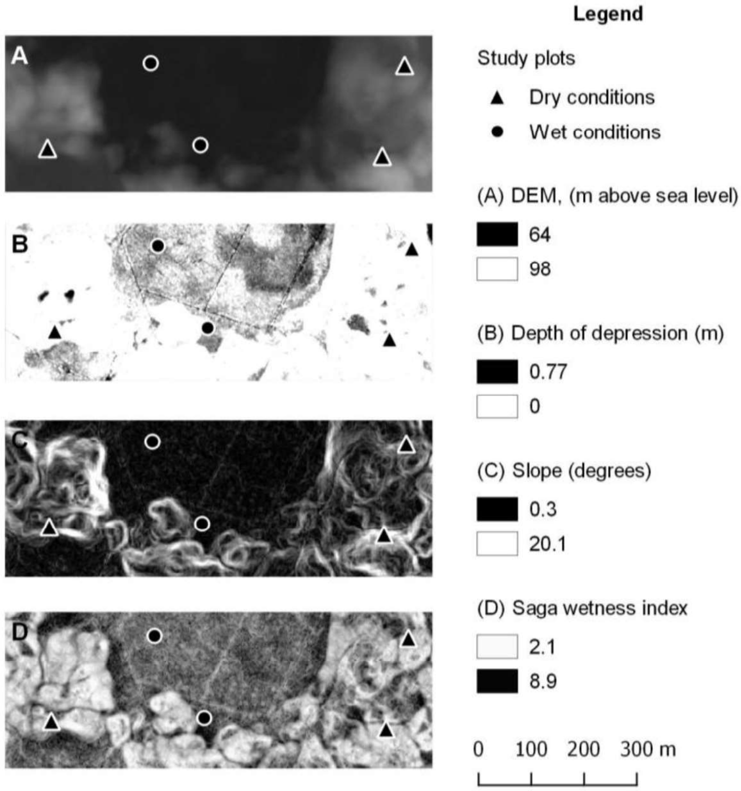


**Figure 2.** Example of data sampling from various raster layers.

**Data statistical analysis**

Mean values of various indices derived from remote sensing data were compared using One-Way ANOVA test in SPSS. This analysis was conducted to see which remote sensing indices shows statistically significant differences between soil wetness classes.

Soil wetness classes were reduced to 2 classes to do binary logistic regression analysis. Binary logistic regression analysis in SPSS is used for binary data, when there are only 2 possible outcomes – true or false. In this case all the study plots with dominant reductimorphic horizon were assumed to be true, and all the study plots with reductimorphic color dominance < 50% were assumed to be false. Results from this analysis were used to generate formulae for soil wetness prediction in other areas.

## RESULTS AND DISCUSSION

One-Way ANOVA test shows, that there is statistically significant difference ($\alpha < 0.05$) for some of used parameters between different soil wetness classes and significantly different parameters vary depending on settings of quaternary deposits.

Binary logistic regression analysis, similarly to One-Way ANOVA test, shows that various wetness prediction algorithms for different quaternary deposits gives results with various precision, therefore they should be analyzed separately. Results of binary logistic regression analysis are used to get coefficients for soil wetness probability prediction. Depression detection algorithm gives best results for wetness prediction for soils on moraine sediments. Resultant formula gives result from 0 to 1, where 0 means dry conditions and 1 – wet conditions. Field data classification gives 94.6% accuracy when cut value is set to 0.15.

$$\frac{\exp(-3.645 + 48.749x)}{\exp(-3.645 + 48.749x) + 1} \tag{2}$$

where x – average depth of depression from raster with resolution 2 m in 10 m radius.

There are similar trends for soils on clayey sediments, however drainage systems are widely used in these areas and natural water flow is disturbed, so wetness indices are predicting soil wetness conditions with lesser accuracy. Field data classification gives 79,8% accuracy when cut value is set at 0.35. To improve quality of soil wetness prediction slope and saga wetness index values are added to formula:

$$\frac{\exp(5.260 - 2.205x + 4.749y - 0.966z)}{\exp(5.260 - 2.205x + 4.749y - 0.966z) + 1} \tag{3}$$

where x – average slope from raster with resolution 5 m; y – depth of depression from raster with resolution 2 m; z – value of saga wetness index from raster with resolution 1 m. All values are taken as averages from area of 10 m radius.

Hydraulic conductivity for soils on fluvial sediments is higher, so local depressions are less important for determination of soil wetness. Field data classification gives 94.1% accuracy when cut value is set to 0.5. Saga wetness index and slope values are used in soil wetness prediction:

$$\frac{\exp(-11.305 + 1.905x - 0.05y + 2.232z - 2.505m)}{\exp(-11.305 + 1.905x - 0.05y + 2.232z - 2.505m) + 1} \tag{4}$$

where x – saga wetness index value from raster with resolution 1 m; y – saga wetness index value from raster with resolution 2 m; z – average slope from raster with resolution 1 m; m – average slope from raster with resolution 5 m. All values are taken as averages from area of 10 m radius.

Sentinel-2 multispectral imagery together with saga wetness index and slope values is used in classification and predicting of soil wetness on eolian sediments. Field data classification gives 100% accuracy when cut value is set to 0.5. Resulting formula is:

$$\frac{\exp(-9{,}313.517 + 8{,}427.14x + 0.388y + 197.023z + 32.007m)}{\exp(-9{,}313.517 + 8{,}427.14x + 0.388y + 197.023z + 32.007m) + 1} \tag{5}$$

where x – NDVI value (Sentinel-2 scene from 30.08.2017); y – value of infrared band (Sentinel-2 scene from 30.08.2017); z – saga wetness index value from raster with resolution 2 m; m – average slope from raster with resolution 5 m. All values are taken as averages from area of 10 m radius.

Spatial distribution of various quaternary sediment types in Latvia is fragmented and topography has largely been formed as a result of last Weichselian event of Pleistocene glaciation. Main processes that affected sedimentation in Latvia were transgressive and regressive processes of glacial accumulation as well as proglacial meltwater activity (Zelcs & Markots, 2004).

Proposed methodology for wet areas detection in forest are based on various indices derived from LiDAR based DEM and multispectral satellite imagery. Similar data sources are used in other studies (Case et al., 2004; Ågren et al., 2014), however they used ready to use models and accuracy of those were analyzed. Accuracy of wet areas detection of *depth-to-water* model proposed by Murphy et al. (2011) in Swedish case study was 85% (Ågren et al., 2014), which is similar to proposed methodology, but it doesn't consider variation in quaternary deposits.

## CONCLUSIONS

Predicting of wet soils spatial distribution using LiDAR data and multispectral satellite imagery is a perspective method and can be used in practice for planning of forestry operations. The results of statistical analysis show that using the data obtained in field works, the accuracy of soil wetness classification of soils on moraine, fluvial and eolian sediments exceeds 94%, whereas on the clayey sediments it is close to 80%.

This study shows that different geological deposits have various effect on the spatial distribution of soil moisture. This means that different geological settings must be considered when designing a soil moisture map.

An essential disadvantage of introducing this method in practice is the lack of precise geospatial data on roads and watercourses in Latvia. These data are needed to make DEM corrections to do accurate modeling of water runoff.

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