TANEL TAMM

Use of local statistics in remote sensing of grasslands and forests

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67

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Use of local statistics in remote sensing of grasslands and forests

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TABLE OF CONTENTS

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.

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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 lead 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 lead 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; Montaghi 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 asses 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 3×3 to 7×7 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; Hyyppa 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^2 can be estimated with acceptable accuracy RMSE = 0.3 kg/m^2.

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 (κ) = 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 (κ = 0.98) and ALOS PALSAR L-band HH backscatter and HH/VV ratio data (κ = 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 became 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:

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

where $|..|$ label the absolute value, $\langle .. \rangle$ 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 $\langle .. \rangle$ 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 γ_{total} can be defined as:

$$\gamma_{total} = \gamma_{temporal} \gamma_{SNR} \gamma_{bias} \gamma_{other} \tag{2.2}$$

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

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

2.1.1. SNR Decorrelation

γ_{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. γ_{SNR} is defined as (Just and Bamler, 1994):

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

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

$$SNR_{sat} = \frac{\sigma^0_{sat} - NESZ_{sat}}{NESZ_{sat}} \tag{2.4}$$

where σ^0_{sat} 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 loose 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: 5×21 for relative orbit number (RON) RON58, 5×19 for RON80 and 5×19 for RON160, producing a footprint on the ground of ≈ 71 m $\times$ 69 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 km $\times$ 9 km **Ref. I** study area (Figure 1) around Rannu parish, 37 agricultural grasslands were used in this study. On the grasslands the
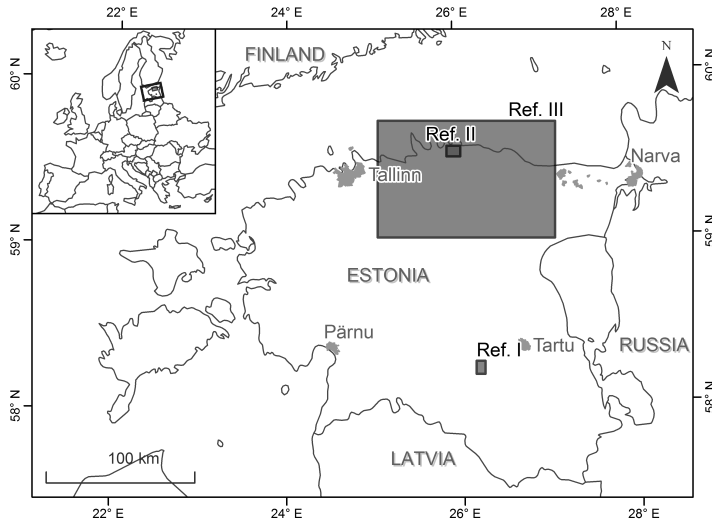
Figure 1. Location of the study areas in Estonia denoted as Ref. I, Ref. II and Ref. III.

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/ Descending	Acquisition Time (UTC)	Sub-Swath	Incidence Angle		Ground Range Resolution az × rg, m	
				Near	Far	Near	Far
58	Ascending	16:04	3	44.6	45.0	21.60 × 4.98	21.60 × 4.95
80	Descending	04:34	2	39.0	39.5	21.70 × 4.93	21.70 × 4.87
160	Ascending	15:56	2	37.9	38.4	21.70 × 5.05	21.70 × 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 × 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
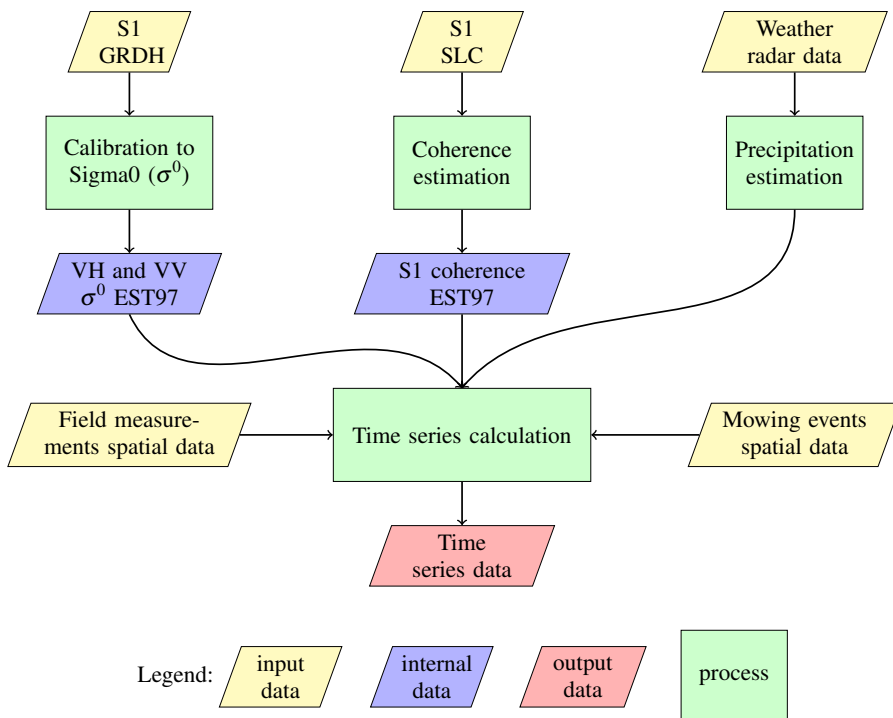
Figure 2. Flowchart of the processing chain.

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 Sürgavere, 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 × 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 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 ≤0.25 mm and >0.25mm. 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 µm 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 Nilson, 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.
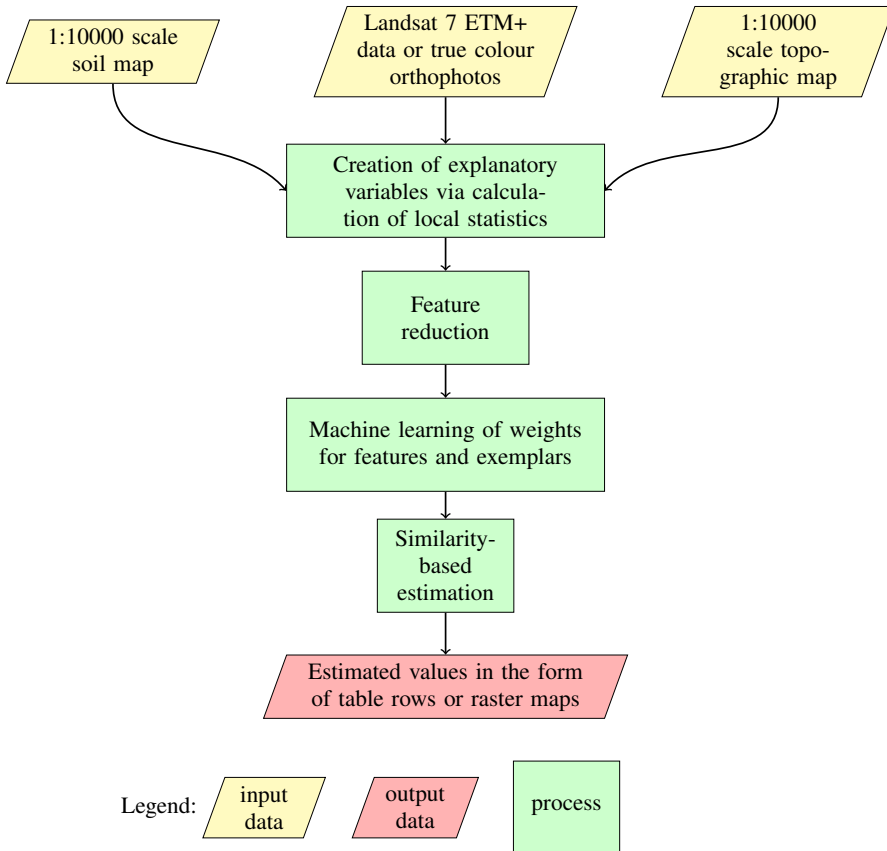
Figure 3. Flowchart of the forest parameters estimation chain used in study **Ref. III**.

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 150×150 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 κ-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 m^3 ha^{-1} (41 %) RMSE and 74.64 m^3 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 space-borne 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.

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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 kujutistelt lokaalse huviala piires. Lokaalne huviala võib olla määratletud uuritavat kohta ümbritseva alaga, mis on ringi, ruudu või muu kujuga. Lokaalne huviala võib olla piirtletud 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 lookalstatistikute kasutusvõimalusi ortofotodel põhinevas metsade kaugseires;
3. täiendada olemasolevaid metsade kaugseire metoodikaid läbi tunnuste eelvaliku ja masinõppe meetodite kasutamise riigimetsa takseerandmete inventuuriks.

Käesolev doktoritöö koosneb kolmest peatükist. Peatükk I annab ülevaate aktuaalsetest kaugseire uurimistöö 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 rakenduste 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 statistikuid näidati, et lokaalselt arvutatud keskväärtus on kõige väärtuslikum tunnus. Järeldati, et nii statistiliste kui ka struktuursete lokaalstatistikute kasutamisega saab lisada pikslipõhistele kaugseire hinnangutele olulist andmestikku.

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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^{-1}..." is "...74.64 m^3 ha^{-1}..."

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 references to the figures must stay unchanged.

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Professional career

2017–...	University of Tartu, Faculty of Science and Technology, Institute of Ecology and Earth Sciences, Researcher (0.10)
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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:

14.09.2015–18.09.2015	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 tehisõppe 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

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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.

Ilona Vares, Master's Diploma, 2014, (sup) Tanel Tamm; Raivo Aunap, Spatial and temporal pattern of The Estonian Rescue Board fire accidents in periood 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.

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2015

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2014

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2010

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2016–2017	Niitmise automaatne tuvastamine satelliitseirega
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2017	Andmemudelite loomine UML/GML abil ja ruumiandmete levitamine WFS teenusega
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Villem Voormansik, magistrikraad, 2016, (juh) Tanel Tamm; Martin Jüssi, Võsastumise tõttu muutunud põllupiiride objektipõhine tuvastamine kaugseire andmetel, Tartu Ülikool, Loodus- ja täppisteaduste valdkond, ökoloogia ja maateaduste instituut.

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Anni Sisas, magistrikraad, 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.

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Publikatsioonid

2016

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