

TANEL TAMM

Use of local statistics in remote sensing  
of grasslands and forests





**TANEL TAMM**

Use of local statistics in remote sensing  
of grasslands and forests



UNIVERSITY OF TARTU  
Press

Department of Geography, Institute of Ecology and Earth Sciences, Faculty of Science and Technology, University of Tartu, Estonia

This dissertation was accepted for the commencement of the degree of *Doctor philosophiae* in **geoinformatics** at the University of Tartu on 4<sup>th</sup> of June 2018 by the Scientific Council of the Institute of Ecology and Earth Sciences at the University of Tartu.

Supervisors:

Dr. Kalle Remm, Senior Research Fellow in Geoinformatics  
Department of Geography  
University of Tartu  
Tartu, Estonia

Dr. Kārlis Zālīte, Research Fellow in Remote Sensing of Vegetation  
Department of Remote Sensing  
Tartu Observatory, University of Tartu  
Tõravere, Estonia

Opponent:

Dr. Mariana Belgiu, Assistant Professor  
Faculty of Geo-Information Science and Earth Observation  
University of Twente  
Enschede, The Netherlands

Commencement:

Scientific Council Room in the University Main Building,  
Ülikooli 18, Tartu, on August 28<sup>th</sup> 2018 at 14:15

Publication of this thesis is granted by the Institute of Ecology and Earth Sciences, University of Tartu.

ISSN 1406-1295  
ISBN 978-9949-77-787-7 (print)  
ISBN 978-9949-77-788-4 (pdf)

Copyright: Tanel Tamm, 2018

University of Tartu Press  
<http://www.tyk.ee/>

# TABLE OF CONTENTS

|   |           |
|---|-----------|
| <b>LIST OF ORIGINAL PUBLICATIONS</b>                              | <b>7</b>  |
| <b>LIST OF ABBREVIATIONS</b>                                      | <b>8</b>  |
| <b>I. INTRODUCTION</b>  | <b>10</b> |
| 1.1. Background . . . . .   | 10        |
| 1.1.1. Remote sensing of agricultural areas . . . . .             | 12        |
| 1.1.2. Remote sensing of forests . . . . .                        | 14        |
| 1.1.3. Local statistics in remote sensing of vegetation . . . . . | 15        |
| 1.2. Objectives and progress of this work . . . . .               | 16        |
| <b>II. MONITORING OF GRASSLANDS WITH SAR</b>                      | <b>18</b> |
| 2.1. SAR interferometric temporal coherence . . . . .             | 20        |
| 2.1.1. SNR Decorrelation . . . . .                                | 21        |
| 2.1.2. Estimation Bias . . . . .                                  | 21        |
| 2.2. Materials . . . . .  | 21        |
| 2.2.1. Mowing events and field measurements . . . . .             | 21        |
| 2.2.2. SAR acquisitions and processing . . . . .                  | 23        |
| 2.2.3. Precipitation data . . . . .                               | 24        |
| 2.3. Summary of the study results and discussion . . . . .        | 25        |
| <b>III. MONITORING OF FORESTS WITH OPTICAL SENSORS</b>            | <b>27</b> |
| 3.1. Local statistics for forest remote sensing . . . . .         | 28        |
| 3.1.1. Summary of the study results and discussion . . . . .      | 28        |
| 3.2. Estimating the parameters of forest inventory . . . . .      | 29        |
| 3.2.1. Reduction of features . . . . .                            | 31        |
| 3.2.2. Summary of the study results and discussion . . . . .      | 31        |
| <b>CONCLUSIONS</b>  | <b>33</b> |
| <b>REFERENCES</b>   | <b>34</b> |
| <b>KOKKUVÕTE (SUMMARY IN ESTONIAN)</b>                            | <b>44</b> |
| <b>ACKNOWLEDGEMENTS</b>   | <b>46</b> |
| <b>PUBLICATIONS</b>   | <b>47</b> |
| <b>ERRATA IN PAPERS</b>   | <b>91</b> |

**CURRICULUM VITAE**

**92**

**ELULOOKIRJELDUS (CURRICULUM VITAE IN ESTONIAN)**

**97**

## LIST OF ORIGINAL PUBLICATIONS

This thesis is based on the following original publications which will be referred to in the text with **Ref.** followed by their Roman numerals:

- I Tamm, T.**, Zalite, K., Voormansik, K. and Talgre, L. (2016). Relating Sentinel-1 interferometric coherence to mowing events on grasslands. *Remote Sensing*, 8(10), 802.
- II Tamm, T.**, Remm, K. and Proosa, H. (2010). LSTATS software and its application. In *Proceedings of the Seventh IASTED International Conference: Signal Processing, Pattern Recognition and Applications*; Innsbruck, Austria, 317–324.
- III Tamm, T.** and Remm, K. (2009). Estimating the parameters of forest inventory using machine learning and the reduction of remote sensing features. *International Journal of Applied Earth Observation and Geoinformation*, 11(4): 290–297.

The articles listed above have been printed with the permission of the copyright owners.

### **Author's contribution to the publications:**

**I** The author is partially responsible for the study design and data collection; fully responsible for data processing and creation of figures; partially responsible for interpretation of the results and primarily responsible for writing the article.

**II** The author is partially responsible for the study design; primarily responsible for data collection, data processing and creation of figures; partially responsible for interpretation of the results and primarily responsible for writing the article.

**III** The author is primarily responsible for the study design, data collection and processing; partially responsible for creation of figures and interpretation of the results; primarily responsible for writing the article.

## LIST OF ABBREVIATIONS

|             |  |
|-------------|--|
| ALS         | airborne laser scanning                                |
| ANN         | artificial neural network                              |
| ASCAT       | advanced scatterometer                                 |
| ASPRS       | American Society for Photogrammetry and Remote Sensing |
| az          | azimuth  |
| CAP         | common agricultural policy                             |
| CART        | classification and regression tree                     |
| CBR         | case-based reasoning                                   |
| ENL         | equivalent number of looks                             |
| EO          | earth observation                                      |
| ESA         | European Space Agency                                  |
| GEO         | Group on Earth Observation                             |
| GEOBIA      | geographic object-based image analysis                 |
| GEOSS       | global earth observation system of systems             |
| GIS         | geographic information systems                         |
| GIScience   | geographic information science                         |
| GPT         | SNAP graph processing tool                             |
| HH          | horizontal transmit, horizontal receive                |
| HV          | horizontal receive, vertical transmit                  |
| InSAR       | interferometric SAR                                    |
| IW          | interferometric wide swath mode                        |
| LIDAR       | light detection and ranging                            |
| NASA        | National Aeronautics and Space Administration          |
| NFI         | national forest inventory                              |
| NPA         | national paying agencies                               |
| OBIA        | object-based image analysis                            |
| PA          | precision agriculture                                  |
| PolSAR      | polarimetric SAR                                       |
| PseudoCAPPI | pseudo constant altitude plan position indicator       |
| RF          | random forest  |
| rg          | range  |
| RON         | relative orbit number                                  |
| RMSE        | root mean square error                                 |
| SAR         | synthetic aperture radar                               |
| SfM         | structure from motion                                  |
| SVM         | support vector machine                                 |

|      |                                       |
|------|---------------------------------------|
| SLC  | single look complex                   |
| SNR  | signal-to-noise ratio                 |
| SNAP | Sentinel application platform         |
| TLS  | terrestrial laser scanning            |
| UAS  | unmanned aerial systems               |
| USGS | United States Geological Survey       |
| VH   | vertical transmit, horizontal receive |
| VV   | vertical transmit, vertical receive   |

# I. INTRODUCTION

## 1.1. Background

Remote sensing as a term was formally defined by the American Society for Photogrammetry and Remote Sensing (ASPRS) in 1983, but long before that humans were making measurements without being in direct contact with the object under study. The capability to observe and record a sizeable geographic area at one point in time evolved after the capability to make photographs and to fly with an aircraft (Khorram et al., 2012). The first remotely sensed image of Paris was taken by Gaspard Felix Tournachon from a balloon in 1858 (Jensen, 2014). Jensen (2014) have stated that currently remote sensing is in the phase of exponential growth. The spatial, spectral and radiometric resolution of Earth observation (EO) satellites are increasing and the revisit times are shortening. EO is used to gain information about atmosphere, vegetation, soil, water, ice, minerals and urban infrastructure. The aim is to take full advantage from the daily use of EO data in various fields: weather forecasting, crop monitoring, ice mapping, etc.

Some of the fields of research that the EO community has recently focused on are: object-based image analysis (Blaschke, 2010; Chen et al., 2012; Cheng and Han, 2016; Hussain et al., 2013), machine learning methods (Ball et al., 2017; Belgiu and Dragut, 2016; Mas and Flores, 2008; Maxwell et al., 2018; Mountrakis et al., 2011), geospatial big data (Li et al., 2016; Yang et al., 2017), unmanned aerial systems (UAS) (Bhardwaj et al., 2016; Colomina and Molina, 2014; Wallace et al., 2016), land cover change (Chen et al., 2012; Gomez et al., 2016; Hansen and Loveland, 2012; Hussain et al., 2013), climate change (Kang et al., 2010) and land surface temperature (Li et al., 2013). Recent developments in remote sensing of agriculture and forestry are briefly summarised in sections 1.1.2 and 1.1.1.

Spatial resolution of remote sensing imagery has improved for decades. This allows nowadays to have more than one measurement/pixel per target object. This in turn has lead to rapid developments of geographic object-based image analysis (GEOBIA). Blaschke (2010) described GEOBIA as a significant trend in remote sensing and Geographic Information Science (GIScience) and it has developed into new and evolving paradigm (Blaschke et al., 2014). Cheng and Han (2016) surveyed four types of image object detection methods: template matching-based, knowledge-based, object-based image analysis (OBIA)-based and machine learning-based. They propose that deep learning-based feature representation and weakly supervised learning-based geospatial object detection are the two promising research directions. One example of a weakly supervised learning-

based geospatial object detection methodology has been described by Han et al. (2015).

Remotely sensed data rarely have normal distribution in the scene. This has led to a wide use of non-parametric supervised classifiers like classification and regression tree (CART), support vector machine (SVM), artificial neural network (ANN) and also ensemble classifiers like random forest (RF) that uses set of CARTs for classifying remote sensing data (Belgiu and Dragut, 2016). Belgiu and Dragut (2016) has concluded that classification results achieved with RF compared to decision trees and ANN are better when hyperspectral or multi-source data are used, and RF is faster than SVM or other ensemble classifiers like AdaBoost. However, Ball et al. (2017) concluded that deep learning, a rebranding of ANN, and feature learning are hot and emerging topics in remote sensing.

Besides classification or estimation tasks machine learning is used in many other remote sensing tasks, such as dimensionality reduction, segmentation, change detection, object recognition and detection (Ball et al., 2017). For example, Romero et al. (2016) have introduced the use of single-layer and deep convolution networks for remote sensing data analysis. For feature extraction, they proposed an approach of a greedy layer-wise unsupervised pre-training coupled with a highly efficient algorithm for unsupervised learning of sparse features and illustrated the expressive power of these features for classification tasks, e.g. land-cover classification from multi- and hyperspectral images.

Many different types of new sensors, messaging systems and social networks with more traditional measurement and observation systems are creating the rapidly growing flow of big data (Li et al., 2016). Li et al. (2016) concluded that these massive data flows characterised by four V-s – Volume, Velocity, Variety and Veracity – cannot be handled with traditional approaches and methods. They proposed that further research and development must be carried out in the following areas: spatial indexing and algorithms for real-time data streaming and topology support; conceptual and methodological approaches to explore casual and explanatory relationships; methods to display 3D spatial data with continuous time; assessment of data quality with novel error propagation approaches. One of the main challenges is making the query processing faster with novel spatial indexing. The question is how to organise geospatial data in optimal tiles and find efficient paths (space-filling curves) through these tiles, so that the access to n-dimensional data is done efficiently by referencing to the location of the tile along that path (Li et al., 2016). Working on this challenge Hughes et al. (2015) have described a distributed architecture called GeoMesa for spatio-temporal fusion.

The free and open data policy initiatives by the Copernicus programme, National Aeronautics and Space Administration (NASA), United States Geological Survey (USGS) and other institutions are expected to expand the EO applications sector (Begue et al., 2018; Dong and Xiao, 2016; Jeppesen et al., 2018; Steele-Dunne et al., 2017; Turner et al., 2015). The Group on Earth Observation (GEO) and Global Earth Observation System of Systems (GEOSS) initiative started in 2005 and are examples of administrative efforts for making EO data more easily

accessible (Lautenbacher, 2006; Nativi et al., 2015). Grainger (2017) states that the Copernicus programme vision of seamless chain from remote sensing data to usable information is still largely unrealised and finds that the constraints are not solely technical.

Toth and Jozkow (2016) compiled a review of remote sensing technologies, including platforms and sensors. New sensors and other hardware are being rapidly created. These together with crowdsensing by social media will provide an increasing flood of sensor data. They concluded that algorithmic research and software developments are generally behind so that the full potential of remote sensing data is not exploited. One of the great examples of remote sensing big data applications is cloud-based platform Google Earth Engine. It has been used to conduct various global analyses on societal issues e.g. deforestation and drought (Gorelick et al., 2017). One of the pioneering frameworks of truly global and multidisciplinary data sharing is the GEOSS and its central infrastructure that has been facing several challenges of big data (Nativi et al., 2015). This has led to rapid developments in the use of machine learning and object-based image analyses techniques in remote sensing. In addition, processing is moving closer to data with the rise of EO community platforms for more efficient processing.

### **1.1.1. Remote sensing of agricultural areas**

To meet future food security needs food production must grow substantially, while agriculture's environmental footprint must decrease drastically (Atzberger, 2013). Agricultural policies need unbiased information as input. Likely the best way to get this information is using satellite-based remote sensing (Atzberger, 2013). Considering recent trends in scientific literature some of the main domains of research in remote sensing of agriculture are: soil moisture estimations, (Chan et al., 2016; Hassan-Esfahani et al., 2015; Kornelsen and Coulibaly, 2013; Mohanty et al., 2017; Peng et al., 2017), precision agriculture (PA) (Gago et al., 2015; Khanal et al., 2017; Mulla, 2013; Salami et al., 2014; Schellberg et al., 2008; Zhang and Kovacs, 2012), UAS (Gago et al., 2015; Huang et al., 2013; Salami et al., 2014; Zhang and Kovacs, 2012), assessment of paddy rice cultivation (Dong and Xiao, 2016; Kuenzer and Knauer, 2013), evapotranspiration (Glenn et al., 2010; Gowda et al., 2008), detection and characterisation of agricultural practices (Begue et al., 2018).

Soil moisture estimation has been investigated from global to parcel scale. The Soil Moisture Active Passive (SMAP) mission was planned to provide high-accuracy global maps of soil moisture and freeze/thaw state with temporal resolution of two to three days, that could, for instance, be directly applicable to drought monitoring (Entekhabi et al., 2010). Despite the hardware failure of SMAP radar the soil moisture product from the operational radiometer has been shown to meet the accuracy requirement of the mission (Chan et al., 2016). But the coarser 40 km spatial resolution of the radiometer, that cannot be combined with the finer 1-3 km resolution of the radar measurements does not allow to achieve the combined res-

olution of 10 km and limits missions data products use for many applications (Entekhabi et al., 2010).

Peng et al. (2017) have reviewed various spatial downscaling methods of remotely sensed soil moisture estimations, namely satellite-based, geoinformation-based and model-based. They conclude that there is a need for synthesis of all available data sources. For regional agricultural applications at least daily frequency is needed, which requires the use of time extrapolation methods. There is potential to retrieve soil moisture at 1 km spatial resolution and 6 day temporal resolution using Sentinel-1 data with change detection approach (Hornacek et al., 2012). At parcel scale, Hassan-Esfahani et al. (2015) have evaluated a UAS-based soil moisture estimation using optical, near-infrared and infrared data. Steele-Dunne et al. (2017) have concluded that to develop drought/water stress applications it is essential to improve the depiction of vegetation phenology and water dynamics. They described that the capability to quantitatively use the data of advanced scatterometer (ASCAT) on MetOp could lead to a better soil moisture retrieval and vegetation phenology monitoring.

Zhang and Kovacs (2012) have defined PA as the application of geospatial techniques and sensors to identify variations in the field and deal with them using alternative strategies. In the early days (middle of 1980's) of PA the sensors had few visible or near infrared bands. Whereas, nowadays a wide range of wavelengths are used enabling advanced applications as light detection and ranging (LIDAR), fluorescence spectroscopy, thermal spectroscopy and hyperspectral sensors (Mulla, 2013). The aim is to allow near real time soil, crop and pest management.

The use of UAS for PA applications allow an alternative with lower cost and higher spatial resolution to the use of high and very high resolution satellite imagery (Zhang and Kovacs, 2012). Zhang and Kovacs (2012) suggested that the farmer should be directly participating in the set up, operation and interpretation phases of UAS-based applications. They concluded that the application of UAS in PA is still in its infancy and the main shortcomings are high initial cost, platform reliability, sensor capability, lack of standardised procedures, and strict aviation regulations.

Traditionally visible light and near-infrared sensors have been used in PA to estimate the stress levels of crops but thermal sensors have been found to give promising results by indicating crop stress symptoms before their visual appearance (Khanal et al., 2017). The rapid development of UAS has made it possible to acquire high resolution thermal images with reasonable costs. Furthermore, Khanal et al. (2017) have described that there are many application areas of thermal remote sensing in agriculture: e.g. drought monitoring, crop disease detection, crop maturity and yield. Gago et al. (2015) summarised that the retrieval of chlorophyll fluorescence with UAS should be a priority research topic as it is shown to be a good indicator of photosynthesis and water use efficiency under water stress. They conclude that UAS are surely beneficial and adapted tools for PA and water irrigation management.

Paddy rice mapping on regional to global scale has been an active research topic. Dong and Xiao (2016) have reviewed paddy rice mapping methods and described four categories of algorithms: image-statistic-based approaches, vegetation index data and enhanced image-statistic-based approaches, temporal-analysis-based approaches and phenology-based approaches. Remote sensing can also contribute to various topics related to paddy rice cultivation areas: e.g. harvest prediction modelling, plant disease analyses, and assessment of rice-based greenhouse gas emission (Kuenzer and Knauer, 2013).

### **1.1.2. Remote sensing of forests**

Remotely-sensed data have numerous applications in the field of forest monitoring: e.g. delineating the damaged areas, mapping canopy extent and structure, timber inventory, deforestation (Khorram et al., 2012). The main topics that have recently been investigated by the scientific community are: using airborne and terrestrial LIDAR data to retrieve forest structural parameters (Dassot et al., 2011; Hyyppa et al., 2008; Montagni et al., 2013; van Leeuwen and Nieuwenhuis, 2010; Wallace et al., 2016; Wulder et al., 2012), extraction of forest inventory data (Hyyppa et al., 2008; McRoberts et al., 2010; White et al., 2016), forest stand biomass estimation (Gleason and Im, 2011; Le Toan et al., 2011; Sinha et al., 2015; Wulder et al., 2008), tree species classification (Fassnacht et al., 2016; Korpela et al., 2010), estimation of forest cover change (Hansen et al., 2013).

The suitability of LIDAR data for forest inventory has been established but monitoring of large areas remains challenging due to high costs and complicated logistics (Wulder et al., 2012). Wulder et al. (2012) described a framework to use LIDAR as a sampling tool for large-area estimations. The main goal for using LIDAR sampling was to imitate ground plots, recognising that independent ground data is still needed to calibrate the LIDAR measures. They presented that transect-based applications of LIDAR can be used to timely and cost effectively cover large regions for estimating forest characteristics.

Liang et al. (2016) concluded that terrestrial laser scanning (TLS) can be practically used characterising sample plots in forest, but it has not been accepted as an operational tool. The main reasons for that are lack of automatic and accurate methods for detection of some important tree attributes, e.g. tree species. Furthermore, the cost of the instrument is high. Mobile/personal laser scanning and image-based techniques are capable to provide similar 3D point cloud data with lower cost and high efficiency, whereas the added value of using TLS needs to be demonstrated (Liang et al., 2016).

Wallace et al. (2016) tested two remote sensing techniques: airborne laser scanning (ALS) and structure from motion (SfM) to estimate structural properties of forest using UAS. In denser canopy cover SfM-based estimations of terrain surface produced larger errors than ALS. These errors propagated into the estimation of canopy properties. Nevertheless Wallace et al. (2016) concluded that SfM is still adequate low-cost alternative for forest stand surveys.

White et al. (2016) reviewed the potential of four remote sensing techniques for forest inventory: ALS, TLS, digital aerial photogrammetry and high or very high spatial resolution satellite optical imagery. They concluded that integrated use of digital aerial photogrammetry and ALS is a remote sensing technique that will likely have the greatest impact on forest inventory practices, providing broader set of attributes and enabling the monitoring of growth of forest stands. McRoberts et al. (2010) emphasise that use of LIDAR will lead to greater efficiency and more useful estimates.

Synthetic aperture radar (SAR) is not widely used in the data collection routines of national forest inventory (NFI). Gleason and Im (2011) showed that only 7 % of the selected biomass estimation works used radar as the primary data source. Discrete-return LIDAR (25 %) and multispectral (20 %) sensor types were the most preferred data sources. They concluded that spaceborne/airborne LIDAR will continue to be one of the most important data sources for the estimations of forest biomass.

A later study by Sinha et al. (2015) has concluded that SAR can effectively assess forest biomass and overcome important limitations of optical remote sensing, especially in tropical forests. Longer wavelength and cross-polarisation make SAR more sensitive to biomass than optical sensors. Le Toan et al. (2011) has stated that BIOMASS P-band radar might be the only sensor to provide global knowledge about forest biomass and its changes. The feasibility study of the mission started at 2009 and currently the envisaged launch year is around 2020. Still, interferometric and polarimetric techniques used for biomass estimations need further studies (Sinha et al., 2015).

The relative growth of trees within one vegetation season is rather small, compared to, for example, cereals, which allows the revisit times of remote-sensing-based monitoring of forests in many cases to be quite long. This gives one explanation to the wide use of airborne sensors (64 %) for forest biomass estimation reported by Gleason and Im (2011). Spaceborne sensors have more potential for region-, continental-wide or global estimations and where short revisit times are needed e.g. for delineating the damaged areas caused by forest fires or forest pests.

### **1.1.3. Local statistics in remote sensing of vegetation**

The use of locally computed statistics has been attractive field of research for many years. Boots and Okabe (2007) stated that in the fields of geography, geographic information systems (GIS) and remote sensing there has been an extensive development of indicators that describe the properties of spatial subsets also named as windows, neighbourhoods, masks or kernels. In this thesis the term local statistics is defined as statistical measures computed inside the local area of interest from a remotely sensed image. The local area of interest can be defined by a kernel (e.g circular, rectangular, etc.) surrounding the point of interest or by a polygon representing the area as vector layer of geospatial data set or segmented

portions of an image. LSTATS software presented in **Ref. II** supported both types of local areas of interest for calculating local spatial statistics.

Following, some examples where local statistics were used in remote sensing are listed. For instance, Haralick et al. (1973) considered eight nearest-neighbour resolution cells to extract textural features for image classification. Lee (1980) used local mean and variance in a  $3 \times 3$  to  $7 \times 7$  window for image enhancement and noise filtering. Dutra and Huber (1999) extracted local statistics from ERS-1 and ERS-2 SAR data and compared with other features for land cover estimation. Getis and Aldstadt (2004) described a local statistics model for constructing spatial weights matrices for spatial regression models. Mercier et al. (2008) used local statistics for change detection using significantly different (e.g. different sensors) acquisitions. Johnson and Xie (2011) proposed a multi-scale segmentation approach that used local statistics to refine under- and over-segmented regions and showed that it can improve the creation of image objects.

The main difficulty in multitemporal SAR-image-based change detection is the speckle noise. A classical approach to handle this issue is the use of the ratio of the local means in the neighbourhood of each pair of colocated pixels (Inglada and Mercier, 2007). To consider also the changes that take place at the structural texture level, possibly not changing the mean value, Inglada and Mercier (2007) proposed a similarity measure which depends on the four first statistical moments of the pixels inside the analysis window.

When the target object is much larger than the pixel of an image, the value of one pixel can be quite random in relation to target property being estimated. Preferably all pixels within the target object should be considered when conducting a remote sensing estimation. Besides statistical attributes, also structural properties of the image should be exploited. In many cases the geometric shape of the target object is defined with the spatial data already available, for example the borders of a forest stand or agricultural parcel. If the geometric shape is not available the delineation of the target object from the remote sensing data can be a challenging task.

## 1.2. Objectives and progress of this work

The aim of current thesis is to analyse approaches for remote sensing of grasslands and forests that are based on local statistics. More precisely, the objectives are:

1. to introduce SAR variables for monitoring of mowing events on grasslands based on temporal interferometric coherence;
2. to demonstrate the applicability of local statistics in remote sensing of forests based on true colour orthophotos;
3. to complement the existing forest remote sensing methodologies with a case study describing feature reduction technique and machine learning approach for the estimation of NFI data.

One of the obligations set by the European Union Common Agricultural Policy

(CAP) is to maintain grasslands by mowing or grazing on a yearly basis. National paying agencies (NPA) validate the mowing requirement usually with on-site field inspections in limited areas. Considering the need for more automatic solutions the following hypothesis was formed: C-band SAR 12-day repeat pass interferometric coherence rises after a mowing event. The article **Ref. I** in this thesis analysed the relationship between the C-band SAR 12-day repeat pass interferometric coherence and mowing events of grasslands. In this study average as a local statistic was calculated using pixels inside parcel polygons. It was shown in the paper that VH (vertical transmit, horizontal receive) and VV (vertical transmit, vertical receive) polarisation coherence values after the mowing event were statistically significantly higher than those from before the mowing event.

There are many applications and programming packages that can be used to calculate local statistics, for instance presented by Pebesma (2004); Rosenberg and Anderson (2011); Unwin (1996). The motivation to write the article **Ref. II** was the claim that one can find not widely used local statistics that could be useful in forest remote sensing based on true colour orthophotos. The LSTATS software developed by Kalle Remm in the Department of Geography, University of Tartu was introduced in the article **Ref. II** to promote the field of spatial statistics. Kernel-based local statistics were reviewed in the context of forest remote sensing. Results indicated that local statistics investigated in this study can be most useful for distinguishing shadowed management passages, spruce canopies, groups of tree crowns and clearings in forest.

Large amount of NFI data is collected with on-site field works. Plenty of research has investigated the use of remote sensing techniques to optimise the data collection process, e.g. (Beaudoin et al., 2014; Hyypä et al., 2008; Tomppo and Katila, 1991). To contribute to this field of research the following hypotheses were formed: first cluster analyses can be used for reduction of remote sensing features; second remote sensing approach that is based on machine learning can give estimates with high accuracy using large NFI data set, Landsat 7 images and true colour orthophotos. A study **Ref. III** for evaluating the estimation of parameters of NFI stands in Estonia was conducted using a machine learning application on Landsat 7 ETM+, chromatic orthophotos and auxiliary vector data from basic and soil maps. Circular kernel radii ranging from 10 m to 120 m were used to calculate local statistics based on remote sensing images. The developed methodology proved to give estimations with moderate accuracy reaching 36 % root mean square error (RMSE) for stand volume. Locally computed average was the most useful feature when compared to different statistical and structural texture indicators. It was suggested to use cluster analysis as pre-selection method of features because it could be used for both nominal and continues variables.

## II. MONITORING OF GRASSLANDS WITH SAR

Analysing 12 years (2000-2011) of daily 1 km resolution MODIS Terra and 10 years (2002-2011) MODIS Aqua data Whitcraft et al. (2015) showed that many important agricultural areas are so persistently and pervasively covered by clouds that less than half of their modelled 8 day composites would be even 70 % clear of cloud cover. Authors also concluded that in these areas and time periods, optical polar-orbiting imaging is not likely to be a viable option for operational monitoring of agricultural areas. This leads us to the main motivation for using SAR in remote sensing of grasslands — the ability of spaceborne SAR signal to penetrate clouds in all but extreme weather conditions and thereby to acquire continuous data in space and time for large areas.

There are various technical approaches that have been studied to use SAR data for grasslands monitoring. The most natural and simplest way is to use radar backscatter values. More complex techniques use polarimetric properties of SAR signal (polarimetric SAR (PolSAR)) and also amplitude and phase difference from a pair of images (Interferometric SAR (InSAR)). Speckle in SAR images makes it hard to interpret one single SAR pixel value as a measurement for natural scatterers. To overcome this issue local statistics are widely used in SAR data processing and analyses. The following paragraphs give a short summary of these SAR techniques in the context of grasslands monitoring.

For monitoring grassland parcels with spaceborne SAR the most widely spread approach is to use backscatter intensity values as independent variables. Following are some examples of this approach. Based on ERS-1 C-band SAR vertical transmit, vertical receive (VV) polarisation backscatter and ground-truth measurements Dobson et al. (1992) suggest that grass-covered surfaces are distinguishable from forested areas and near-surface soil moisture retrieval is possible for grass-covered soil. Further, using backscatter measurements from the same remote sensing instrument Moreau and Le Toan (2003) reported that for water-saturated Andean grasslands (*bofedal*) biomass values up to 2 kg/m<sup>2</sup> can be estimated with acceptable accuracy RMSE = 0.3 kg/m<sup>2</sup>.

Mowing as one of the most common management practices on grasslands has also been in focus of many studies. Schuster et al. (2011) results indicate that TerraSAR-X horizontal transmit, horizontal receive (HH) polarisation temporal signature profiles of backscatter values could be used to detect mowing events on semi-natural grasslands. The relationship of COSMO-SkyMed, Envisat ASAR and ALOS PALSAR backscatter values to the Normalized Differential Vegetation Index (NDVI), Normalised Difference Water Index (NDWI), and soil moisture

index (MI) values was analysed by Wang, Ge, and Li Wang et al. (2013). Without ground truth measurements they concluded that during peak season and on non-rainy dates X-band HH-polarisation backscatter values could be useful to detect grazing or mowing activities on pastures at paddock scale. Also Schuster et al. (2015) suggest that intra-annual TerraSAR-X HH-polarisation backscatter time series can be used for the detection of mowing events and even for direct pixel-based mapping purposes. In contrast, Dusseux et al. (2014) concluded that the longer wavelength Radarsat-2 C-band HH/VV intensity ratio could not be used to discriminate mowing on grasslands.

The estimation of grasslands habitat types using spaceborne SAR backscatter data has also been in the interest of many researchers. Schuster et al. (2015) demonstrated that mapping of seven semi-natural grasslands habitat types is achievable (Kappa coefficient ( $\kappa$ ) = 0.89) with using intra-annual dense time series of high spatial resolution X-band TerraSAR-X HH-polarisation backscatter values. They also showed that TerraSAR-X ensures the creation of appropriate time series more reliably compared to RapidEye. Similarly Barrett et al. (2014) reported very high accuracies for classifying five types of grasslands among other land cover types using machine learning methods and Envisat ASAR, ERS-2 C-band SAR VV ( $\kappa$  = 0.98) and ALOS PALSAR L-band HH backscatter and HH/VV ratio data ( $\kappa$  = 0.95). However, the use of backscatter from one channel (e.g., VV or HH) is problematic, due to changes caused by different vegetation orientation effects and meteorological conditions, which change the backscatter greatly even if the vegetation itself does not change (Bouman and van Kasteren, 1990).

As mentioned above PolSAR techniques have also been used in the studies of grasslands remote sensing. Applying new polarimetric approach with Air-SAR C-, L- and P-band fully polarimetric measurements from July 3, 1991 Hoekman and Vissers (2003) reported good results for classification of 14 agricultural land cover types (including grasslands): overall accuracy 90.4 % using C-band data. Voormansik et al. (2013) and Voormansik et al. (2016) demonstrated that several C-band and X-band polarimetric parameters are sensitive to mowing events on grasslands in cases where the grass was left on the ground after the event. The main drawback of PolSAR techniques to become commonly used is the need for fully polarimetric or dual polarimetric co-pol data. There are no sensors available yet that can provide such data at global scale and with dense regular time series. For instance, Sentinel-1 can offer only dual polarisation modes that are not co-pol: VV + VH (vertical transmit, horizontal receive (VH)) or HH + HV (horizontal transmit, vertical receive (HV)).

InSAR-based approaches have also shown potential for remote sensing of grasslands. The detection of mowing events on grasslands has been studied by Zalite et al. (2016, 2014), where it was described that COSMO-SkyMed 1-day X-band HH-polarisation interferometric coherence is much higher after a mowing event on grasslands. However, meteorological conditions have an important influence on backscatter and interferometric coherence of vegetation (Askne et al., 1997; Santoro et al., 2002). Rainfall right before one or both of the images in the pair of

two interferometric acquisitions probably causes temporal decorrelation.

Copernicus program and its open data policy has created an opportunity to use dense time series of C-band SAR measurements for change detection and temporal signatures-based retrieval techniques. The research results summarised in this section indicate that InSAR-based mowing detection might have more potential compared to backscatter and PolSAR-based techniques. Based on these considerations the hypothesis that C-band SAR 12-day repeat pass interferometric coherence rises after a mowing event was tested analysing Sentinel-1 C-band SAR interferometric coherence in **Ref. I**.

## 2.1. SAR interferometric temporal coherence

Coherence is the amplitude of the complex correlation coefficient. Given two complex SAR images  $s_1$  and  $s_2$  (e.g., Sentinel-1A single look complex (SLC) products), coherence is defined as:

$$\gamma = \frac{|\langle s_1 s_2^* \rangle|}{\sqrt{\langle s_1 s_1^* \rangle \langle s_2 s_2^* \rangle}}, \quad 0 \leq \gamma \leq 1 \quad (2.1)$$

where  $|\cdot|$  label the absolute value,  $\langle \cdot \rangle$  label the operation of spatial averaging, and  $*$  labels the complex conjugate product.

In the theoretical situation when the positions and physical properties of the scatterers within the averaging window  $\langle \cdot \rangle$  are the same for both images  $s_1$  and  $s_2$ , the coherence amplitude extends to the maximum value of 1. While change in the positions or properties of the scatterers lead to the decrease of coherence values. In addition, a decrease of the coherence value can be caused by a mismatch in the imaging properties of the two acquisitions caused by volume scattering, processing errors, and other reasons — an exhaustive description is presented in Hanssen (2001). Local statistics, specifically spatial averaging, has the central role in the computation of complex correlation coefficient. Due to the relatively small ( $\sim 150$  m) baselines between two Sentinel-1 interferometric acquisitions volume decorrelation is negligible in the context of this study.

On the other hand, temporal decorrelation is caused by changes in the scatterers, properties and positions between the acquisitions times. Regions covered by vegetation are typically more changing in time having thus higher temporal decorrelation and lower coherence than non-vegetated areas. To estimate the temporal decorrelation term one needs to consider additional decorrelation sources. The estimated coherence  $\gamma_{total}$  can be defined as:

$$\gamma_{total} = \gamma_{temporal} \gamma_{SNR} \gamma_{bias} \gamma_{other} \quad (2.2)$$

where  $\gamma_{total}$  is the calculated coherence from Equation (2.1),  $\gamma_{temporal}$  is the temporal decorrelation,  $\gamma_{SNR}$  is decorrelation due to sensor noise (signal-to-noise ratio (SNR)),  $\gamma_{bias}$  is influenced by the size of the averaging window, and  $\gamma_{other}$  are the other terms mentioned before as being negligible in the case of Sentinel-1A. The

evaluation of  $\gamma_{SNR}$  and  $\gamma_{bias}$  decorrelation terms are given in the following subsections.

### 2.1.1. SNR Decorrelation

$\gamma_{SNR}$  is caused by the sensor's thermal noise. Due to the relatively weak C-band signal backscatter from grasslands vegetation, this term has to be considered.  $\gamma_{SNR}$  is defined as (Just and Bamler, 1994):

$$\gamma_{SNR} = \frac{1}{\sqrt{\left(1 + \frac{1}{SNR_{sat1}}\right) \left(1 + \frac{1}{SNR_{sat2}}\right)}} \quad (2.3)$$

where  $SNR_{sat}$  is calculated for each of the two images in the interferometric pair according to:

$$SNR_{sat} = \frac{\sigma_{sat}^0 - NESZ_{sat}}{NESZ_{sat}} \quad (2.4)$$

where  $\sigma_{sat}^0$  is the spatially averaged backscattering coefficient of the area under investigation in the respective acquisition, and  $NESZ_{sat}$  is a range-dependent noise parameter that can be calculated using look-up tables provided in the Sentinel-1 metadata. The parameters in Equation (2.4) are in linear scale.

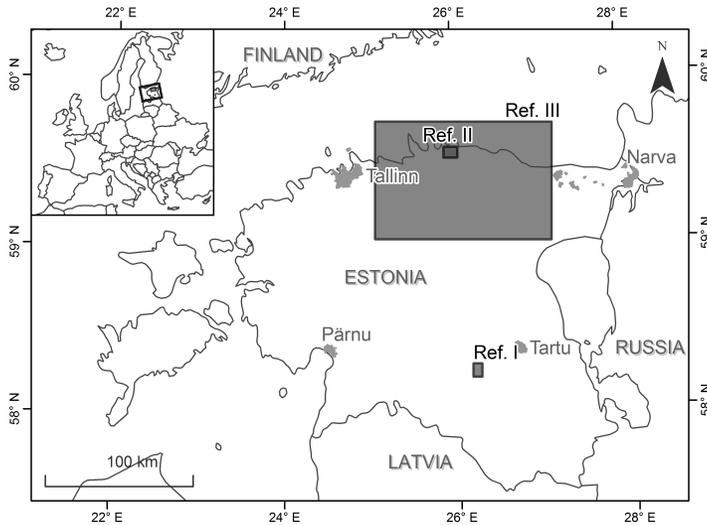
### 2.1.2. Estimation Bias

Estimation of coherence is biased towards higher values, decreasing the contrast between low and high coherence areas (Touzi et al., 1999). By using larger averaging windows in Equation (2.1) the bias can be decreased. At the same time one will lose spatial resolution when using larger windows. Therefore, the choice of window size must consider the size of the study object: in this case, the size of grasslands as well as the expected coherence range. In this study averaging windows with the following sizes (azimuth (az)  $\times$  range (rg)) were used:  $5 \times 21$  for relative orbit number (RON) RON58,  $5 \times 19$  for RON80 and  $5 \times 19$  for RON160, producing a footprint on the ground of  $\approx 71 \text{ m} \times 69 \text{ m}$  for all geometries. This resulted in the equivalent number of looks (ENL) of 50 for RON58, and 46 for RON80 and RON160. The chosen window sizes assured that the estimated coherence was not heavily biased, with the maximum bias value of 0.14–0.15 given true coherence of 0.

## 2.2. Materials

### 2.2.1. Mowing events and field measurements

For a proper analysis the actual mowing events have to be precisely determined in space and time. Inside the  $6 \text{ km} \times 9 \text{ km}$  **Ref. I** study area (Figure 1) around Rannu parish, 37 agricultural grasslands were used in this study. On the grasslands the



**Figure 1.** Location of the study areas in Estonia denoted as Ref. I, Ref. II and Ref. III.

main species were red clover (*Trifolium pratense* subsp. *sativum*), alfalfa (*Medicago sativa*), timothy-grass (*Phleum pratense*), meadow fescue (*Festuca pratensis*), red fescue (*Festuca rubra*). These grasslands were used to produce fodder, therefore grass was collected after the mowing events. GPS logs from tractors were used to acquire the most accurate measurements of mowing events in space and time, recording the start and end times of each mowing event and digitising the spatial extent of the event. 77 mowing events were determined in the 2015 vegetation season: 27 events in June, 19 in July, 9 in August, and 22 in September. Grasslands were mowed several times: 38 first, 30 second, and 9 third mows were determined. The extent of the mowed area varied between 2.2 ha and 43.2 ha (mean area of 11.9 ha).

To have more detailed look on the relations of temporal coherence and vegetation properties six grasslands (marked as G1 through G6) were monitored from May to September 2015 on a weekly basis, measuring the vegetation height, wet and dry above-ground biomass, and soil moisture. The transect method (10 measurements in straight line after every 25 m) was used for the field survey. Vegetation height was determined with a measuring tape, and the recorded value represents the height of the majority of vegetation at the measurement point interpreted visually by the field worker. Soil moisture was measured in the upper 5 cm layer using two hand-held conductivity probes: Delta-T ML2x and Extech MO750. Inside a 0.5 m × 0.5 m square all vegetation was cut and weighed to measure the wet above-ground biomass. Further it was dried and weighed again to provide the dry above-ground biomass.

**Table 1.** Sentinel-1A interferometric wide swath mode relative orbit numbers (RONs) used in the study and their parameters. The values are given for the study area. Azimuth (az), range (rg) (ESA, 2013).

| RON | Ascending/<br>Descending | Acquisition<br>Time (UTC) | Sub-Swath | Incidence Angle |      | Ground Range<br>Resolution az $\times$ rg, m |                     |
|-----|--------------------------|---------------------------|-----------|-----------------|------|--|---------------------|
|     |                          |                           |           | Near            | Far  | Near   | Far                 |
| 58  | Ascending                | 16:04                     | 3         | 44.6            | 45.0 | 21.60 $\times$ 4.98                          | 21.60 $\times$ 4.95 |
| 80  | Descending               | 04:34                     | 2         | 39.0            | 39.5 | 21.70 $\times$ 4.93                          | 21.70 $\times$ 4.87 |
| 160 | Ascending                | 15:56                     | 2         | 37.9            | 38.4 | 21.70 $\times$ 5.05                          | 21.70 $\times$ 4.99 |

**Table 2.** Acquisition dates for the RONs used in the study.

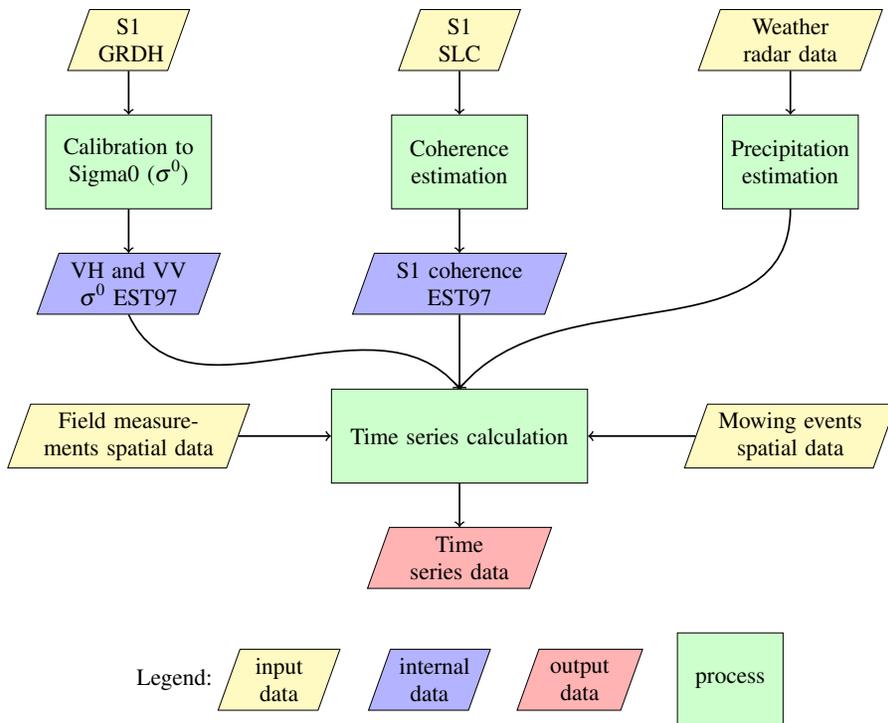
| RON | May       |    |    |    | June    |    |  |  |
|-----|-----------|----|----|----|---------|----|--|--|
| 58  | 1         | 13 | 25 | 6  | 18      | 30 |  |  |
| 160 |           | 8  | 20 | 1  | 13      | 25 |  |  |
| 80  | 3         | 15 | 27 | 8  | 20      |    |  |  |
| RON | July      |    |    |    | August  |    |  |  |
| 58  |           | 12 | 24 | 5  | 17      | 29 |  |  |
| 160 | 7         | 19 | 31 | 12 | 24      |    |  |  |
| 80  | 2         | 14 | 26 | 7  | 19      | 31 |  |  |
| RON | September |    |    |    | October |    |  |  |
| 58  | 10        |    |    | 4  | 16      | 28 |  |  |
| 160 | 5         | 17 | 29 | 11 | 23      |    |  |  |
| 80  |           | 12 | 24 | 6  |         |    |  |  |

## 2.2.2. SAR acquisitions and processing

Dual-pol data (VV + VH) from the C-band SAR remote sensing satellite Sentinel-1A were used in this study. Interferometric wide swath mode (IW) acquisitions from three geometries were used: RON58, RON80, and RON160. An overview of the properties of geometries is given in Table 1. With some exceptions, acquisitions were made every 12 days for each geometry. The data was delivered as SLC products. Acquisition dates for each geometry are given in Table 2. Relatively small orbital InSAR baselines in the order of 150 m is ensured by the Sentinel-1 orbit maintenance strategy (Yague-Martinez et al., 2016).

The Sentinel application platform (SNAP) tool (version 2.0.0) provided by the European Space Agency (ESA) was used for processing the Sentinel-1A images (Figure 2). The work flow was automated with Python 3 and the SNAP Graph Processing Tool (GPT). The coherence images and backscattering coefficients for VH and VV polarisations were calculated for each 12-day image pairs that were available.

An 80 m  $\times$  250 m area around the field survey measurement transect was used to get the average coherence and backscatter measurements. The following parameters were calculated from the images for each acquisition date: average



**Figure 2.** Flowchart of the processing chain.

coherence values for VV and VH; average backscatter values for VV and VH; time separation in days between the mowing event and the first acquisition in an interferometric pair. These parameters were collected also for three acquisitions before and three after a mowing event for each geometry. Inside buffering was used to exclude data on the border and outside the outline of a mowing event from the calculations. The size of the inside buffer was determined based on the coherence window size and geolocation accuracy of Sentinel-1.

The inside buffering and calculation of average values from images was automated using the ArcGIS Python package *arcpy*. The *matplotlib* Python package (Hunter et al., 2007) was used for visualisation.

### 2.2.3. Precipitation data

The effect precipitation has on coherence values was analysed. To investigate the effect precipitation has on repeat pass interferometric coherence the precipitation amounts before the first interferometric pair images after the mowing events were estimated using a DualPol weather radar. The weather radar is located in Sür-gavere, 50 km to the north–west of the study area. It was produced by Vaisala Group, and it operates in the C-band (at wavelength of 5.33 cm).

The 15-minute scan files provided by the Estonian Weather Service were processed with the *wradlib* Python package (Heistermann et al., 2013) to generate

pseudo constant altitude plan position indicator (PseudoCAPPI) estimates in the height of 500 m (Figure 2). Precipitation estimates for the Sentinel-1A acquisitions were created by averaging 300 m  $\times$  300 m pixels from the 3 h accumulated rainfall estimates.

### 2.3. Summary of the study results and discussion

Coherence values decrease before a mowing event and increase after it. The time separation between the event and first image in the InSAR pair has to be considered. Based on the time separation between the coherence measurement and the mowing event, coherence values were divided into six 12-day interval groups. The median VH and VV coherence values of after-the-event groups were statistically significantly higher compared to the first group before the event. The group containing coherence measurements from 0 to 12 days after a mowing event gave the best separation between mowed and not mowed grasslands. The influence of a mowing event was significant even after 24 to 36 days. Using 1-day interferometric pairs of X-band SAR data Zalite et al. (2016) have also concluded that the increase of coherence after a mowing event is observable. In this study a C-band radar with a longer wavelength was used. This might be the major reason why statistically significant differences could be presented and the coherence stays higher for a period of up to 36 days after an event.

When comparing VH and VV polarisation, it was concluded that the relative increase after a mowing event for VH coherence was slightly higher than for VV coherence. Similarly, El Hajj et al. (2014) concluded that the X-band HV polarisation is more sensitive to grasslands parameters than HH. When analysing sugarcane harvest Baghdadi et al. (2009) also described that the co-pol channels (HH and VV) have a slightly lower potential.

Precipitation diminished the increase of coherence after a mowing event. When the 3-h precipitation estimates were larger than 0.25 mm, the VH and VV coherence values after a mowing event generally remained under 0.25. Further, the 0.25 mm threshold allowed to group measurements from all three image acquisition geometries that were used in the study into two groups. Considering this, the coherence values were divided into two groups with 3-h precipitation estimates  $\leq 0.25$  mm and  $> 0.25$  mm. Median VH and VV coherence from RON160 showed significant difference between these two groups. Precipitation before one or both of the image acquisitions changes the dielectric constant and the structure of the vegetation and may decrease the coherence. Similar decrease of coherence due to precipitation has been described by (Ahmed et al., 2011; Zalite et al., 2016). On the other hand coherence values from RON80 and RON58 geometries showed no significant difference between the groups. The 3-h precipitation estimates of RON80 and RON58 acquisitions were small and might not have significantly affected the coherence. Additionally, the rather small sample size (55 to 77 measurements depending on RON) and the accuracy of precipitation estimates (1 h estimates RMSE 0.95 mm) must be considered when interpreting these results.

The weekly measurements taken on six grasslands reveal the complex relationship between mowing events and coherence. Very high coherence was rarely observed. It was registered that farming activities also weaken the increase of coherence after a mowing event. Field measurements also indicated that in the case of rapidly growing vegetation the 12-day interferometric coherence is not temporally dense enough for the mowing detection. With Sentinel-1B being operational, 6-day coherence products can now be created. With 6-day coherence rapid vegetation growth has less influence on the increase of coherence after mowing event.

Field measurements show that the higher the soil moisture and sparser the vegetation the stronger the increase of coherence after a mowing event. Still, the operational parcel-level estimation of soil moisture based on satellite remote sensing is challenging. For instance, Hornacek et al. (2012) stated that 1 km spatial resolution could be achievable with using Sentinel-1 data.

Height of the residual grass after a mowing event affects the resulting coherence values. Coherence stays low if the grass is cut to 0.3 m and pressed to the ground. In contrast, Voormansik et al. (2016) and Yang et al. (2015) have found that when vegetation is left on the ground the mowing event is more distinguishable with SAR data using polarimetric techniques.

Morning dew was likely one additional source of decorrelation. On early morning acquisitions dew changes the positions and properties of scatterers, thus decreasing the coherence. It was also observed that shallower incidence angles resulted in lower coherence values on average. Using polarimetric methods for harvest detection Adams et al. (2013) has stated that shallower incidence angles are preferred. Differences between VH and VV polarisation were also observed. These are probably caused by varying soil roughness and vegetation structure. Considering all the above mentioned findings it was concluded that there is potential to develop mowing detection algorithms and applications using C-band SAR temporal interferometric coherence.

Considering these findings, it was concluded that there is potential to develop mowing detection algorithms and applications using C-band SAR temporal interferometric coherence. The finding that statistically significant relation exists between C-band SAR 12-day interferometric coherence measurements and mowing events is the most important result of this thesis. When compared to the previous studies (Dusseux et al., 2014; Schuster et al., 2011, 2015; Voormansik et al., 2013, 2016; Wang et al., 2013; Zalite et al., 2016, 2014) the effect is relevant in the context of SAR remote sensing of mowing events on grasslands. For instance Dusseux et al. (2014) has concluded that the C-band HH/VV intensity ratio could not be used to discriminate mowing on grasslands. The result is also important because this novel approach can have practical value for validating CAP rules.

### III. MONITORING OF FORESTS WITH OPTICAL SENSORS

The use of local statistics in the domain of optical remote sensing of forests was analysed in the studies **Ref. II** and **Ref. III**. The amount of the incident sunlight in the visible and infrared wavelength ranges (also called optical wavelengths) that is absorbed by earth surface materials differs depending on the wavelength. The absorption characteristics of materials are determined by the chemical compositions and can be so complex in nature that many current earth observation instruments do not have sufficient spectral resolution to capture these properties. Majority of reflectance from the vegetation is in the optical wavelengths. Healthy vegetation has water absorption bands near 1.4, 1.9 and 2.7  $\mu\text{m}$  in the middle infrared range and chlorophyll absorption bands in the blue and red region in the visible range allowing our eyes to see plants as green. If the plant dies or suffers stress the water content changes and the chlorophyll absorption decreases, which results in vegetation appearing yellowish. These absorption characteristics of vegetation allow to monitor the health of vegetation and characterise different types of vegetation and lead to the wide use of the optical wavelengths in the remote sensing of forests (Richards, 2012).

Forest remote sensing methods could be divided between empirical, e.g. k-nearest neighbours method (Franco-Lopez et al., 2001; Latifi et al., 2010) and physical e.g. directional multispectral forest reflectance model (Kuusk and Nilsson, 2000). White et al. (2016) reviewed the potential of four remote sensing technologies for forest inventories: airborne laser scanning, terrestrial laser scanning, digital aerial photogrammetry, and high spatial resolution (1-10 m)/very high spatial resolution (<1 m) satellite optical imagery. They concluded that the coupling of digital aerial photogrammetry and airborne laser scanning will likely have greatest impact on the forest inventory practices in the next decade. A new review after the operational use of Sentinel-2A and Sentinel-2B is necessary to assess the potential of these new satellites for forest inventory practices.

The value of using local statistics in the estimations of forest remote sensing has been stressed by Kilpeläinen and Tokola (1999); Tuominen and Pekkarinen (2005); Wing et al. (2015); Wolter et al. (2009). Using the area that surrounds the pixel, as well as using image objects/segments or vector data to construct explanatory variables from remote sensing data adds context to the single pixel measurements. It allows us to use texture. Haralick (1979) divided the texture in image data into either statistical or structural. Statistical texture describes the statistical distribution of values. Structural texture describes the spatial distribution of val-

ues. Examples of statistical texture measures are the average of pixel values within the area of interest (Tuominen and Pekkarinen, 2005) and local variance (Coops and Culvenor, 2000; Wolter et al., 2009). Examples of structural texture measures used in forest remote sensing are locally calculated variograms and correlograms (Muinonen et al., 2001) and local Moran's I spatial auto-correlation (Purkis et al., 2006). Both types of texture measures can be calculated with LSTATS software that was introduced in **Ref. II**. The claim that one can find local statistics that are not widely used, but could be useful in forest remote sensing, was the major motivation to perform the analyses and write article **Ref. II**. The distinctive local statistics of LSTATS for forest remote sensing are elaborated in section 3.1.

The quantity of NFI data is huge and it is ever growing. At the same time the volumes of remote sensing data are also increasing and the capabilities of creating new features based on the remote sensing data are advancing. This leads to a situation where machine learning methods that are effectively capable of exploiting these resources are being increasingly applied in remote sensing studies and applications. A study to test the hypothesis that machine-learning-based remote sensing approach can give estimates with high accuracy using large NFI data set, Landsat 7 images and true colour orthophotos was carried out and described in **Ref. III**. Section 3.2 sums up this research and discusses the results.

### **3.1. Local statistics for forest remote sensing**

Higher resolution allows to have more measurements or pixels per study object. This in turn makes the use of local statistics more attractive. A study to review the LSTATS software and to test the claim that one can find not widely used local statistics that could be useful in forest remote sensing was carried out in North-Estonia (Figure 1) **Ref. II**. Goal was to look for and review LSTATS specific functions not commonly used in other software packages. 0.4 m true colour orthophotos from June and July 2002 were used. To get information about the forest stands being analysed stand-based forest inventory data from 2001 and 2002 were used. Test sites were areas with diverse canopies within a small area and where the special properties of structural texture statistics are revealed. The specific functions for numerical variables were searched analysing three common GIS software packages: IDRISI, ArcGIS Desktop, Definiens Developer. Specific functions of LSTATS were tested on forest stands. Functions from the reference software packages with most similar properties compared to LSTATS specific statistics were tested on the same areas. Currently the functions for calculating local statistics are used in Constud application and in an online calculator (Remm, 2014). Source code of LSTATS functions is freely available from the online calculator.

#### **3.1.1. Summary of the study results and discussion**

Ten local statistics for numerical variables were detected that were specific to LSTATS software. Most of these were structural texture indices: stripedness,

gradient direction, gradient strength, Moran's I, Moran's I weighted by the reverse value of distance, difference between centre and boundary, homogeneity of neighbours. The statistical texture indices were: share of values exceeding the local mean, coefficient of variation and factor of kurtosis. Based on the visual analyses with the use of forest inventory data as reference, it was concluded that local statistics of LSTATS could be helpful in the following forest remote sensing tasks: distinguishing shadowed management passages/strips (list of local statistics: Moran's I, Moran's I weighted by the reverse value of distance and difference between centre and boundary); isolating groups of tree crowns (Moran's I weighted by the reverse value of distance); allocating clearings (homogeneity of neighbours, share of values exceeding the local mean and coefficient of variation); delineating spruce canopies in forest (homogeneity of neighbours).

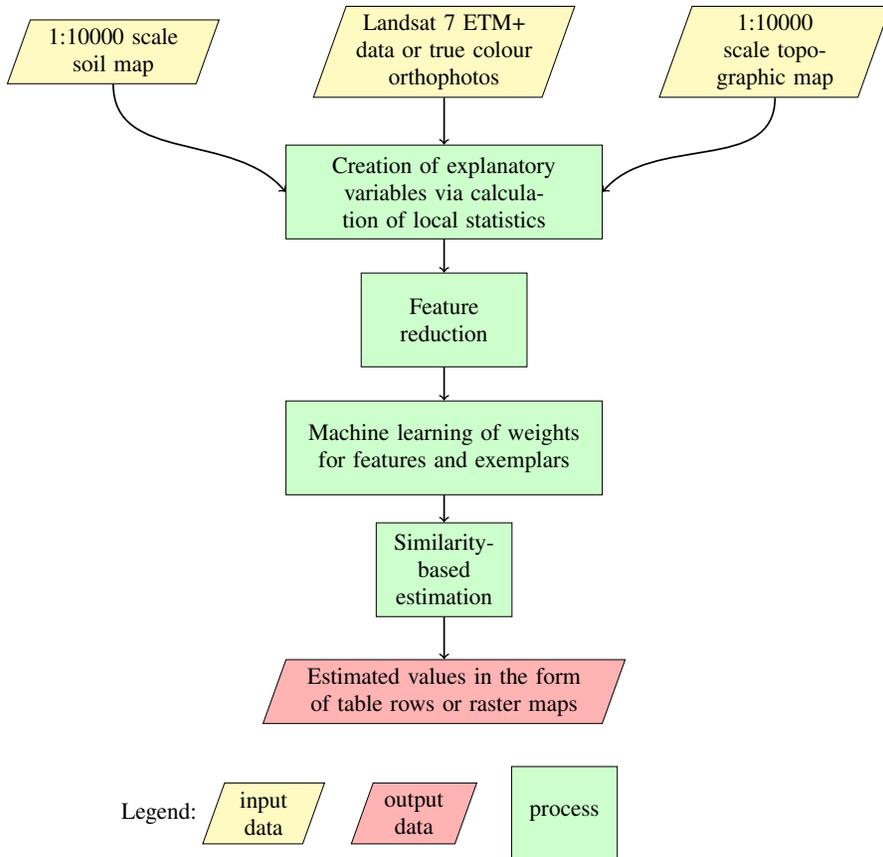
Ke and Quackenbush (2011) reviewed methods for automatic individual tree-crown detection from passive remote sensing data and concluded that most of algorithms use single band data. Smoothing Gaussian filters are often used in pre-processing of the images. The use of structural texture indicators, such as Moran's I weighted by the reverse value of distance, could add valuable information for tree-crown detection.

Image- or photo-interpretation has been developed by empirical experience for more than 150 years and is still widely used (Jensen, 2014). For example, Bastin et al. (2017) recently estimated global forest extent in dryland biomes based on the photo-interpretation of more than 210000 0.5 ha sample plots. Besides the use of kernel-based local statistic maps described in previous paragraph in the automated remote sensing systems, they could also provide helpful ancillary information to conduct a photo-interpretation task over forested areas. In the context of this thesis the results of **Ref. II** showed that local statistics are applicable for remote sensing of forests using true colour orthophotos.

### 3.2. Estimating the parameters of forest inventory

A study was carried out **Ref. III** to test the following hypotheses: first cluster analyses can be used for reduction of remote sensing features; second remote sensing approach that is based on machine learning can give estimates with high accuracy using large NFI data set, Landsat 7 images and true colour orthophotos. The goal was to analyse the use of a machine learning application for the estimation of NFI parameters (Figure 3). Landsat 7 ETM+ from 6-th of July 2001 data with 30 m spatial resolution and true colour orthophotos from June and July 2002 with 1 m resolution together with basic and soil maps were used. The following inventory parameters from the NFI stands were involved in the experiment: the dominant tree species according to tree stem volume in the primary layer, maturity classes, mean annual increment of the stand volume and stand volume. Training and validation data were created: 1846 randomly located sample points on orthophotos for training and 712 for validation; 969 points on the satellite image for training and 660 points for validation. A study area in the northern part of

Estonia was chosen for the experiment (Figure 1). Local statistics were computed for all possible combinations of the radii of the kernels (from 10 to 50 m) and input bands. The following local statistics were used: locally calculated average, the proportion over the average, the standard deviation, the coefficient of variation, the mode from statistical texture indicators and the auto-correlation index Moran's I and Moran's I weighted with the reverse value of distance from structural texture indicators.



**Figure 3.** Flowchart of the forest parameters estimation chain used in study **Ref. III**.

In the experiment the MLNN software (Remm, 2004) was used for machine learning and the LSTATS software (Remm, 2005) for calculating local statistics. Currently both have been combined into Constud software described first in (Remm and Remm, 2008). The machine learning software is using case-based reasoning (CBR) methodology that is especially capable in circumstances where a large number of measurements on a complicated predictable variable exist. It was able to estimate different types of dependent variables: continuous, multi- and binomial and complex characteristics (e.g. stand formula in forest). The CBR methodology is also known as similarity-based reasoning. It has been defined

as a multidisciplinary science that is based on the usage of former experiences at a minimal level of generalisation (Aha, 1998). The MLNN machine learning process of a dependent variable is an iterative search for the best set of weights for exemplars and for features (explanatory variables). The leave-one-out cross-validation (LOOC) indicator is used in the machine learning process to measure the accuracy of a given set of exemplar and feature weights. The principle of LOOC is that the predicted value for every training instance is calculated using all other instances, leaving the current instance out. A more comprehensive description of the machine learning process can be found from Constud tutorial (Remm and Kelviste, 2011).

### 3.2.1. Reduction of features

Large number of features can be composed when combining statistics, radii and input bands — in this study 150 features. To simplify and optimise the learning process a preliminary feature selection could be used. Principal components analysis (PCA) is a widely used method for the reduction of data dimensionality (Castro-Esau et al., 2004; Chica-Olmo and Abarca-Hernandez, 2000; Mohammed et al., 2011; Ranson et al., 2001) and correlation matrices have commonly been used in feature pre-selection (Tuominen and Pekkarinen, 2005). Li et al. (2012) proposed alternative feature reduction framework called locality-preserving dimensionality reduction and demonstrated that it outperforms several traditional alternatives for feature reduction.

PCA generalises raw variables into smaller number of linearly uncorrelated synthetic variables that are called principal components. It is difficult to interpret and to use these components when the input variables have updated values from new measurements. It is challenging to use very large correlation matrices like  $150 \times 150$  features in study **Ref. III**. Also different parameters of statistical correspondence have to be used to compare nominal and continuous variables. In this study this led to the decision to use cluster analysis (k-means clustering algorithm) and regression analysis in the comparison of feature reduction methods instead of PCA. The goal of feature reduction in this study was to decrease the number of explanatory variables from 150 to 30 with different methods and then compare accuracy of estimations with Student's *t*-test and  $\kappa$ -analyses (Congalton and Green, 2009).

### 3.2.2. Summary of the study results and discussion

The cluster analysis can be used for the feature reduction method and was chosen because it can handle both nominal and numerical data. 30 explanatory variables were chosen out of 150 and a CBR-based machine learning estimation was conducted. In both cases, when using orthophotos or Landsat images, the stand volume in the primary layer (the stand-based accuracy  $76.54 \text{ m}^3 \text{ ha}^{-1}$  (41 %) RMSE and  $74.64 \text{ m}^3 \text{ ha}^{-1}$  (36 %) RMSE respectively) and dominant tree species ( $\kappa = 0.38$  and  $\kappa = 0.41$  respectively) were recognised more accurately than the the maturity

class of the forest stand and the mean annual increment of stand volume. The most valuable feature from orthophotos was the average saturation value of image colour within a 30-m radius. From the satellite images the standard deviation of ETM+ band 6.2 within a radius of 80 m was most useful. Features that use Moran's I weighted with the reverse value of the distance obtained relatively high indicator values.

Using orthophotos with near-infrared channel and locally calculated variograms for estimating stand volume Muinonen et al. (2001) have reported stand-level accuracy of 18 to 27 % RMSE. Avitabile and Camia (2018) assessed four Europe-wide remote-sensing-based forest maps using harmonised NFI statistics from 26 countries. The national-level accuracy of the maps ranged from 29 % to 40 % RMSE and the pixel-level accuracy from 58 % to 67 % RMSE. In this study forest attribute maps were created with the stand-level accuracy of 39 % RMSE for stand volume and 43 % RMSE for the stand mean annual increment. In the context of this thesis it can be concluded that machine-learning-based remote sensing approach analysed in **Ref. III** did not give estimates with high accuracy. Still moderate accuracy reaching 36 % RMSE for stand volume was achieved.

## CONCLUSIONS

This thesis studies approaches for remote sensing of grasslands and forests based on local statistics. The capability of modern hardware and software to effectively process large image data sets allows to use local statistics to improve remote sensing estimations more than before. Locally computed statistics are a fundamental part of GEOBIA that is one of the hot topics in current remote sensing research. The work is presented in three chapters. Chapter I gives an overview about recent developments in remote sensing research in general, trends in the domains of remote sensing of agricultural areas and forests and in the field of local statistics in remote sensing of vegetation. Chapter II focuses on monitoring of grasslands with SAR. Chapter III is devoted to monitoring of forests with optical sensors.

It is shown that there is potential to develop mowing detection algorithms and applications using C-band SAR temporal interferometric coherence. The results demonstrate that after a mowing event, median VH and VV polarisation 12-day interferometric coherence values are statistically significantly higher than those from before the event. The sooner after the mowing event the first interferometric acquisition is taken, the higher the coherence. Morning dew, precipitation, farming activities, such as sowing or ploughing, high residual straws after the cut and rapid growth of grass are causing the coherence to decrease and impede the distinction of a mowing event. In the future, six-day interferometric coherence should also be analysed in relation to mowing events to alleviate some of these factors. Nevertheless, the results presented in this thesis offer a strong basis for further research and development activities towards the practical use of spaceborne C-band SAR data for mowing detection.

The use of following local statistics: Moran's I, Moran's I weighted by the reverse value of distance, difference between centre and boundary, homogeneity of neighbours, share of values exceeding the local mean and coefficient of variation can be useful for estimation of forest parameters from true colour orthophotos. These statistics could also add helpful ancillary information to conduct photo-interpretation tasks over forested areas.

With the estimation of NFI data it is demonstrated that the case-based reasoning (a machine learning method) is well suited for empirical solutions of remote sensing tasks where there are many different data sources available. In addition, cluster analysis can be used as pre-selection method for the reduction of remote sensing features. Locally computed average is the most useful feature when compared to different texture indicators. It is concluded that the use of local statistics adds valuable data to pixel-based remote sensing estimations.

## REFERENCES

- Adams, J. R., Rowlandson, T. L., McKeown, S. J., Berg, A. A., McNairn, H., and Sweeney, S. J. (2013). Evaluating the Cloude-Pottier and Freeman-Durden scattering decompositions for distinguishing between unharvested and post-harvest agricultural fields. *CANADIAN JOURNAL OF REMOTE SENSING*, 39(4):318–327.
- Aha, D. (1998). The omnipresence of case-based reasoning in science and application. *KNOWLEDGE-BASED SYSTEMS*, 11(5-6):261–273. 17th SGES International Conference on Knowledge-Based Systems and Applied Artificial Intelligence (Expert Systems 97), CAMBRIDGE, ENGLAND, DEC 15-17, 1997.
- Ahmed, R., Siqueira, P., Hensley, S., Chapman, B., and Bergen, K. (2011). A survey of temporal decorrelation from spaceborne L-Band repeat-pass InSAR. *REMOTE SENSING OF ENVIRONMENT*, 115(11, SI):2887–2896.
- Askne, J. I. H., Dammert, P. B. G., Ulander, L. M. H., and Smith, G. (1997). C-band repeat-pass interferometric sar observations of the forest. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, 35(1):25–35.
- Atzberger, C. (2013). Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs. *REMOTE SENSING*, 5(2):949–981.
- Avitabile, V. and Camia, A. (2018). An assessment of forest biomass maps in Europe using harmonized national statistics and inventory plots. *FOREST ECOLOGY AND MANAGEMENT*, 409:489–498.
- Baghdadi, N., Boyer, N., Todoroff, P., El Hajj, M., and Begue, A. (2009). Potential of SAR sensors TerraSAR-X, ASAR/ENVISAT and PALSAR/ALOS for monitoring sugarcane crops on Reunion Island. *REMOTE SENSING OF ENVIRONMENT*, 113(8):1724–1738.
- Ball, J. E., Anderson, D. T., and Chan, C. S. (2017). Comprehensive survey of deep learning in remote sensing: theories, tools, and challenges for the community. *JOURNAL OF APPLIED REMOTE SENSING*, 11.
- Barrett, B., Nitze, I., Green, S., and Cawkwell, F. (2014). Assessment of multi-temporal, multi-sensor radar and ancillary spatial data for grasslands monitoring in Ireland using machine learning approaches. *REMOTE SENSING OF ENVIRONMENT*, 152:109–124.
- Bastin, J.-F., Berrahmouni, N., Grainger, A., Maniatis, D., Mollicone, D., Moore, R., Patriarca, C., Picard, N., Sparrow, B., Abraham, E. M., Aloui, K., Atesoglu, A., Attorre, F., Bassullu, C., Bey, A., Garzuglia, M., Garcia-Montero, L. G., Groot, N., Guerin, G., Laestadius, L., Lowe, A. J., Mamane, B., Marchi, G., Patterson, P., Rezende, M., Ricci, S., Salcedo, I., Diaz, A. S.-P., Stolle, F., Surappaeva, V., and Castro, R. (2017). The extent of forest in dryland biomes. *SCIENCE*, 356(6338):635+.

- Beaudoin, A., Bernier, P. Y., Guindon, L., Villemaire, P., Guo, X. J., Stinson, G., Bergeron, T., Magnussen, S., and Hall, R. J. (2014). Mapping attributes of Canada's forests at moderate resolution through kNN and MODIS imagery. *CANADIAN JOURNAL OF FOREST RESEARCH-REVUE CANADIENNE DE RECHERCHE FORESTIERE*, 44(5):521–532.
- Begue, A., Arvor, D., Bellon, B., Betbeder, J., de Abelleira, D., Ferraz, R. P. D., Lebourgeois, V., Lelong, C., Simoes, M., and Veron, S. R. (2018). Remote Sensing and Cropping Practices: A Review. *REMOTE SENSING*, 10(1).
- Belgiu, M. and Dragut, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 114:24–31.
- Bhardwaj, A., Sam, L., Akanksha, Javier Martin-Torres, F., and Kumar, R. (2016). UAVs as remote sensing platform in glaciology: Present applications and future prospects. *REMOTE SENSING OF ENVIRONMENT*, 175:196–204.
- Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 65(1):2–16.
- Blaschke, T., Hay, G. J., Kelly, M., Lang, S., Hofmann, P., Addink, E., Feitosa, R. Q., van der Meer, F., van der Werff, H., van Coillie, F., and Tiede, D. (2014). Geographic Object-Based Image Analysis - Towards a new paradigm. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 87:180–191.
- Boots, B. and Okabe, A. (2007). Local statistical spatial analysis: Inventory and prospect. *INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE*, 21(4):355–375.
- Bouman, B. A. and van Kasteren, H. W. (1990). Ground-based x-band (3-cm wave) radar backscattering of agricultural crops. ii. wheat, barley, and oats; the impact of canopy structure. *REMOTE SENSING OF ENVIRONMENT*, 34(2):107–119.
- Castro-Esau, K., Sanchez-Azofeifa, G., and Caelli, T. (2004). Discrimination of lianas and trees with leaf-level hyperspectral data. *REMOTE SENSING OF ENVIRONMENT*, 90(3):353–372.
- Chan, S. K., Bindlish, R., O'Neill, P. E., Njoku, E., Jackson, T., Colliander, A., Chen, F., Burgin, M., Dunbar, S., Piepmeier, J., Yueh, S., Entekhabi, D., Cosh, M. H., Caldwell, T., Walker, J., Wu, X., Berg, A., Rowlandson, T., Pacheco, A., McNairn, H., Thibeault, M., Martinez-Fernandez, J., Gonzalez-Zamora, A., Seyfried, M., Bosch, D., Starks, P., Goodrich, D., Prueger, J., Palecki, M., Small, E. E., Zreda, M., Calvet, J.-C., Crow, W. T., and Kerr, Y. (2016). Assessment of the SMAP Passive Soil Moisture Product. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, 54(8):4994–5007.
- Chen, G., Hay, G. J., Carvalho, L. M. T., and Wulder, M. A. (2012). Object-based change detection. *INTERNATIONAL JOURNAL OF REMOTE SENSING*, 33(14):4434–4457.
- Cheng, G. and Han, J. (2016). A survey on object detection in optical remote sensing images. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 117:11–28.
- Chica-Olmo, M. and Abarca-Hernandez, F. (2000). Computing geostatistical image texture for remotely sensed data classification. *COMPUTERS & GEOSCIENCES*,

- 26(4):373–383. Annual Conference of the Royal-Geographical-Society/Institute-of-British-Geographers, UNIV EXETER, EXETER, ENGLAND, JAN, 1997.
- Colomina, I. and Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing: A review. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 92:79–97.
- Congalton, R. G. and Green, K. (2009). *Assessing the accuracy of remotely sensed data: principles and practices 2nd ed.* Taylor and Francis Group.
- Coops, N. and Culvenor, D. (2000). Utilizing local variance of simulated high spatial resolution imagery to predict spatial pattern of forest stands. *REMOTE SENSING OF ENVIRONMENT*, 71(3):248–260.
- Dassot, M., Constant, T., and Fournier, M. (2011). The use of terrestrial LiDAR technology in forest science: application fields, benefits and challenges. *ANNALS OF FOREST SCIENCE*, 68(5, SI):959–974.
- Dobson, M., Pierce, L., Sarabandi, K., Ulaby, F., and Sharik, T. (1992). PRELIMINARY-ANALYSIS OF ERS-1 SAR FOR FOREST ECOSYSTEM STUDIES. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, 30(2):203–211.
- Dong, J. and Xiao, X. (2016). Evolution of regional to global paddy rice mapping methods: A review. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 119:214–227.
- Dusseux, P., Corpetti, T., Hubert-Moy, L., and Corgne, S. (2014). Combined use of multi-temporal optical and radar satellite images for grassland monitoring. *REMOTE SENSING*, 6(7):6163–6182.
- Dutra, L. and Huber, R. (1999). Feature extraction and selection for ERS-1/2 InSAR classification. *INTERNATIONAL JOURNAL OF REMOTE SENSING*, 20(5):993–1016.
- El Hajj, M., Baghdadi, N., Belaud, G., Zribi, M., Cheviron, B., Courault, D., Hagolle, O., and Charron, F. (2014). Irrigated Grassland Monitoring Using a Time Series of TerraSAR-X and COSMO-SkyMed X-Band SAR Data. *REMOTE SENSING*, 6(10):10002–10032.
- Entekhabi, D., Njoku, E. G., O’Neill, P. E., Kellogg, K. H., Crow, W. T., Edelstein, W. N., Entin, J. K., Goodman, S. D., Jackson, T. J., Johnson, J., Kimball, J., Piepmeier, J. R., Koster, R. D., Martin, N., McDonald, K. C., Moghaddam, M., Moran, S., Reichle, R., Shi, J. C., Spencer, M. W., Thurman, S. W., Tsang, L., and Van Zyl, J. (2010). The Soil Moisture Active Passive (SMAP) Mission. *PROCEEDINGS OF THE IEEE*, 98(5):704–716.
- ESA (2013). *Sentinel-1 User Handbook*. European Space Agency. [https://sentinel.esa.int/documents/247904/685163/Sentinel-1\\_User\\_Handbook](https://sentinel.esa.int/documents/247904/685163/Sentinel-1_User_Handbook) [Accessed: 25 April 2017].
- Fassnacht, F. E., Latifi, H., Sterenczak, K., Modzelewska, A., Lefsky, M., Waser, L. T., Straub, C., and Ghosh, A. (2016). Review of studies on tree species classification from remotely sensed data. *REMOTE SENSING OF ENVIRONMENT*, 186:64–87.
- Franco-Lopez, H., Ek, A., and Bauer, M. (2001). Estimation and mapping of forest stand density, volume, and cover type using the k-nearest neighbors method. *REMOTE SENSING OF ENVIRONMENT*, 77(3):251–274.
- Gago, J., Douthe, C., Coopman, R. E., Gallego, P. P., Ribas-Carbo, M., Flexas, J.,

- Escalona, J., and Medrano, H. (2015). UAVs challenge to assess water stress for sustainable agriculture. *AGRICULTURAL WATER MANAGEMENT*, 153:9–19.
- Getis, A. and Aldstadt, J. (2004). Constructing the spatial weights matrix using a local statistic. *GEOGRAPHICAL ANALYSIS*, 36(2):90–104. North American Meeting of the Regional-Science-Association-International, San Juan, PR, NOV, 2002.
- Gleason, C. J. and Im, J. (2011). A Review of Remote Sensing of Forest Biomass and Biofuel: Options for Small-Area Applications. *GISCIENCE & REMOTE SENSING*, 48(2):141–170.
- Glenn, E. P., Nagler, P. L., and Huete, A. R. (2010). Vegetation Index Methods for Estimating Evapotranspiration by Remote Sensing. *SURVEYS IN GEOPHYSICS*, 31(6):531–555.
- Gomez, C., White, J. C., and Wulder, M. A. (2016). Optical remotely sensed time series data for land cover classification: A review. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 116:55–72.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *REMOTE SENSING OF ENVIRONMENT*, 202:18–27.
- Gowda, P. H., Chavez, J. L., Colaizzi, P. D., Evett, S. R., Howell, T. A., and Tolk, J. A. (2008). ET mapping for agricultural water management: present status and challenges. *IRRIGATION SCIENCE*, 26(3):223–237.
- Grainger, A. (2017). Citizen Observatories and the New Earth Observation Science. *REMOTE SENSING*, 9(2).
- Han, J., Zhang, D., Cheng, G., Guo, L., and Ren, J. (2015). Object Detection in Optical Remote Sensing Images Based on Weakly Supervised Learning and High-Level Feature Learning. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, 53(6):3325–3337.
- Hansen, M. C. and Loveland, T. R. (2012). A review of large area monitoring of land cover change using Landsat data. *REMOTE SENSING OF ENVIRONMENT*, 122(SI):66–74.
- Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., and Townshend, J. R. G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *SCIENCE*, 342(6160):850–853.
- Hanssen, R. F. (2001). *Radar interferometry: data interpretation and error analysis*, volume 2. Springer Science & Business Media.
- Haralick, R. M. (1979). Statistical and structural approaches to texture. *PROCEEDINGS OF THE IEEE*, 67(5):786–804.
- Haralick, R. M., Shanmugam, K., and Dinstein, I. (1973). Textural features for image classification. *IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS*, 3(6):610–621.
- Hassan-Esfahani, L., Torres-Rua, A., Jensen, A., and McKee, M. (2015). Assessment of Surface Soil Moisture Using High-Resolution Multi-Spectral Imagery and Artificial Neural Networks. *REMOTE SENSING*, 7(3):2627–2646.
- Heistermann, M., Jacobi, S., and Pfaff, T. (2013). Technical note: An open source library

- for processing weather radar data (wradlib). *HYDROLOGY AND EARTH SYSTEM SCIENCES*, 17(2):863–871.
- Hoekman, D. and Vissers, M. (2003). A new polarimetric classification approach evaluated for agricultural crops. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, 41(12, 1):2881–2889.
- Hornacek, M., Wagner, W., Sabel, D., Truong, H.-L., Snoeij, P., Hahmann, T., Diedrich, E., and Doubkova, M. (2012). Potential for High Resolution Systematic Global Surface Soil Moisture Retrieval via Change Detection Using Sentinel-1. *IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING*, 5(4, SI):1303–1311.
- Huang, Y., Thomson, S. J., Hoffmann, W. C., Lan, Y., and Fritz, B. K. (2013). Development and prospect of unmanned aerial vehicle technologies for agricultural production management. *INTERNATIONAL JOURNAL OF AGRICULTURAL AND BIOLOGICAL ENGINEERING*, 6(3):1–10.
- Hughes, J. N., Annex, A., Eichelberger, C. N., Fox, A., Hulbert, A., and Ronquest, M. (2015). Geo Mesa: a distributed architecture for spatio-temporal fusion. In Pellechia, MF and Palaniappan, K and Doucette, PJ and Dockstader, SL and Seetharaman, G, editor, *GEOSPATIAL INFORMATICS, FUSION, AND MOTION VIDEO ANALYTICS V*, volume 9473 of *Proceedings of SPIE*. SPIE. Conference on Geospatial Informatics, Fusion, and Motion Video Analytics V, Baltimore, MD, APR 20-21, 2015.
- Hunter, J. D. et al. (2007). Matplotlib: A 2d graphics environment. *COMPUTING IN SCIENCE AND ENGINEERING*, 9(3):90–95.
- Hussain, M., Chen, D., Cheng, A., Wei, H., and Stanley, D. (2013). Change detection from remotely sensed images: From pixel-based to object-based approaches. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 80:91–106.
- Hyypä, J., Hyypä, H., Leckie, D., Gougeon, F., Yu, X., and Maltamo, M. (2008). Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. *INTERNATIONAL JOURNAL OF REMOTE SENSING*, 29(5):1339–1366. Workshop on 3D Remote Sensing in Forestry, Univ Nat Resources & Appl Life Sci, Vienna, AUSTRIA, FEB, 2006.
- Inglada, J. and Mercier, G. (2007). A new statistical similarity measure for change detection in multitemporal SAR images and its extension to multiscale change analysis. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, 45(5, 2):1432–1445.
- Jensen, J. R. (2014). *Remote Sensing of the Environment: An Earth Resource Perspective Pearson New International Edition*. Pearson Education Limited.
- Jeppesen, J. H., Ebeid, E., Jacobsen, R. H., and Toftegaard, T. S. (2018). Open geospatial infrastructure for data management and analytics in interdisciplinary research. *COMPUTERS AND ELECTRONICS IN AGRICULTURE*, 145:130–141.
- Johnson, B. and Xie, Z. (2011). Unsupervised image segmentation evaluation and refinement using a multi-scale approach. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 66(4):473–483.
- Just, D. and Bamler, R. (1994). Phase statistics of interferograms with applications to synthetic aperture radar. *APPLIED OPTICS*, 33(20):4361–4368.

- Kang, S., Xu, Y., You, Q., Fluegel, W.-A., Pepin, N., and Yao, T. (2010). Review of climate and cryospheric change in the Tibetan Plateau. *ENVIRONMENTAL RESEARCH LETTERS*, 5(1).
- Ke, Y. and Quackenbush, L. J. (2011). A review of methods for automatic individual tree-crown detection and delineation from passive remote sensing. *INTERNATIONAL JOURNAL OF REMOTE SENSING*, 32(17):4725–4747.
- Khanal, S., Fulton, J., and Shearer, S. (2017). An overview of current and potential applications of thermal remote sensing in precision agriculture. *COMPUTERS AND ELECTRONICS IN AGRICULTURE*, 139:22–32.
- Khorrarn, S., Koch, F. H., van der Wiele, C. F., and Nelson, S. A. (2012). *Remote sensing*. Springer Science & Business Media.
- Kilpeläinen, P. and Tokola, T. (1999). Gain to be achieved from stand delineation in landsat tm image-based estimates of stand volume. *FOREST ECOLOGY AND MANAGEMENT*, 124(2-3):105–111.
- Kornelsen, K. C. and Coulibaly, P. (2013). Advances in soil moisture retrieval from synthetic aperture radar and hydrological applications. *JOURNAL OF HYDROLOGY*, 476:460–489.
- Korpela, I., Orka, H. O., Maltamo, M., Tokola, T., and Hyyppä, J. (2010). Tree Species Classification Using Airborne LiDAR - Effects of Stand and Tree Parameters, Downsizing of Training Set, Intensity Normalization, and Sensor Type. *SILVA FENNICA*, 44(2):319–339.
- Kuenzer, C. and Knauer, K. (2013). Remote sensing of rice crop areas. *INTERNATIONAL JOURNAL OF REMOTE SENSING*, 34(6):2101–2139.
- Kuusik, A. and Nilson, T. (2000). A directional multispectral forest reflectance model. *REMOTE SENSING OF ENVIRONMENT*, 72(2):244–252.
- Latifi, H., Nothdurft, A., and Koch, B. (2010). Non-parametric prediction and mapping of standing timber volume and biomass in a temperate forest: application of multiple optical/LiDAR-derived predictors. *FORESTRY*, 83(4):395–407.
- Lautenbacher, C. C. (2006). The global earth observation system of systems: science serving society. *SPACE POLICY*, 22(1):8–11.
- Le Toan, T., Quegan, S., Davidson, M. W. J., Balzter, H., Paillou, P., Papathanassiou, K., Plummer, S., Rocca, F., Saatchi, S., Shugart, H., and Ulander, L. (2011). The BIOMASS mission: Mapping global forest biomass to better understand the terrestrial carbon cycle. *REMOTE SENSING OF ENVIRONMENT*, 115(11, SI):2850–2860.
- Lee, J.-S. (1980). Digital image-enhancement and noise filtering by use of local statistics. *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE*, 2(2):165–168.
- Li, S., Dragicevic, S., Castro, F. A., Sester, M., Winter, S., Coltekin, A., Pettit, C., Jiang, B., Haworth, J., Stein, A., and Cheng, T. (2016). Geospatial big data handling theory and methods: A review and research challenges. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 115:119–133.
- Li, W., Prasad, S., Fowler, J. E., and Bruce, L. M. (2012). Locality-Preserving Dimensionality Reduction and Classification for Hyperspectral Image Analysis. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, 50(4):1185–1198.

- Li, Z.-L., Tang, B.-H., Wu, H., Ren, H., Yan, G., Wan, Z., Trigo, I. F., and Sobrino, J. A. (2013). Satellite-derived land surface temperature: Current status and perspectives. *REMOTE SENSING OF ENVIRONMENT*, 131:14–37.
- Liang, X., Kankare, V., Hyypä, J., Wang, Y., Kukko, A., Haggren, H., Yu, X., Kaartinen, H., Jaakkola, A., Guan, F., Holopainen, M., and Vastaranta, M. (2016). Terrestrial laser scanning in forest inventories. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 115:63–77.
- Mas, J. F. and Flores, J. J. (2008). The application of artificial neural networks to the analysis of remotely sensed data. *INTERNATIONAL JOURNAL OF REMOTE SENSING*, 29(3):617–663.
- Maxwell, A. E., Warner, T. A., and Fang, F. (2018). Implementation of machine-learning classification in remote sensing: an applied review. *INTERNATIONAL JOURNAL OF REMOTE SENSING*, 39(9):2784–2817.
- McRoberts, R. E., Tomppo, E. O., and Naesset, E. (2010). Advances and emerging issues in national forest inventories. *SCANDINAVIAN JOURNAL OF FOREST RESEARCH*, 25(4):368–381.
- Mercier, G., Moser, G., and Serpico, S. B. (2008). Conditional copulas for change detection in heterogeneous remote sensing images. *IEEE TRANSACTIONS ON GEO-SCIENCE AND REMOTE SENSING*, 46(5):1428–1441.
- Mohammed, A. A., Minhas, R., Wu, Q. M. J., and Sid-Ahmed, M. A. (2011). Human face recognition based on multidimensional PCA and extreme learning machine. *PATTERN RECOGNITION*, 44(10-11, SI):2588–2597.
- Mohanty, B. P., Cosh, M. H., Lakshmi, V., and Montzka, C. (2017). Soil Moisture Remote Sensing: State-of-the-Science. *VADOSE ZONE JOURNAL*, 16(1).
- Montaghi, A., Corona, P., Dalponte, M., Gianelle, D., Chirici, G., and Olsson, H. (2013). Airborne laser scanning of forest resources: An overview of research in Italy as a commentary case study. *INTERNATIONAL JOURNAL OF APPLIED EARTH OBSERVATION AND GEOINFORMATION*, 23:288–300.
- Moreau, S. and Le Toan, T. (2003). Biomass quantification of Andean wetland forages using ERS satellite SAR data for optimizing livestock management. *REMOTE SENSING OF ENVIRONMENT*, 84(4):477–492.
- Mountrakis, G., Im, J., and Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 66(3):247–259.
- Muinonen, E., Maltamo, M., Hyppänen, H., and Vainikainen, V. (2001). Forest stand characteristics estimation using a most similar neighbor approach and image spatial structure information. *REMOTE SENSING OF ENVIRONMENT*, 78(3):223–228.
- Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *BIOSYSTEMS ENGINEERING*, 114(4, SI):358–371. International Symposium on Sensing in Agriculture in Memory of Dahlia Greidinger (AGRI-SENSING), Haifa, ISRAEL, FEB, 2011.
- Nativi, S., Mazzetti, P., Santoro, M., Papeschi, F., Craglia, M., and Ochiai, O. (2015). Big Data challenges in building the Global Earth Observation System of Systems. *ENVIRONMENTAL MODELLING & SOFTWARE*, 68:1–26.

- Pebesma, E. (2004). Multivariable geostatistics in S: the gstat package. *COMPUTERS & GEOSCIENCES*, 30(7):683–691.
- Peng, J., Loew, A., Merlin, O., and Verhoest, N. E. C. (2017). A review of spatial downscaling of satellite remotely sensed soil moisture. *REVIEWS OF GEOPHYSICS*, 55(2):341–366.
- Purkis, S., Myint, S., and Riegl, B. (2006). Enhanced detection of the coral *Acropora cervicornis* from satellite imagery using a textural operator. *REMOTE SENSING OF ENVIRONMENT*, 101(1):82–94.
- Ranson, K., Sun, G., Kharuk, V., and Kovacs, K. (2001). Characterization of forests in Western Sayani Mountains, Siberia from SIR-C SAR data. *REMOTE SENSING OF ENVIRONMENT*, 75(2):188–200.
- Remm, K. (2004). Case-based predictions for species and habitat mapping. *ECOLOGICAL MODELLING*, 177(3-4):259–281.
- Remm, K. (2005). Correlations between forest stand diversity and landscape pattern in otepää nature park, estonia. *JOURNAL FOR NATURE CONSERVATION*, 13(2):137–145.
- Remm, K. (2014). An online calculator for spatial data and its applications. *COMPUTATIONAL ECOLOGY AND SOFTWARE*, 4(1):22.
- Remm, K. and Kelviste, T. (2011). *Constud Tutorial*. Chair of Geoinformatics and Cartography, University of Tartu.
- Remm, M. and Remm, K. (2008). Case-based estimation of the risk of enterobiasis. *ARTIFICIAL INTELLIGENCE IN MEDICINE*, 43(3):167–177.
- Richards, J. A. (2012). *Remote Sensing Digital Image Analysis: An Introduction*. Springer Science & Business Media.
- Romero, A., Gatta, C., and Camps-Valls, G. (2016). Unsupervised Deep Feature Extraction for Remote Sensing Image Classification. *IEEE TRANSACTIONS ON GEO-SCIENCE AND REMOTE SENSING*, 54(3):1349–1362.
- Rosenberg, M. S. and Anderson, C. D. (2011). PASSaGE: Pattern Analysis, Spatial Statistics and Geographic Exegesis. Version 2. *METHODS IN ECOLOGY AND EVOLUTION*, 2(3):229–232.
- Salami, E., Barrado, C., and Pastor, E. (2014). UAV Flight Experiments Applied to the Remote Sensing of Vegetated Areas. *REMOTE SENSING*, 6(11):11051–11081.
- Santoro, M., Askne, J., Smith, G., and Fransson, J. E. S. (2002). Stem volume retrieval in boreal forests from ers-1/2 interferometry. *REMOTE SENSING OF ENVIRONMENT*, 81(1):19–35.
- Schellberg, J., Hill, M. J., Gerhards, R., Rothmund, M., and Braun, M. (2008). Precision agriculture on grassland: Applications, perspectives and constraints. *EUROPEAN JOURNAL OF AGRONOMY*, 29(2-3):59–71.
- Schuster, C., Ali, I., Lohmann, P., Frick, A., Foerster, M., and Kleinschmit, B. (2011). Towards Detecting Swath Events in TerraSAR-X Time Series to Establish NATURA 2000 Grassland Habitat Swath Management as Monitoring Parameter. *REMOTE SENSING*, 3(7):1308–1322.
- Schuster, C., Schmidt, T., Conrad, C., Kleinschmit, B., and Foerster, M. (2015). Grassland habitat mapping by intra-annual time series analysis - Comparison of RapidEye

- and TerraSAR-X satellite data. *INTERNATIONAL JOURNAL OF APPLIED EARTH OBSERVATION AND GEOINFORMATION*, 34:25–34.
- Sinha, S., Jeganathan, C., Sharma, L. K., and Nathawat, M. S. (2015). A review of radar remote sensing for biomass estimation. *INTERNATIONAL JOURNAL OF ENVIRONMENTAL SCIENCE AND TECHNOLOGY*, 12(5):1779–1792.
- Steele-Dunne, S. C., McNairn, H., Monsivais-Huertero, A., Judge, J., Liu, P.-W., and Papathanassiou, K. (2017). Radar Remote Sensing of Agricultural Canopies: A Review. *IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING*, 10(5, 2):2249–2273.
- Tomppo, E. and Katila, M. (1991). Satellite image-based national forest inventory of Finland for publication in the IGARSS 91 digest. In *IGARSS 91 - REMOTE SENSING : GLOBAL MONITORING FOR EARTH MANAGEMENT, VOLS 1-4*, pages 1141–1144. 1991 INTERNATIONAL GEOSCIENCE AND REMOTE SENSING SYMP - REMOTE SENSING : GLOBAL MONITORING FOR EARTH MANAGEMENT ( IGARSS 91 ), ESPOO, FINLAND, JUN 03-06, 1991.
- Toth, C. and Jozkow, G. (2016). Remote sensing platforms and sensors: A survey. *ISPRS JOURNAL OF PHOTOGRAMMETRY AND REMOTE SENSING*, 115:22–36.
- Touzi, R., Lopes, A., Bruniquel, J., and Vachon, P. W. (1999). Coherence estimation for sar imagery. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, 37(1):135–149.
- Tuominen, S. and Pekkarinen, A. (2005). Performance of different spectral and textural aerial photograph features in multi-source forest inventory. *REMOTE SENSING OF ENVIRONMENT*, 94(2):256–268.
- Turner, W., Rondinini, C., Pettorelli, N., Mora, B., Leidner, A. K., Szantoi, Z., Buchanan, G., Dech, S., Dwyer, J., Herold, M., Koh, L. P., Leimgruber, P., Taubenboeck, H., Wegmann, M., Wikelski, M., and Woodcock, C. (2015). Free and open-access satellite data are key to biodiversity conservation. *BIOLOGICAL CONSERVATION*, 182:173–176.
- Unwin, A. (1996). Exploratory spatial analysis and local statistics. *COMPUTATIONAL STATISTICS*, 11(4):387–400.
- van Leeuwen, M. and Nieuwenhuis, M. (2010). Retrieval of forest structural parameters using LiDAR remote sensing. *EUROPEAN JOURNAL OF FOREST RESEARCH*, 129(4):749–770.
- Voormansik, K., Jagdhuber, T., Olesk, A., Hajnsek, I., and Papathanassiou, K. P. (2013). Towards a detection of grassland cutting practices with dual polarimetric terrasars-x data. *INTERNATIONAL JOURNAL OF REMOTE SENSING*, 34(22):8081–8103.
- Voormansik, K., Jagdhuber, T., Zalite, K., Noorma, M., and Hajnsek, I. (2016). Observations of Cutting Practices in Agricultural Grasslands Using Polarimetric SAR. *IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING*, 9(4):1382–1396.
- Wallace, L., Lucieer, A., Malenovsky, Z., Turner, D., and Vopenka, P. (2016). Assessment of Forest Structure Using Two UAV Techniques: A Comparison of Airborne Laser Scanning and Structure from Motion (SfM) Point Clouds. *FORESTS*, 7(3).
- Wang, X., Ge, L., and Li, X. (2013). Pasture monitoring using sar with cosmo-skymed, envisat asar, and alos palsar in otway, australia. *REMOTE SENSING*, 5(7):3611–3636.

- Whitcraft, A. K., Vermote, E. F., Becker-Reshef, I., and Justice, C. O. (2015). Cloud cover throughout the agricultural growing season: Impacts on passive optical earth observations. *REMOTE SENSING OF ENVIRONMENT*, 156:438–447.
- White, J. C., Coops, N. C., Wulder, M. A., Vastaranta, M., Hilker, T., and Tompalski, P. (2016). Remote Sensing Technologies for Enhancing Forest Inventories: A Review. *CANADIAN JOURNAL OF REMOTE SENSING*, 42(5, SI):619–641.
- Wing, B. M., Ritchie, M. W., Boston, K., Cohen, W. B., and Olsen, M. J. (2015). Individual snag detection using neighborhood attribute filtered airborne lidar data. *REMOTE SENSING OF ENVIRONMENT*, 163:165–179.
- Wolter, P. T., Townsend, P. A., and Sturtevant, B. R. (2009). Estimation of forest structural parameters using 5 and 10 meter SPOT-5 satellite data. *REMOTE SENSING OF ENVIRONMENT*, 113(9):2019–2036.
- Wulder, M. A., White, J. C., Fournier, R. A., Luther, J. E., and Magnussen, S. (2008). Spatially explicit large area biomass estimation: Three approaches using forest inventory and remotely sensed imagery in a GIS. *SENSORS*, 8(1):529–560.
- Wulder, M. A., White, J. C., Nelson, R. F., Naesset, E., Orka, H. O., Coops, N. C., Hilker, T., Bater, C. W., and Gobakken, T. (2012). Lidar sampling for large-area forest characterization: A review. *REMOTE SENSING OF ENVIRONMENT*, 121:196–209.
- Yague-Martinez, N., Prats-Iraola, P., Rodriguez Gonzalez, F., Brcic, R., Shau, R., Geudtner, D., Eineder, M., and Bamler, R. (2016). Interferometric processing of sentinel-1 tops data. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*.
- Yang, C., Yu, M., Hu, F., Jiang, Y., and Li, Y. (2017). Utilizing Cloud Computing to address big geospatial data challenges. *COMPUTERS ENVIRONMENT AND URBAN SYSTEMS*, 61(SI):120–128.
- Yang, H., Zhao, C., Yang, G., Li, Z., Chen, E., Yuan, L., Yang, X., and Xu, X. (2015). Agricultural crop harvest progress monitoring by fully polarimetric synthetic aperture radar imagery. *JOURNAL OF APPLIED REMOTE SENSING*, 9.
- Zalite, K., Antropov, O., Praks, J., Voormansik, K., and Noorma, M. (2016). Monitoring of Agricultural Grasslands With Time Series of X-Band Repeat-Pass Interferometric SAR. *IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING*, 9(8, SI):3687–3697.
- Zalite, K., Voormansik, K., Praks, J., Antropov, O., and Noorma, M. (2014). Towards detecting mowing of agricultural grasslands from multi-temporal cosmo-skymed data. In *Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International*, pages 5076–5079. IEEE.
- Zhang, C. and Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: a review. *PRECISION AGRICULTURE*, 13(6):693–712.

## KOKKUVÕTE (SUMMARY IN ESTONIAN)

### Lokaalstatistikute kasutamine rohumaade ja metsade kaugseires

Kaugseire on objekti või nähtuse kohta informatsiooni kogumine olemata sellega füüsilises kontaktis. Jensen (2014) on väitnud, et kaugseire valdkond on eksponentsiaalse kasvu faasis. Maa kaugseire (*Earth observation* (EO)) satelliitide ruumiline, spektraalne ja radiomeetriline lahutusvõime suureneb ja ülesvõtteid tehakse järjest tihedamalt. Maa kaugseiret kasutatakse näiteks atmosfääri, taimestiku, mulla, vee, jää, mineraalide ja linna taristu kohta teabe saamiseks. Eesmärgiks on saada kaugseirest igapäevaelus maksimaalset kasu näiteks ilmaennustamisel, põllukultuuride kasvu jälgimisel ja jää kaardistamisel, meretranspordi paremaks planeerimiseks.

Arengud riist- ja tarkvaras on loonud võimalused töödelda efektiivselt väga suurt hulka kaugseire andmeid. Senisest laiaulatuslikumalt on võimalik kasutada kaugseire hinnangute täiustamiseks lokaalstatistikuid. Käesoleva doktoritöö kontekstis on lokaalstatistikud statistilised näitajad, mis arvutatakse kaugseire kujutiselt lokaalse huviala piires. Lokaalne huviala võib olla määratletud uuritavat kohta ümbritseva alaga, mis on ringi, ruudu või muu kujuga. Lokaalne huviala võib olla piiritletud ka polügooniga, mis pärineb olemasolevast vektorandmestikust või on kaugseire kujutiselt segmenteeritud. Üks aktuaalsemaid teemasid kaugseire alases uurimistöös on geograafiline objektipõhine pildianalüüs (*geographic object-based image analysis* (GEOBIA)) ning lokaalstatistikutel on selles oluline osa. Käesolev doktoritöö analüüsib lokaalstatistikute kasutamist rohumaade ja metsade kaugseires eesmärgiga:

1. esitleda tehisava-radari interferomeetrilisel koherentsusel põhinevaid tunnuseid niitmiste seireks rohumaadel;
2. näidata lokaalstatistikute kasutusvõimalusi ortofotodel põhinevas metsade kaugseires;
3. täiendada olemasolevaid metsade kaugseire meetodikaid läbi tunnuste eelvaliku ja masinõppe meetodite kasutamise riigimetsa takseerandmete inventuuriks.

Käesolev doktoritöö koosneb kolmest peatükist. Peatükk I annab ülevaate aktuaalsetest kaugseire uurimistöös suundadest, arengutest põllumajandusmaade ja metsade kaugseires ning lokaalstatistikute kasutamisest taimkatte kaugseires. Peatükk II käsitleb rohumaade monitoorimist tehisava-radari (*synthetic aperture radar* (SAR)) abil ning peatükk III metsade kaugseiret kasutades optilisi sensoreid.

Doktoritöö tulemusena selgus, et C-laineala tehisava-radari interferomeetrilise koherentsuse kasutamisel on potentsiaali niitmise tuvastamise algoritmide ja raskenduste väljaarendamiseks. Tulemused näitasid, et pärast niitmist on VH ja VV polarisatsiooni 12-päeva interferomeetrilise koherentsuse mediaan väärtused statistiliselt oluliselt kõrgemad võrreldes niitmise eelse olukorraga. Koherentsus on seda kõrgem, mida väiksem on ajaline vahe niitmise ja pärast seda üles võetud esimese interferomeetrilise mõõtmise vahel. Teisalt hommikune kaste, sademed, põllutööde teostamine, näiteks külvamine või kündmine, kõrgelt niitmine ja kiire rohu kasv pärast niitmist vähendavad koherentsust ja raskendavad niitmise tuvastamist. Selleks, et eelpoolnimetatud mõjusid vähendada tuleks tulevikus uurida 6-päeva koherentsuse ja niitmise sündmuste vahelisi seoseid. Käesolevas doktoritöös esitatud tulemused loovad tugeva aluse edasisteks uuringuteks ja arendusteks eesmärgiga võtta C-laineala tehisava-radari andmed niitmise tuvastamisel praktikas kasutusele.

Doktoritöös leiti, et ortofotodel põhinevate metsa kaugseire hinnangute andmisel on abi lokaalstatistikute kasutamisest. Näidati, et kasulikud võivad olla järgmised lokaalstatistikud: Morani I, kaugusega kaalutud Morani I, erinevus keskosa ja äärte vahel, naabrite homogeensus, üle keskmise olevate väärtuste osakaal ja variatsiooni koefitsient. Lisaks võivad need statistikud olla kasulikud ka pildi tõlgenduse (*photo-interpretation*) ülesannete lahendamisel metsastel aladel.

Käesoleva doktoritöö raames läbi viidud riigimetsa takseerandmete (*national forest inventory* (NFI)) kaugseire hinnangu tulemused on mõõduka täpsusega. Leiti, et klasteranalüüsi saab kasutada kaugseire tunnuste eelvaliku meetodina ning näidistel põhinev järeldamine (*case-based reasoning* (CBR)) sobib hästi selliste kaugseire ülesannete empiirilisteks lahendusteks, kus sisendandmetena on kasutatavad väga paljud erinevad andmeallikad, näiteks optilised sensorid satelliitidel ja lennukitel, täiendavad kaardiandmed, jne. Võrreldes erinevaid tekstuuri statisti- kuid näidati, et lokaalselt arvatud keskväärtnus on kõige väärtuslikum tunnus. Järeldati, et nii statistiliste kui ka struktuursete lokaalstatistikute kasutamisega saab lisada pikslipõhistele kaugseire hinnangutele olulist andmestikku.

## ACKNOWLEDGEMENTS

The long journey to this thesis has been possible only thanks to many special people. I am deeply grateful for the inspiration, advice and support. Although I cannot mention everyone here, my special gratitude goes to:

**Kalle Remm**, my co-supervisor and co-author who introduced me to the wonderful world of machine learning and remote sensing. You gave me the inspiration to look deeper and to do science. Thank you for starting the journey and supporting me on the way.

**Kārlis Zālīte**, my co-supervisor, co-author and partner whose great skills and deep knowledge have educated me in radar remote sensing and scientific writing. You have done great work and this has enabled me to finish the journey. Thank you very much for that.

**Kaupo Voormansik**, my co-author and partner whose enthusiasm, courage, leadership and support has helped me to come through the most difficult times towards finishing the thesis. You have both taught me principles of SAR and kept the positive attitude — you can do it! I am very grateful for that.

**Tõnu Oja**, whose support and endless patience have enabled me to work towards the completion of thesis. Thank you very much.

I would also like to say many thanks to **Kristel Lelov-Brossard** from Urban Planning Department of Tallinn City for understanding and supporting my academic ambitions.

I am thankful to Priit Adler, Rein Ahas, Raivo Aunap, Ave Kargaja, Kalev Koppel, Raido Kukk, Kiira Mõisja, Hans Orru, Ivari Rannama, Mart Reinola, Jüri Roosaare, Valentina Sagris, Edgar Sepp and other colleagues and friends for various kinds of support.

All this has not been possible without the irreplaceable support from my family, especially from my wife **Kadri Tamm**. My deepest gratitude to you.

## **PUBLICATIONS**

## **ERRATA IN PAPERS**

### **Publication I**

1. On page 10, word "backscatter" should be used instead of word "coherence" in the last sentence of the first paragraph. The corrected version is: "... and backscatter measurements ...".

### **Publication III**

1. In the Abstract, unit " $m^3$ " should be used instead of " $m^{-3}$ ". For instance the corrected version of "...74.64  $m^{-3}$  ha<sup>-1</sup>..." is "...74.64  $m^3$  ha<sup>-1</sup>..."
2. On page 292, Figure 2 has been erroneously switched with Figure 3. In the corrected version Figures 2 and 3 have to be switched so that Figure 2 on page 292 illustrates the process of machine learning and estimation (currently Figure 3) and Figure 3 on page 293 illustrates the technological schema of map generatrion (currently Figure 2). The captions and referenes to the figures must stay unchanged.

# CURRICULUM VITAE

## General information

First name            Tanel  
Last name            Tamm  
Date of birth        28.01.1981

## Professional career

2017–...            University of Tartu, Faculty of Science and Technology, Institute of Ecology and Earth Sciences, Researcher (0.10)  
2017–...            KappaZeta Ltd, developer of EO applications (1.00)  
2016–2017        University of Tartu, Faculty of Science and Technology, Institute of Ecology and Earth Sciences, Researcher (0.60)  
2016–2017        Tartu Observatory, Researcher (0.50)  
2012–2016        University of Tartu, Faculty of Science and Technology, Institute of Ecology and Earth Sciences, Researcher (1.00)  
2005–2012        Urban Planning Department of Tallinn City, manager of geoinformatics unit (1.00)  
2003–2004        University of Tartu, Support Units, Department of Research and Institutional Development, Cartographer and spatial data manager (0.1)

## Education

2005–...            University of Tartu, Faculty of Biology and Geography, Institute of Geography, PhD in Geography  
2003–2005        University of Tartu, Faculty of Biology and Geography, Institute of Geography, MSc in Geoinformatics and Cartography  
1999–2003        University of Tartu, Faculty of Physics and Chemistry, BSc in Environmental Technology  
1987–1999        High School - Saaremaa Ühisgümnaasium

## **Additional career information**

### **Projects:**

|           |  |
|-----------|--|
| 2016–2017 | Detection of mowing events with satellite-based monitoring   |
| 2015      | Assessment of climate change impacts and elaboration of adaptation instruments in the field of planning, land use, health and rescue management (KATI) |
| 2012–2014 | Geoinformatic development of biodiversity, soil and earth data systems (ERMAS)   |
| 2010–2012 | Creation of 3D application for Tallinn Old Town  |
| 2006–2012 | Creation and development of Tallinn Spatial Database   |
| 2005–2012 | Development of Tallinn Register of Development Plans   |

### **Training courses:**

|                           |   |
|---------------------------|---|
| 14.09.2015–<br>18.09.2015 | 6th Advanced training course in land remote sensing - European Space Agency (ESA) |
|---------------------------|---|

### **Courses presented:**

|      |  |
|------|--|
| 2017 | Modelling with UML/GML and Web Feature Service |
| 2015 | PostgreSQL/PostGIS and GeoServer (WMS) Basics  |
| 2013 | ArcGIS Software                                |

## **Academic degrees**

Tanel Tamm, Master's Degree, 2005, (sup) Kalle Remm, Riigimetsa takseerandmete kasutamine Eesti metsade kaugseires tehiseõppe rakenduse abil (Using National Forest Inventory data in the remote sensing of Estonian forests with a machine learning approach), University of Tartu, Faculty of Biology and Geography, Institute of Geography.

## **Honours & awards**

III price in the National Competition of Students Scientific Research in Natural Sciences  
2003

## Supervised dissertations

Villem Voormansik, Master's Diploma, 2016, (sup) Tanel Tamm; Martin Jüssi, Object-based mapping of secondary forest succession on agricultural land with remote sensing data, University of Tartu, Faculty of Science and Technology, Institute of Ecology and Earth Sciences.

Martin Jüssi, Master's Diploma, 2015, (sup) Kaupo Voormansik; Tanel Tamm; Karlis Zalite, Synthetic Aperture Radar based flood mapping in the Alam-Pedja Nature Reserve in years 2005-2011, University of Tartu, Faculty of Science and Technology, Institute of Ecology and Earth Sciences.

Anni Sisas, Master's Diploma, 2015, (sup) Kaupo Voormansik; Tanel Tamm, Detecting built-up areas from radar satellite Sentinel-1A measurements, University of Tartu, Faculty of Science and Technology, Institute of Ecology and Earth Sciences.

Iloona Vares, Master's Diploma, 2014, (sup) Tanel Tamm; Raivo Aunap, Spatial and temporal pattern of The Estonian Rescue Board fire accidents in period 2009-2013, University of Tartu, Faculty of Science and Technology, Institute of Ecology and Earth Sciences.

## Publications

### 2016

Tamm, Tanel; Zalite, Karlis; Voormansik, Kaupo; Talgre, Liina (2016). Relating Sentinel-1 Interferometric Coherence to Mowing Events on Grasslands. *Remote Sensing*, 8 (10, 802), 1–19.10.3390/rs8100802.

Sepp, Mait; Tamm, Tanel; Sagris, Valentina (2016). The Future Climate Regions in Estonia. *International Baltic Earth Secretariat Publication No 9, June 2016: 1. Baltic Earth Conference Multiple Drivers for Earth system changes in the Baltic Sea region. Nida, Lithuania 13-17. June 2016.*. Ed. Marcus Reckermann, Silke Köppen. International Baltic Earth Secretariat Helmholtz-Zentrum Geesthacht GmbH, 185–185.

### 2015

Olesk, Aire; Voormansik, Kaupo; Tamm, Tanel; Noorma, Mart; Praks, Jaan. (2015). Seasonal effects on the estimation of height of boreal and deciduous forests from interferometric TanDEM-X coherence data. *SPIE: SPIE Remote Sensing, Toulouse, France, 21-24 September 2015*. SPIE Digital Library: Spie - International Society For Optical Engineering, 1–8.10.1117/12.2194340.

### 2014

Kaasik, Marko; Pindus, Mihkel; Tamm, Tanel; Orru, Hans (2014). The Porosity Concept Applied to Urban Canopy Improves the Results of Gaussian Dispersion Modelling of Traffic-

Dominated Emissions. In: Steyn, Douw; Mathur, Rohit (Ed.). *Air Pollution Modelling and its Application XXII* (417–420).. Springer.10.1007/978-3-319-04379-1.

Kesanurm, Kaisa; Teinemaa, Erik; Kaasik, Marko; Tamm, Tanel; Lai, Taavi; Orru, Hans (2014). Country-wide health impact assessment of airborne particulate matter in Estonia. In: Steyn, Douw; Builtjes, Peter; Timmermans, Renske (Ed.). *Air Pollution Modelling and its Application* (47–51).. Springer.10.1007/978-94-007-5577-2.

### 2013

Oja, Tõnu; Sagris, Valentina; Tamm, Tanel; Uuemaa, Evelyn (2013). Development of tools for spatial data integration and analysis: applied for biodiversity and cultural heritage. In: .EUROGI, Dublin, 7-8.03.2013.

### 2011

Orru, H.; Maasikmets, M.; Lai, T.; Tamm, T.; Kaasik, M.; Kimmel, V.; Orru, K.; Merisalu, E.; Forsberg, B. (2011). Health impacts of particulate matter in five major Estonian towns: main sources of exposure and local differences. *Air Quality, Atmosphere & Health*, 4, 247–258.10.1007/s11869-010-0075-6.

### 2010

Tamm, T.; Remm, K.; Proosa, H. (2010). LSTATS software and its application. *Proceedings of the Seventh IASTED International Conference: Signal Processing, Pattern Recognition and Applications; Innsbruck, Austria; 17-19.02.2010*. Ed. Zagar, B.; Kuijper, A.; Sahbi, H. ACTA Press, 317–324.

### 2009

Tamm, T.; Remm, K. (2009). Estimating the parameters of forest inventory using machine learning and the reduction of remote sensing features. *International Journal of Applied Earth Observation and Geoinformation*, 11 (4), 290–297.

Orru, H.; Teinemaa, E.; Lai, T.; Tamm, T.; Kaasik, M.; Kimmel, V.; Kangur, K.; Merisalu, E.; Forsberg, B. (2009). Health impact assessment of particulate pollution in Tallinn using fine spatial resolution and modelling techniques. *Environmental Health*, 8, 7.10.1186/1476-069X-8-7.

Orru, H.; Teinemaa, E.; Lai, T.; Tamm, T.; Kaasik, M.; Kimmel, V.; Forsberg, B.; Kangur, K.; Merisalu, E. (2009). Health impact assessment of locally emitted particulate matter in Tallinn using sectioning and modeling techniques. *Abstracts: 7th International Conference on Air Quality - Science and Application. Istanbul, 24-27 March 2009*. Ed. Hu, R.M.; Khaiwal, R.; Chemel, C.; Newbold, H.; Incecik, S.; Kahya, C.; Sokhi, R.S. UK, 99–99.

## 2008

Orru, H.; Teinemaa, E.; Lai, T.; Tamm, T.; Kaasik, M.; Kimmel, V.; Forsberg, B.; Merisalu, E.; Kangur, K. (2008). Health impact assessment of locally emitted particulate matter in Tallinn using clustering and modeling techniques. *Epidemiology, 19: ISEE 20th Annual Conference; Pasadena, California; October 12-16, 2008. s226. (6).*

## 2005

Roose, A.; Aunap, R.; Tamm, T. (2005). A framework and techniques for environmental mapping of the Estonian monitoring data. *GIS Planet 2005 Proceedings. May 30-June 2, 2005, Estoril: GIS Planet 2005; Estoril, Portugal; 30 May-2 June, 2005.* Ed. Goodchild, M. Lisboa: Instituto Geografico Portugues.

# ELULOOKIRJELDUS

## Üldandmed

|          |            |
|----------|------------|
| Eesnimi  | Tanel      |
| Perenimi | Tamm       |
| Sünniaeg | 28.01.1981 |

## Töökohad ja ametid

|           |   |
|-----------|---|
| 2017–...  | Tartu Ülikool, Loodus- ja täppisteaduste valdkond, ökoloogia ja maateaduste instituut, Teadur (0,10)        |
| 2017–...  | KappaZeta OÜ, kaugseire rakenduste arendaja (1,00)  |
| 2016–2017 | Tartu Ülikool, Loodus- ja täppisteaduste valdkond, Ökoloogia ja maateaduste instituut, Teadur (0,60)        |
| 2016–2017 | Tartu Observatoorium, Teadur (0,50)   |
| 2012–2016 | Tartu Ülikool, Loodus- ja täppisteaduste valdkond, ökoloogia ja maateaduste instituut, Teadur (1,00)        |
| 2005–2012 | Tallinna Linnaplaneerimise Amet, geoinformaatika osakonna juhataja (1,00)                                   |
| 2003–2004 | Tartu Ülikool, Tugiüksused, Teadus-ja arendusosakond, Kartograaf, ruumiantmete haldaja ja analüüsija (0,10) |

## Haridustee

|           |   |
|-----------|---|
| 2005–...  | Tartu Ülikool doktoriõpe, Bioloogia-Geograafia teaduskond, eriala: geograafia                                 |
| 2003–2005 | Tartu Ülikool magistriõpe, Bioloogia-Geograafia teaduskond, eriala: geoinformaatika ja kartograafia           |
| 1999–2003 | Tartu Ülikool bakalaureuseõpe, Füüsika- Keemiateaduskond, eriala: keskkonnatehnoloogia (ökotehnoloogia suund) |
| 1987–1999 | Saaremaa Ühisgümnaasium   |

## Teenistuskäigu lisainfo

### Projektid:

|           |  |
|-----------|--|
| 2016–2017 | Niitmise automaatne tuvastamine satelliitseirega   |
| 2015      | Kliimamuutuste mõjude hindamine ja kohanemismeetmete väljatöötamine planeeringute, maakasutuse, inimese tervise ja päästevõimekuse teemas (KATI) |
| 2012–2014 | Elurikkuse, mulla ja maapõue andmesüsteemide geoinformaatiline arendus (ERMAS)   |
| 2010–2012 | Tallinna Vanalinna 3D rakenduse loomine  |
| 2006–2012 | Tallinna ruumiandmete registri loomine ja arendamine   |
| 2005–2012 | Tallinna planeeringute registri arendamine   |

### Koolitused:

|                           |  |
|---------------------------|--|
| 14.09.2015–<br>18.09.2015 | 6th Advanced training course in land remote sensing - Euroopa Kosmose Agentuur (ESA) |
|---------------------------|--|

### Antud

#### õppeained:

|      |   |
|------|---|
| 2017 | Andmemudelite loomine UML/GML abil ja ruumiandmete levitamine WFS teenusega |
| 2015 | PostgreSQL/PostGIS ja GeoServeri (WMS) alused                               |
| 2013 | Tarkvara ArcGIS   |

## Teaduskraadid

Tanel Tamm, magistrakraad (teaduskraad), 2005, (juh) Kalle Remm, Riigimetsa takseerandmete kasutamine Eesti metsade kaugseires tehisõppe rakenduse abil, Tartu Ülikool, Bioloogia-geografiateaduskond, Geograafia instituut.

## Teaduspreemiad ja tunnustused

2003. aasta üliõpilaste teadustööde riikliku konkursi III preemia bio-geoteaduste kategoorias

## Juhendatud väitekirjad

Villem Voormansik, magistrikaad, 2016, (juh) Tanel Tamm; Martin Jüssi, Võsastumise tõttu muutunud põllupiiride objektipõhine tuvastamine kaugseire andmetel, Tartu Ülikool, Loodus- ja täppisteaduste valdkond, ökoloogia ja maateaduste instituut.

Martin Jüssi, magistrikaad, 2015, (juh) Kaupo Voormansik; Tanel Tamm; Karlis Zalite, Synthetic Aperture Radar based flood mapping in the Alam-Pedja Nature Reserve in years 2005-2011 (Üleujutuste kaardistamine tehisava-radari mõõtmiste baasil Alam-Pedja looduskaitsealal 2005-2011 aastatel), Tartu Ülikool, Loodus- ja tehnoloogiateaduskond, Tartu Ülikooli Ökoloogia- ja Maateaduste Instituut, Geograafia osakond.

Anni Sisas, magistrikaad, 2015, (juh) Kaupo Voormansik; Tanel Tamm, Ehitiste tuvastamine radarsatelliidi Sentinel-1A mõõtmiste põhjal, Tartu Ülikool, Loodus- ja tehnoloogiateaduskond, Tartu Ülikooli Ökoloogia- ja Maateaduste Instituut, Geograafia osakond.

Iлона Vares, magistrikaad, 2014, (juh) Tanel Tamm; Raivo Aunap, Päästeameti tulekahjusündmuste ajalis-ruumiline muster perioodil 2009-2013, Tartu Ülikool, Loodus- ja tehnoloogiateaduskond, Tartu Ülikooli Ökoloogia- ja Maateaduste Instituut, Geograafia osakond.

## Publikatsioonid

### 2016

Tamm, Tanel; Zalite, Karlis; Voormansik, Kaupo; Talgre, Liina (2016). Relating Sentinel-1 Interferometric Coherence to Mowing Events on Grasslands. *Remote Sensing*, 8 (10, 802), 1–19.10.3390/rs8100802.

Sepp, Mait; Tamm, Tanel; Sagris, Valentina (2016). The Future Climate Regions in Estonia. *International Baltic Earth Secretariat Publication No 9, June 2016: 1. Baltic Earth Conference Multiple Drivers for Earth system changes in the Baltic Sea region. Nida, Lithuania 13-17. June 2016.* Ed. Marcus Reckermann, Silke Köppen. International Baltic Earth Secretariat Helmholtz-Zentrum Geesthacht GmbH, 185–185.

### 2015

Olesk, Aire; Voormansik, Kaupo; Tamm, Tanel; Noorma, Mart; Praks, Jaan. (2015). Seasonal effects on the estimation of height of boreal and deciduous forests from interferometric TanDEM-X coherence data. *SPIE: SPIE Remote Sensing, Toulouse, France, 21-24 September 2015*. SPIE Digital Library: Spie - International Society For Optical Engineering, 1–8.10.1117/12.2194340.

Sepp, Mait; Tamm, Tanel; Sagris, Valentina (2015). Tulevikukliima regioonid Eestis. Antti Roose (Toim.). Kliimamuutustega kohanemine Eestis - valmis vääramatuks jõuks? (38–48).. Tartu Ülikooli Kirjastus. (Publicationes Instituti Geographici Universitatis Tartuensis; 112).

Tamm, Tanel (2015). Paduvihmadest põhjustatud üleujutuste modelleerimine - Pärnu näide. Antti Roose (Toim.). Kliimamuutustega kohanemine Eestis - valmis vääramatuks jõuks? (79–85). Tartu Ülikooli Kirjastus. (Publicationes Instituti Geographici Universitatis Tartuensis; 112).

Sepp, Mait; Sagris, Valentina; Tamm, Tanel (2015). Eesti asub kliimamuutuste tulipunktis. Eesti Loodus, 66 (8), 8–13.

## 2014

Kaasik, Marko; Pindus, Mihkel; Tamm, Tanel; Orru, Hans (2014). The Porosity Concept Applied to Urban Canopy Improves the Results of Gaussian Dispersion Modelling of Traffic-Dominated Emissions. In: Steyn, Douw; Mathur, Rohit (Ed.). Air Pollution Modelling and its Application XXII (417–420).. Springer.10.1007/978-3-319-04379-1.

Kesanurm, Kaisa; Teinemaa, Erik; Kaasik, Marko; Tamm, Tanel; Lai, Taavi; Orru, Hans (2014). Country-wide health impact assessment of airborne particulate matter in Estonia. In: Steyn, Douw; Builtjes, Peter; Timmermans, Renske (Ed.). Air Pollution Modelling and its Application (47–51).. Springer.10.1007/978-94-007-5577-2.

Tamm, Tanel; Lang, Mait; Metsur, Mait (2014). Maa-ameti kaugseireandmete kasutamine ETAKi maakattetiüüpide objektipõhisel tuvastamisel. Aan, Anne; Narusk, Kirke (Toim.). Kaugseire Eestis 2014 (104–110).. Keskkonnaagentuur.

Voormansik, Kaupo; Tamm, Tanel; Olesk, Aire; Zalite, Karlis; Praks, Jaan (2014). Polarimeetrilise tehisava-radari kasutusvõimalustest Eesti keskkonnaseires RADARSAT-2 Rannu 2013. a andmestiku põhjal. Aan, Anne ; Narusk, Kirke (Toim.). Kaugseire Eestis 2014 (94–104).. Keskkonnaagentuur.

Voormansik, Kaupo; Tamm, Tanel (2014). Polarimeetrilised radarid seiravad keskkonda. Horisont, 6, 52–58.

## 2013

Sagris, Valentina; Tamm, Tanel (2013). Akadeemiliste ruumiandmete infrastruktuur: andmete koostalitusvõime ja teenused. XII Eesti Ökoloogiakonverents, Tartu, 18–19.10.2013.

Oja, Tõnu; Sagris, Valentina; Tamm, Tanel; Uemaa, Evelyn (2013). Development of tools for spatial data integration and analysis: applied for biodiversity and cultural heritage. In: .EUROGI, Dublin, 7-8.03.2013.

## 2011

Orru, H.; Maasikmets, M.; Lai, T.; Tamm, T.; Kaasik, M.; Kimmel, V.; Orru, K.; Merisalu, E.; Forsberg, B. (2011). Health impacts of particulate matter in five major Estonian towns: main sources of exposure and local differences. *Air Quality, Atmosphere & Health*, 4, 247–258.10.1007/s11869-010-0075-6.

## 2010

Orru, Hans; Teinemaa, Erik; Lai, Taav; Merisalu, Eda; Tamm, Tanel; Kaasik, Marko; Kimmel, Veljo; Orru, Kati; Forsberg, Bertil (2010). Peened osakesed välisõhus ja neist tuleneva tervisemõju hindamine Tallinnas, Tartus, Kohtla-Järvel, Narvas ja Pärnus. *Eesti Arst*, 89 (4), 242–250.

Tamm, T.; Remm, K.; Proosa, H. (2010). LSTATS software and its application. *Proceedings of the Seventh IASTED International Conference: Signal Processing, Pattern Recognition and Applications; Innsbruck, Austria; 17-19.02.2010*. Ed. Zagar, B.; Kuijper, A.; Sahbi, H. ACTA Press, 317–324.

## 2009

Tamm, T.; Remm, K. (2009). Estimating the parameters of forest inventory using machine learning and the reduction of remote sensing features. *International Journal of Applied Earth Observation and Geoinformation*, 11 (4), 290–297.

Orru, H.; Teinemaa, E.; Lai, T.; Tamm, T.; Kaasik, M.; Kimmel, V.; Kangur, K.; Merisalu, E.; Forsberg, B. (2009). Health impact assessment of particulate pollution in Tallinn using fine spatial resolution and modelling techniques. *Environmental Health*, 8, 7.10.1186/1476-069X-8-7.

Orru, H.; Teinemaa, E.; Lai, T.; Tamm, T.; Kaasik, M.; Kimmel, V.; Forsberg, B.; Kangur, K.; Merisalu, E. (2009). Health impact assessment of locally emitted particulate matter in Tallinn using sectioning and modeling techniques. *Abstracts: 7th International Conference on Air Quality - Science and Application. Istanbul, 24-27 March 2009*. Ed. Hu, R.M.; Khaiwal, R.; Chemel, C.; Newbold, H.; Incecik, S.; Kahya, C.; Sokhi, R.S. UK, 99–99.

## 2008

Orru, H.; Teinemaa, E.; Lai, T.; Tamm, T.; Kaasik, M.; Kimmel, V.; Forsberg, B.; Merisalu, E.; Kangur, K. (2008). Health impact assessment of locally emitted particulate matter in

Tallinn using clustering and modeling techniques. *Epidemiology*, 19: ISEE 20th Annual Conference; Pasadena, California; October 12-16, 2008. s226. (6).

Orru, H.; Teinemaa, E.; Lai, T.; Tamm, T.; Kaasik, M.; Kimmel, V.; Merisalu, E. (2008). Välisõhu kvaliteedi mõju inimeste tervisele Tallinna linnas. *Keskkonnatehnika*, 1, 20–23.

## **2005**

Roose, A.; Aunap, R.; Tamm, T. (2005). A framework and techniques for environmental mapping of the Estonian monitoring data. *GIS Planet 2005 Proceedings. May 30-June 2, 2005, Estoril: GIS Planet 2005; Estoril, Portugal; 30 May-2 June, 2005*. Ed. Goodchild, M. Lisboa: Instituto Geografico Portugues.

## DISSERTATIONES GEOGRAPHICAE UNIVERSITATIS TARTUENSIS

1. **Вийви Руссак.** Солнечная радиация в Тыравере. Тарту, 1991.
2. **Urmás Peterson.** Studies on Reflectance Factor Dynamics of Forest Communities in Estonia. Tartu, 1993.
3. **Ülo Suursaar.** Soome lahe avaosa ja Eesti rannikumere vee kvaliteedi analüüs. Tartu, 1993.
4. **Kiira Aaviksoo.** Application of Markov Models in Investigation of Vegetation and Land Use Dynamics in Estonian Mire Landscapes. Tartu, 1993.
5. **Kjell Wepling.** On the assessment of feasible liming strategies for acid sulphate waters in Finland. Tartu, 1997.
6. **Hannes Palang.** Landscape changes in Estonia: the past and the future. Tartu, 1998.
7. **Eiki Berg.** Estonia's northeastern periphery in politics: socio-economic and ethnic dimensions. Tartu, 1999.
8. **Valdo Kuusemets.** Nitrogen and phosphorus transformation in riparian buffer zones of agricultural landscapes in Estonia. Tartu, 1999.
9. **Kalev Sepp.** The methodology and applications of agricultural landscape monitoring in Estonia. Tartu, 1999.
10. **Rein Ahas.** Spatial and temporal variability of phenological phases in Estonia. Tartu, 1999.
11. **Эрки Таммиксаар.** Географические аспекты творчества Карла Бэра в 1830–1840 гг. Тарту, 2000.
12. **Garri Raagmaa.** Regional identity and public leaders in regional economic development. Tartu, 2000.
13. **Tiit Tammaru.** Linnastumine ja linnade kasv Eestis nõukogude aastatel. Tartu, 2001.
14. **Tõnu Mauring.** Wastewater treatment wetlands in Estonia: efficiency and landscape analysis. Tartu, 2001.
15. **Ain Kull.** Impact of weather and climatic fluctuations on nutrient flows in rural catchments. Tartu, 2001.
16. **Robert Szava-Kovats.** Assessment of stream sediment contamination by median sum of weighted residuals regression. Tartu, 2001.
17. **Heno Sarv.** Indigenous Europeans east of Moscow. Population and Migration Patterns of the Largest Finno-Ugrian Peoples in Russia from the 18<sup>th</sup> to the 20<sup>th</sup> Centuries. Tartu, 2002.
18. **Mart Külvik.** Ecological networks in Estonia — concepts and applications. Tartu, 2002.
19. **Arvo Järvet.** Influence of hydrological factors and human impact on the ecological state of shallow Lake Võrtsjärv in Estonia. Tartu, 2004.
20. **Katrin Pajuste.** Deposition and transformation of air pollutants in coniferous forests. Tartu, 2004.

21. **Helen Sooväli.** *Saaremaa waltz*. Landscape imagery of Saaremaa Island in the 20th century. Tartu, 2004.
22. **Antti Roose.** Optimisation of environmental monitoring network by integrated modelling strategy with geographic information system — an Estonian case. Tartu, 2005.
23. **Anto Aasa.** Changes in phenological time series in Estonia and Central and Eastern Europe 1951–1998. Relationships with air temperature and atmospheric circulation. Tartu, 2005.
24. **Anneli Palo.** Relationships between landscape factors and vegetation site types: case study from Saare county, Estonia. Tartu, 2005.
25. **Mait Sepp.** Influence of atmospheric circulation on environmental variables in Estonia. Tartu, 2005.
26. **Helen Alumäe.** Landscape preferences of local people: considerations for landscape planning in rural areas of Estonia. Tartu, 2006.
27. **Aarne Luud.** Evaluation of moose habitats and forest reclamation in Estonian oil shale mining areas. Tartu, 2006.
28. **Taavi Pae.** Formation of cultural traits in Estonia resulting from historical administrative division. Tartu, 2006.
29. **Anneli Kährik.** Socio-spatial residential segregation in post-socialist cities: the case of Tallinn, Estonia. Tartu, 2006.
30. **Dago Antov.** Road user perception towards road safety in Estonia. Tartu, 2006.
31. **Üllas Ehrlich.** Ecological economics as a tool for resource based nature conservation management in Estonia. Tartu, 2007.
32. **Evelyn Uuemaa.** Indicatory value of landscape metrics for river water quality and landscape pattern. Tartu, 2007.
33. **Raivo Aunap.** The applicability of gis data in detecting and representing changes in landscape: three case studies in Estonia. Tartu, 2007.
34. **Kai Treier.** Trends of air pollutants in precipitation at Estonian monitoring stations. Tartu, 2008.
35. **Kadri Leetmaa.** Residential suburbanisation in the Tallinn metropolitan area. Tartu, 2008.
36. **Mare Remm.** Geographic aspects of enterobiasis in Estonia. Tartu, 2009.
37. **Alar Teemusk.** Temperature and water regime, and runoff water quality of planted roofs. Tartu, 2009.
38. **Kai Kimmel.** Ecosystem services of Estonian wetlands. Tartu, 2009.
39. **Merje Lesta.** Evaluation of regulation functions of rural landscapes for the optimal siting of treatment wetlands and mitigation of greenhouse gas emissions. Tartu, 2009.
40. **Siiri Silm.** The seasonality of social phenomena in Estonia: the location of the population, alcohol consumption and births. Tartu, 2009.
41. **Ene Indermitte.** Exposure to fluorides in drinking water and dental fluorosis risk among the population of Estonia. Tartu, 2010.

42. **Kaido Soosaar.** Greenhouse gas fluxes in rural landscapes of Estonia. Tartu, 2010.
43. **Jaan Pärn.** Landscape factors in material transport from rural catchments in Estonia. Tartu, 2010.
44. **Triin Saeu.** Simulated potato crop yield as an indicator of climate variability in Estonia. Tartu, 2011.
45. **Katrin Rosenvald.** Factors affecting EcM roots and rhizosphere in silver birch stands. Tartu, 2011.
46. **Ülle Marksoo.** Long-term unemployment and its regional disparities in Estonia. Tartu, 2011, 163 p.
47. **Hando Hain.** The role of voluntary certification in promoting sustainable natural resource use in transitional economies. Tartu, 2012, 180 p.
48. **Jüri-Ott Salm.** Emission of greenhouse gases CO<sub>2</sub>, CH<sub>4</sub>, and N<sub>2</sub>O from Estonian transitional fens and ombrotrophic bogs: the impact of different land-use practices. Tartu, 2012, 125 p.
49. **Valentina Sagris.** Land Parcel Identification System conceptual model: development of geoinfo community conceptual model. Tartu, 2013, 161 p.
50. **Kristina Sohar.** Oak dendrochronology and climatic signal in Finland and the Baltic States. Tartu, 2013, 129 p.
51. **Riho Marja.** The relationships between farmland birds, land use and landscape structure in Northern Europe. Tartu, 2013, 134 p.
52. **Olle Järv.** Mobile phone based data in human travel behaviour studies: New insights from a longitudinal perspective. Tartu, 2013, 168 p.
53. **Sven-Erik Enno.** Thunderstorm and lightning climatology in the Baltic countries and in northern Europe. Tartu, 2014, 142 p.
54. **Kaupo Mändla.** Southern cyclones in northern Europe and their influence on climate variability. Tartu, 2014, 142 p.
55. **Riina Vaht.** The impact of oil shale mine water on hydrological pathways and regime in northeast Estonia. Tartu, 2014, 111 p.
56. **Jaanus Veemaa.** Reconsidering geography and power: policy ensembles, spatial knowledge, and the quest for consistent imagination. Tartu, 2014, 163 p.
57. **Kristi Anniste.** East-West migration in Europe: The case of Estonia after regaining independence. Tartu, 2014, 151 p.
58. **Piret Pungas-Kohv.** Between maintaining and sustaining heritage in landscape: The examples of Estonian mires and village swings. Tartu, 2015, 210 p.
59. **Mart Reimann.** Formation and assessment of landscape recreational values. Tartu, 2015, 127 p.
60. **Järvi Järveoja.** Fluxes of the greenhouse gases CO<sub>2</sub>, CH<sub>4</sub> and N<sub>2</sub>O from abandoned peat extraction areas: Impact of bioenergy crop cultivation and peatland restoration. Tartu, 2015, 171 p.

61. **Raili Torga.** The effects of elevated humidity, extreme weather conditions and clear-cut on greenhouse gas emissions in fast growing deciduous forests. Tartu, 2016, 128 p.
62. **Mari Nuga.** Soviet-era summerhouses On homes and planning in post-socialist suburbia. Tartu, 2016, 179 p.
63. **Age Poom.** Spatial aspects of the environmental load of consumption and mobility. Tartu, 2017, 141 p.
64. **Merle Muru.** GIS-based palaeogeographical reconstructions of the Baltic Sea shores in Estonia and adjoining areas during the Stone Age. Tartu, 2017, 132 p.
65. **Ülle Napa.** Heavy metals in Estonian coniferous forests. Tartu, 2017, 129 p.
66. **Liisi Jakobson.** Mutual effects of wind speed, air temperature and sea ice concentration in the Arctic and their teleconnections with climate variability in the eastern Baltic Sea region. Tartu, 2018, 118 p.