The effect of forest canopy on remote sensing observations in the boreal region

Juval Cohen

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The effect of forest canopy on remote sensing observations in the boreal region

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Remote sensing techniques are often used for monitoring various processes in the boreal environment. Typical satellite sensor types for this purpose are Synthetic Aperture Radar (SAR), optical, and passive microwave sensors. Many of the observed targets on the ground are covered by forest canopy. Vegetation considerably influences the signal behavior, especially for the most commonly used microwave and optical wavelengths. It is therefore necessary to consider the effect of forest canopy on the observed signal in order to provide reliable estimations of geophysical phenomena on the ground. Various models describing the interaction of electromagnetic radiation with forest canopy have been developed, but many of these are overly complex with high ancillary data requirements. For retrieval purposes, simple models are preferred.

This thesis aims at increasing the understanding of how vegetation, and particularly forest canopy, influence remote sensing observations in boreal environments. The focus is mainly on SAR instruments, but also passive microwave and optical sensors are investigated. The capability of a simple zeroth-order model in simulating the effect of vegetation on the remote sensing signal is first quantified by a spatial analysis of optical, SAR, and passive microwave remote sensing data. Then, the influence of vegetation in SAR remote sensing is further examined through two practical applications; mapping floods under various forest conditions, and detecting soil freezing/thawing in boreal forests.

The results demonstrate that despite using a relatively simple model, the extinction of electromagnetic signals in forest canopy was well estimated. Due to both sufficient estimation accuracy and simplicity, the presented model can be considered applicable in near real-time monitoring applications. Floods were well detected in open areas due to specular reflection of the water surface and in dense forests due to double bouncing between flood surface and tree trunks. Yet, in low tree and sparse forest areas, the detection of floods was less successful. The forest backscattering model was capable of separating between the backscatter contributions originating from the ground surface and from the forest canopy, thus enabling the identification of frozen and thawed terrain in forests.

Keywords Boreal forest, forward model, floods, soil freeze-thaw, Synthetic Aperture Radar**ISBN (printed)** 978-952-60-3887-2**ISBN (pdf)** 978-952-60-3888-9**ISSN (printed)** 1799-4934**ISSN (pdf)** 1799-4942**Location of publisher** Helsinki**Location of printing** Helsinki**Year** 2020**Pages** 117**urn** <http://urn.fi/URN:ISBN:978-952-60-3888-9>

Tekijä

Juval Cohen

Väitöskirjan nimi

Latvuston vaikutus kaukokartoitushavaintoihin havumetsävyöhykkeellä

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Kaukokartoitusmenetelmiä käytetään usein pohjoisten alueiden prosessien seurannassa. Tyypillisiä satelliittiantureita tähän tarkoitukseen ovat synteettisen apertuurin tutkat (SAR), optiset ja passiiviset mikroaaltoanturit. Monet seurannan alla olevista kohteista ovat kuitenkin metsän peitossa. Kasvillisuus, ja erityisesti metsän latvusto vaikuttavat merkittävästi säteilyn etenemiseen, varsinkin yleisimmin käytetyillä mikroaalto- ja optisilla aallonpituuksilla. Näin ollen, jotta luotettavia arvioita maanpäällisistä geofysikaalisista ilmiöistä voitaisiin saada, on syytä huomioida kasvillisuuden vaikutuksia havaittuun säteilyyn. Sähkömagneettisen säteilyn vuorovaikutusta puuston kanssa selittäviä malleja on jo kehitetty, mutta monet niistä ovat liian monimutkaisia ja vaativat runsaasti oheistietoa. Käytännön sovelluksiin suositetaan siksi yksinkertaisia malleja.

Tämän opinnäytetyön tavoitteena on lisätä ymmärrystä siitä, miten kasvillisuus ja etenkin metsän latvusto vaikuttavat kaukokartoitushavaintoihin pohjoisella havumetsävyöhykkeellä. Painopiste on pääasiassa SAR-tutkissa, mutta myös passiivisia mikroaalto- ja optisia antureita tutkitaan. Yksinkertaisen nollakertomallin kykyä simuloida kasvillisuuden vaikutusta kaukokartoitussignaaliin arvioidaan ensin analysoimalla optisen-, SAR- ja passiivisen mikroaltoinstrumentin kaukokartoitushavaintoja. Sitten kasvillisuuden vaikutusta SAR-kaukokartoitukseen tutkitaan yksityiskohtaisemmin kahden käytännön sovelluksen avulla; tulvien kartoittaminen eri metsäolosuhteissa ja maaperän jäätyminen/sulamisen havaitseminen havumetsävyöhykkeen metsissä.

Tulokset osoittavat, että suhteellisen yksinkertaisesta mallista huolimatta sähkömagneettisten signaalien käyttäytymistä metsien latvustossa onnistuttiin arvioimaan hyvin. Sekä hyvän arviointitarkkuuden että yksinkertaisuuden vuoksi esitettyä mallia voidaan pitää soveltuvana lähes reaaliaikaisissa seurantasovelluksissa. Tulvat havaittiin hyvin avoimilla alueilla veden pinnalla tapahtuvan peiliheijastuksen, sekä tiheissä metsissä tulvan pinnan ja puiden runkojen välisen kaksinkertaisen sironnan ansiosta. Matala- ja harvapuustoisilla metsäalueilla tulvien havaitseminen oli kuitenkin vaikeampaa. Metsän takaisinsirontamalli pystyi erottamaan maan pinnalta ja puustosta peräisin olevat takaisinsirontaosuudet, mikä mahdollisti routaantuneen ja sulan maaston tunnistamisen metsissä.

Avainsanat**ISBN (painettu)** 978-952-60-3887-2**ISBN (pdf)** 978-952-60-3888-9**ISSN (painettu)** 1799-4934**ISSN (pdf)** 1799-4942**Julkaisupaikka** Helsinki**Painopaikka** Helsinki**Vuosi** 2020**Sivumäärä** 117**urn** <http://urn.fi/URN:ISBN:978-952-60-3888-9>

Preface

This work has been carried out at the Finnish Meteorological Institute. I began my studies at the Department of Mechanical Engineering, at the Helsinki University of Technology (which during my studies changed to Aalto University). I continued my Master's studies at the Department of Built Environment, having remote sensing as my major research field. In my childhood, I remember watching satellite and aerial images, being fascinated by what the Earth looks like from a distance and trying to detect different targets on the ground. Therefore I feel that I have chosen the right field for my studies and work.

I would like to thank Prof. Juan M. Lopez-Sanchez for reviewing my work, and Dr. Yrjö Rauste for reviewing my work and acting as the official opponent at the defence. I'm truly grateful to the Finnish Meteorological Institute, where my career started by writing my Master's thesis, for providing a flexible and professional working environment. In particular, I want to express my gratitude to Dr. Juha Lemmetyinen and Prof. Jouni Pulliainen for directing, guiding and encouraging me throughout the research process. Special thanks also to Prof. Miina Rautiainen and Prof. Henrik Haggren from Aalto University for helping and instructing me.

I'm thankful to my parents for providing a supportive and solid background to start with. Finally, I wish to thank my dear wife Usva for helping me to make the right decisions, and together with our lovely children; Liel, Miya, Aviad and Benaya, for making my life interesting all these years.

Helsinki, 12 June 2020
Juval Cohen

Contents

Preface	1
List of Abbreviations and Symbols	5
List of Symbols	7
List of Publications	8
Author's Contribution.....	9
1. Introduction.....	11
2. Literature review	14
2.1 SAR remote sensing	14
2.2 Boreal forests in remote sensing applications	17
2.3 Simulation of remotely sensed signal from forests.....	19
2.4 Forest floods.....	20
2.5 Soil frost detection with SAR	21
3. Materials and methods.....	23
3.1 Forest forward model.....	23
3.2 Retrieval method.....	28
3.3 Mapping forest floods	29
3.4 Soil frost detection	30
3.5 Forest data	32
4. Results	35
4.1 Application of the forest model – multi-sensor analysis	35
4.2 SAR forest model in flooded terrain	38
4.3 Mapping forest floods	41
4.3.1 Flood detection in various forest conditions.....	41
4.3.2 Validation against manual in situ observations.....	42
4.4 Detecting soil frost/thaw	43
4.4.1 Backscatter vs. air temperature.....	43
4.4.2 Linear classification of F/T soil state	45
4.4.3 Soil F/T maps	46
5. Discussion.....	49

6. Summary and conclusions	52
References	55
Publication 1.....	63

List of Abbreviations and Symbols

AISA	Airborne Imaging Spectrometer for Applications
CC	Canopy Closure
CHP	Coarse Haplic Podzol
CoReH2O	Cold Regions Hydrology High-Resolution Observatory
DEM	Digital Elevation Model
ESA	European Space Agency
FHP	Fine Haplic Podzol
F/T	Frost/Thaw
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HA	Haplic Arenosol
HUT	Helsinki University of Technology
HUTRAD	Helsinki University of Technology RADiometer
IEEE	Institute of Electrical and Electronics Engineers
JPL	Jet Propulsion Laboratory
LiDAR	Light Detection And Ranging
LUKE	Natural Resources Institute Finland
MS-NFI	Multi-Sensor National Forest Inventory
NFI	National Forest Inventory
NIR	Near Infra-Red
NLS	National Land Survey
RCS	Radar Cross Section
RMSE	Root Mean Square Error
SAR	Synthetic Aperture Radar

STD	STandard Deviation
SV	Stem Volume
SYKE	Finnish Environment Institute
TH	Tree Height
TSX	TerraSAR-X
UG	Umbric Gleysol
UTM	Universal Transverse Mercator

List of Symbols

a	Cell area size
B	Corner reflection constant
T	Temperature
T_B	Brightness temperature
t	Canopy transmissivity
r	Reflectivity
r^2	Coefficient of determination
$\mathbf{w}$	2-D separation line
X	Feature vector matrix
$\mathbf{y}$	F/T discriminant vector
α	Microwave radiation
K_e	Canopy extinction coefficient
κ'_e	Effective canopy extinction coefficient
θ	Incidence angle
ρ	Optical reflectance
σ^0	Sigma nought

List of Publications

This doctoral dissertation consists of a summary, and of the following publications, which are referred to in the text by their numerals

- 1.** Cohen, Juval; Lemmetyinen, Juha; Pulliainen, Jouni; Heinilä, Kirsikka; Montomoli, Francesco; Seppänen, Jaakko; Hallikainen, Martti T. 2015. The Effect of Boreal Forest Canopy in Satellite Snow Mapping—A Multisensor Analysis. *IEEE Transactions on Geoscience and Remote Sensing*, volume 53, issue 12, pages 6593-6607. DOI: 10.1109/TGRS.2015.2444422.
- 2.** Cohen, Juval; Riihimäki, Henri; Pulliainen, Jouni; Lemmetyinen, Juha; Heilimo, Jyri. 2016. Implications of Boreal Forest Stand Characteristics for X-Band SAR Flood Mapping Accuracy. *Remote Sensing of Environment*, volume 186, pages 47-63. DOI: 10.1016/j.rse.2016.08.016.
- 3.** Cohen, Juval; Rautiainen, Kimmo; Ikonen, Jaakko; Lemmetyinen, Juha; Smolander, Tuomo; Vehviläinen, Juho; Pulliainen, Jouni. 2019. A Modeling-Based Approach for Soil Frost Detection in the Northern Boreal Forest Region with C-Band SAR. *IEEE Transactions on Geoscience and Remote Sensing*, volume 57, issue 2, pages 1069-1083. DOI: 10.1109/TGRS.2018.2864635.

Author's Contribution

Publication 1: The Effect of Boreal Forest Canopy in Satellite Snow Mapping—A Multisensor Analysis.

The author was the main contributor in this paper. The author prepared the forest parameters from the LiDAR point cloud data, processed and analyzed the optical, SAR and passive microwave data, and was responsible for writing the manuscript. The co-authors were responsible for collecting and preprocessing the AISA and the HUTRAD datasets, and they helped with writing and editing the manuscript.

Publication 2: Implications of Boreal Forest Stand Characteristics for X-Band SAR Flood Mapping Accuracy.

The author was the main contributor in this paper. The author developed the flood detection algorithm, processed and analyzed the SAR data, prepared the forest parameters from the LiDAR point clouds and was responsible for writing the manuscript. Henri Riihimäki collected the manual in situ observations from Evo and Kolari test areas and participated in writing the manuscript. The other co-authors helped in editing the manuscript.

Publication 3: A Modeling-Based Approach for Soil Frost Detection in the Northern Boreal Forest Region with C-Band SAR.

The author was the main contributor in this paper. The author was responsible for developing the soil F/T estimation method, data processing and analysis, as well as writing the manuscript. Jaakko Ikonen provided the soil maps and preprocessed the in situ station data. The other co-authors were responsible for maintaining the in situ stations and helped with writing and editing the manuscript.

1. Introduction

Remote sensing has become an important tool for observing the Earth. By measuring the emitted or scattered electromagnetic radiation, remote sensing enables the detection and monitoring of various objects and processes in the atmosphere, on the Earth surface, and even below the ground level. Remote sensing instruments can be roughly categorized according to their platform, the used electromagnetic spectrum, and the sensor properties. Active sensors send pulses and measure the returned radiation, whereas passive sensors only measure the incoming radiation while relying on external energy sources such as the sun, the target itself, or man-made transmitters. Sensors with coherent nature control, or take into consideration, the phase of the radiation, whereas incoherent sensors consider only the total energy of the radiation. Some sensors also control the polarimetric properties of the electromagnetic waves, by sending or receiving radiation only in a certain polarization. The sensor type also determines the size of one sample over the target, usually referred to as spatial resolution. The most typical platforms used for remote sensing are spaceborne (satellites) and airborne (airplanes, drones, helicopters). Ground based platforms are also used for small scale remote sensing or for reference measurements intended for calibration and validation of spaceborne or airborne measurements.

Earth observation instruments typically operate in the visible and infra-red spectrum range, many times referred to as optical instruments, or in the microwave spectrum of the electromagnetic waves. The visible, infra-red and microwave spectrum of the electromagnetic waves are useful in remote sensing of the Earth surface, because the atmosphere is almost completely transparent in these wavelengths, causing minimal interference to the signal. As a general rule, the electromagnetic signal reacts only to targets larger than the signal's wavelength. The electromagnetic radiation in specific wavelengths can, however, be absorbed by small particles such as water, carbon dioxide and ozone molecules, due to electromagnetic interaction between the signal and the specific molecules. The following paragraphs explain the basic principles of the optical and microwave remote sensing.

Optical sensors are typically passive and incoherent, and measure the reflectance of the target at several different channels (wavelengths), thus offering multi-layer information about the physical properties of the target. For instance, the reflectance of snow is high in all visual channels, but low in the infra-red channels of approximately 1.5 and 2.0 μm . As a comparison, clouds have a high reflectance both in the visual and in the infra-red channels. Hence, for a human

eye, snow and clouds look very similar, but due to their different reflectance in the infra-red spectrum, the separation of snow and clouds using optical remote sensing is relatively easy (Lillesand, et al., 2008). Optical instruments are dependent on sunlight as the external energy source, and moreover, they cannot penetrate clouds. These two restrictions are meaningful in northern environments, due to dark winters and frequent cloud cover in all seasons.

Spaceborne microwave remote sensing instruments typically operate on the microwave frequency spectrum of L- to Ka-bands, namely 1-40 GHz, corresponding to wavelengths of 0.75-30.0 cm. The main advantage of microwave instruments compared to optical ones, is the ability to gather information from Earth's surface during day and night, and in all weather conditions. Passive microwave instruments, also called radiometers, measure the microwave radiation emitted by the Earth system. The measured radiation is expressed as brightness temperature (T_B), which is the equivalent blackbody temperature of the observed object. In practical passive microwave Earth observation, the T_B is mainly dependent on the permittivity of the target materials. For natural targets, one of the main factors controlling the permittivity is water content, and therefore, passive microwave remote sensing is often used for soil moisture and soil frost/thaw (F/T) state retrievals (Ulaby, et al., 1986; Njoku & Entekhabi, 1996; Schwank, et al., 2004; Rautiainen, et al., 2012). Passive microwave instruments typically provide data with high temporal resolution and large swath widths, but due to the relatively low energy level emitted per unit surface area, the radiation must be collected over a large region. As a result, the spatial resolution of passive microwave data is relatively coarse (Ulaby, et al., 1981; Lillesand, et al., 2008). The importance of active microwave remote sensing has increased in recent decades, especially the use of Synthetic Aperture Radar (SAR) sensors. The main advantages of SAR instruments compared to others, is the combination of high spatial resolution with the option to see Earth's surface during day and night, and in all weather conditions. These properties are very useful in boreal environments due to frequent cloud cover and dark winters. A more detailed review on SAR remote sensing is given in chapter 2.1.

In the northern latitudes, important environmental factors such as snow, vegetation, soil and water processes can be efficiently detected and monitored from space. The extent, condition and properties of these and other factors are observed using the above-mentioned satellite sensors. A large portion of the boreal regions is covered by forests. For an accurate estimation of surface properties in the boreal environments, it is therefore essential to take into consideration the effect of forest canopies on the remote sensing signal.

The main goal of this thesis was to increase the understanding on how vegetation, and particularly forest canopy, influence the remote sensing observations in boreal environments. The focus was mainly on SAR instruments, but also passive microwave and optical sensors were investigated. The capability of a relatively simple radiative transfer model in simulating the effect of vegetation on the remote sensing signal was quantified by a spatial analysis of optical, SAR, and passive-microwave remote sensing data. A simple model that requires relatively little ancillary data was preferred, so that it would be suitable for near

real-time mapping applications covering wide areas. Then, the influence of vegetation in SAR remote sensing was further examined through two practical applications; mapping floods in various forest conditions, and detecting soil freezing/thawing in boreal forests.

Publication 1 is dedicated for testing and validating the radiative transfer model for the three different sensor types; optical, SAR and passive microwave. A comprehensive analysis of a unique dataset including airborne optical, SAR and passive microwave data, as well as spaceborne SAR data is performed over snow covered terrain against LiDAR (Light Detection And Ranging) based forest canopy closure and stem volume data in a test area located near Sodankylä, northern Finland. The goal was to customize the model to a format which will be suitable for near real-time mapping applications of wide areas using different sensor types. This study was also the first one to analyze Ku-band (17.2 GHz) co- and cross-polarized SAR backscatter measurements against various forest properties in the boreal region.

Publication 2 focuses on the influence of vegetation on the X-band SAR backscattering signal in flooded forests. Observations over four test areas in Finland; Kittilä, Pudasjärvi, Kolari and Evo, were collected during spring flood events. The objective was first to investigate and simulate the backscattering mechanisms that occur in flooded areas in various forest conditions, and then, to identify which canopy closure and tree height zones are problematic in the detection of floods if using solely backscatter intensity threshold values for the separation of floods from dry areas. This knowledge is important for the development of a semi-automatic process enabling fast and accurate mapping of floods in both open and forested areas. The initial hypothesis was that for certain areas with sparse canopy closure and low tree height, flood detection using solely SAR backscatter information will be problematic. This study was the first one to define the canopy closure and tree height zones where forest flood detection in the boreal region is problematic.

In publication 3, the C-band SAR backscattering signals of thawed and frozen areas were analyzed with respect to different forest properties, land cover types and weather conditions, in a test area located near Sodankylä, northern Finland. Then, a new approach for the estimation of the F/T state of soil in a boreal forest dominated area was demonstrated. In the proposed method, VV-polarized backscatter was applied in the model optimization, retrieving the forest canopy and ground backscatter contributions. These were then used for identifying the F/T state of soil, by means of a linear classification technique. In situ measurements of air temperature, soil temperature and soil permittivity were used to define frozen and thawed periods. Other available methods for SAR based soil F/T estimation do not explicitly take into consideration forest canopies, hence they are less reliable in forested regions. Besides the scientific novelty, this study provides the ground for the development of a near real-time soil F/T state estimation method based on SAR data.

2. Literature review

This chapter contains a literature review of the topics related to this thesis, which aims to provide the needed background information for a reader to understand the conducted research work. The basic principles of SAR remote sensing are first explained, followed by an overview on the applications, challenges and solutions related to the Earth observation of boreal forest environments. Then, background information regarding the remote sensing of floods and soil freezing/thawing in boreal forest region is provided, with an emphasis on the use of SAR.

2.1 SAR remote sensing

The first Earth observation satellite carrying a SAR instrument was Seasat, launched to space in 1978, and managed by NASA's Jet Propulsion Laboratory (JPL). The following space-borne SAR missions were JPL's Shuttle Imaging Radar (SIR) and Soviet Union's Cosmos experiments in the 1980's, followed by Almaz-1, ERS-1 and JERS-1, launched by the Soviet Union, the European Space Agency (ESA) and Japan respectively, in the beginning of the 1990's. The Canadian Radarsat was sent to space in 1995, followed by e.g. ESA's Envisat ASAR, Japan's ALOS PALSAR, German TerraSAR-X (TSX) etc. in the beginning of the 21'st century. In the last two decades, new SAR constellations have emerged, providing higher temporal resolution and better mission continuity, such as the Italian Cosmo Sky-Med and ESA's Sentinel-1 missions. A new trend in the SAR remote sensing field is the launch of large constellations consisting of many small sized satellites, such as the ICEYE constellation. This approach has many benefits, such as a reduced risk of heavy losses due to a failure of a single satellite, better temporal resolution enabling almost continuous monitoring of targets of interest, smoother data availability over time, better chances for smaller private or public companies to enter the market, leading to increased competition, better data availability and lower prices of products.

In order to understand the basics of SAR, it is essential first to know the operational principle of radars in general. The name "radar" is an acronym for Radio Detection And Ranging. Radars transmit electromagnetic signals and measure the properties of the returning signals which have scattered back from the observed objects to the radar. Information about the target is retrieved by analyzing e.g. the magnitude, polarization, frequency, phase and the time delay (the time it takes for the signal to return to the sensor) of the backscattering signal. Radars can therefore provide useful information regarding the observed object,

such as material, shape, size, distance from radar, velocity etc. The total backscattering power measured by a radar sensor is described by the radar equation, which in a general format can be written as:

$$P_r = \frac{P_t G_t A_r \sigma}{(4\pi)^2 R^3}, \quad (2.1)$$

where P_t and P_r stand for the transmitted and received power (energy), G_t is the gain of the transmitting antenna, R is the distance between the radar and the observed object, A_r is the effective aperture of the receiving antenna, typically proportional to the size of the antenna, and σ , typically referred to as the *radar cross section* (RCS), represents the properties of the observed object in relation to the radar signal properties.

SAR is a side looking radar that sends coherent electromagnetic pulses towards the target area and measures the fraction of the incident energy that is scattered back towards the sensor, often expressed as the *backscatter*. The magnitude (amplitude) as well as the phase of the returning pulses can be measured. Applications utilizing both amplitude and phase information are referred to as *SAR interferometry*. As depicted in Figure 1, the SAR system forms a 2-d image of the observed area, where the axes parallel and perpendicular to the radar movement direction are called azimuth and range, respectively. The SAR system uses a so called *aperture synthesis* method to form a virtual antenna, by combining information of several pulses measured along the movement path (Elachi, 1987). A very large antenna would be required if trying to achieve the same spatial resolution with a physical aperture.

Figure 1. SAR imaging geometry. For each pulse, the locations (resolution cells) from which the signals scatter back are identified in the range direction by measuring the time delay of the returning signal, and in the azimuth direction by the Doppler frequency shift.

The backscattering signal representing a certain resolution cell (pixel) within the whole area covered by one pulse is identified in the range direction by measuring the time delay of the returning signal, and in the azimuth direction by the Doppler frequency shift. In the range direction, backscattering signals returning earlier represent targets closer to the radar, while signals with longer time delay

represent objects further from the radar. In the azimuth direction, returning signals that have a higher frequency than the original transmitted frequency represent areas in front of the radar, while signals with lower frequency represent objects behind the radar. Several pulses covering the same resolution cell are then combined to calculate a value for each cell. The magnitude of the radar backscatter in SAR images is typically expressed using the *backscatter coefficient* σ^0 , defined as the average ratio between the RCS of a set of objects and their areas:

$$\sigma^0 = \langle \frac{\sigma_i}{A_i} \rangle, \quad (2.2)$$

where σ_i is the RCS of one object and A_i is the area associated to that object.

In SAR remote sensing, the observed backscatter is dependent on the shape of the target, the dielectric properties of the target material, the imaging geometry and the properties of the radar signal, namely frequency and polarization (Ulaby, et al., 1981). Considering the shape of the target, the total observed backscatter can be divided into three scattering mechanisms; surface, volume and double bouncing scattering. Surface scattering consists of pulses recorded at the satellite sensor after hitting the target once. Backscatter from the ground layer mostly consists of surface scattering (van Zyl, 1989; Zou, et al., 2015). Volume scattering is strong in targets where the radar pulse scatters randomly once to multiple times inside the target itself, before returning to the satellite sensor. For vegetation in general, and forest canopy in particular, the strongest backscattering mechanism is the volume scattering, especially for higher frequency signals such as C- and X-band, which less penetrate the canopy layer. Double bounce scattering consists of pulses hitting the target twice before recorded at the sensor. This usually occurs in standing objects whose surface is perpendicular to the ground or water surface, such as buildings or tree trunks. The scattering contributions are best identified by SAR polarimetry (Lee & E, 2009; Chen, et al., 2018).

Dielectric properties of the target material determine the penetration of the radar signal, thus affecting also the backscatter. In natural targets, the main factor controlling the signal penetration is water content, which increases the dielectric constant of the material (Ulaby, et al., 1982). In soils, for instance, the signal penetrates deeper into dry soil compared to wet soil, hence the backscatter of wet soil is usually higher than the backscatter of dry soil. In boreal regions, the main backscattering components forming the total backscatter measured at the sensor are the surface scattering contribution from the ground layer back to the sensor, and the volume scattering component from forest canopies (Pulliainen, et al., 1994; 1996; 1999). The double bouncing backscatter contribution can be sometimes notable, for instance when the forest floor is covered with water, causing a strong trunk-water double bouncing signal (Richards, et al., 1987; Hess, et al., 1990; Voormansik, et al., 2014; Martinis & Rieke, 2015).

2.2 Boreal forests in remote sensing applications

Approximately one third of Earth's land areas are covered by forests (FAO, 2010a). Forest biomass has a crucial role in the carbon balance of the Earth, since it is considered a major carbon sink through the photosynthesis process (GTOS, 2009). On the other hand, wood, the principal raw product of forests, has a major impact on the global socio-economic development (FAO, 2010b; Hansen, et al., 2013). Due to the high importance of forests to the environment, industry and climate, it is essential to control, manage and maintain the forests. Vegetation influences the remotely observed signal from space in both optical and microwave regimes, and therefore, remote sensing methods provide an efficient tool for mapping and monitoring forests from a global to a local scale (Tomppo, et al., 2008; White, et al., 2016). Remote sensing methods enable the detection and mapping of various forest properties, such as the biomass, stem volume, canopy closure and tree height. Separation of different tree species is also feasible using remote sensing techniques (Persson, et al., 2018). Optical sensors have been traditionally used for forest mapping, but due to growing data availability, the popularity of SAR techniques in forest mapping and monitoring is increasing (Praks, et al., 2007), especially for areas with frequent cloud cover, such as rainforests and boreal forests. Moreover, enhanced information can be extracted from forests by combining optical and SAR data, due to their complementary nature (Lehmann, et al., 2015). Airborne LiDARs have also been used for smaller scale forest mapping, especially in applications requiring high accuracy (Naesset, 1997). In Finland, nationwide forest mapping and monitoring is conducted primarily by Natural Resources Institute Finland (LUKE). They provide up to date data regarding various forest properties. In this thesis, forest data from LUKE have been used, and in addition, LiDAR based forest maps were generated from LiDAR point cloud data collected by the National Land Survey (NLS) of Finland (see chapter 3.5 for more details about the forest maps used in this study).

The presence of forests often poses a challenge for remote sensing based monitoring of targets on the ground, under the forest canopy. For a correct estimation of the observed target on the ground, it is essential to determine the quantitative influence of the forest cover on the remote sensing signal. The following paragraphs explain how forest canopy influences the total observed signal at the sensor for the mostly used satellite instruments; optical, SAR and passive microwave.

For the active microwave sensors operating at L-, C- or X-bands, forest canopy dampens the signal reaching the ground surface and back to the sensor, while volume scattering within the canopy itself contributes to the total backscatter measured at the sensor. The forest canopy above the ground typically increases the total backscattering coefficient measured at the sensor, especially in frozen soil or wet snow conditions when the backscatter of the forest floor is relatively low (Ulaby, et al., 1986; Pulliainen, et al., 1994; 1999; Koskinen & Hallikainen, 1997; Luojus, et al., 2007). The main factors controlling the penetration level of the microwave signal through forest canopies are the signal frequency and polarization, incidence angle, and the properties of the canopy. Lower frequency

radiation is less sensitive to the tree canopy, hence it penetrates more than higher frequency radiation. Co-polarized signals can better penetrate the canopy than cross-polarized (Evans, et al., 1986; Wu & Sader, 1987; Kuga, et al., 1990), and HH-polarization penetrates better than VV-polarization (Wang, et al., 1995; Bourgeau-Chavez, et al., 2001; Townsend, 2002; Lang & Kasischke, 2008; Pierdicca, et al., 2013) due to the vertical orientation of the tree trunks (Lavender & Lavender, 2017). Higher penetration can be achieved in steep incidence angles, because the signal needs to travel a shorter distance through the canopy before and after hitting the ground surface (Lang, et al., 2008). Deciduous trees are less transparent for microwave radiation during leaf-on conditions (Townsend, 2001; Lang, et al., 2008; Martinis & Rieke, 2015)

Considering passive microwave remote sensing, forest canopy attenuates emission coming from the ground layer, while adding its own contribution to the total emitted microwave radiation. The measured T_B of forested areas is typically higher than that of snow-covered open terrain (Kruopis, et al., 1999; Pampaloni, 2004; Derksen, et al., 2005; Foster, et al., 2005; Pardé, et al., 2005; Lemmetyinen, et al., 2009; Langlois, et al., 2011). A recent study also shows a dependency between air temperature and the microwave transmissivity of the forest canopy in sub-zero conditions (Li, et al., 2019). Due to partial penetration of the microwave radiation through forest canopy, the portion of the canopy backscatter or T_B from the total observed radiation at the sensor is proportional to the total mass or volume of the canopy. Yet, for higher frequency instruments and polarization combinations more sensitive to the tree canopy, also canopy closure can be applied to estimate the portion of the radiation originating from the tree canopy, as shown in Publication 1.

Figure 2. A photograph showing the influence of forest canopy on the optical reflectance in a typical snow-covered boreal forest environment. The relatively dark tree canopies block the visibility to the snow surface, thus decreasing the total observed reflectance. The photograph was taken on the 27th of April 2012, from a mast camera located in Tähtelä, Sodankylä, northern Finland.

In optical remote sensing, due to significantly shorter wavelengths compared to the microwave regime, the signal barely penetrates through the forest canopy, and therefore, the influence of forest canopy on the total measured reflectance can be considered proportional to the canopy closure, namely the fraction of surface area covered by forest canopy from the total surface area. For visual and near infra-red (NIR) wavelengths, the reflectance of snow is significantly higher than the reflectance of tree canopy. For snow covered terrain, shrubby vegetation and forest canopy therefore decrease the total measured reflectance at the sensor (Li, et al., 1995; Schlerf & Atzberger, 2006; Liu, et al., 2008; Salminen, et al., 2009; Niemi, et al., 2012; Cohen, et al., 2013; Heinilä, et al., 2014; Pulliainen, et al., 2014). In Figure 2, a natural color photograph demonstrates the scenery of relatively dark tree canopies above a bright snow surface.

2.3 Simulation of remotely sensed signal from forests

The total electromagnetic signal measured at the sensor is a sum of radiation components originated from different sources or scattering mechanisms. In case of passive microwave radiation, the material itself emits the radiation which is eventually measured at the sensor. The total radiation measured by the sensor thus consists of emission from e.g. the soil, snow and canopy. Also scattering and absorption between surfaces occur. For example, radiation emitted by the soil is partially absorbed and scattered to different directions by the snow layer, and the downwelling canopy emission is scattered from the ground surface towards the sensor. In the case of optical and active microwave remote sensing, the measured signal by the sensor consists of scattered radiation from various targets. In remote sensing applications, the aim is often to examine a certain portion of the scattered radiation, such as that of the soil, vegetation, snow cover or artificial objects. In Earth observation of boreal environments, the target of interest is typically on the ground surface or the soil itself. A major source of signal interference is therefore the forest canopy obscuring the ground surface. Hence, one of the main challenges is to decompose the total measured radiation to the different components, and to extract only the information about the specific target of interest, while ignoring or compensating the effect of other factors on the total measured radiation.

Various forward models simulating the observed signal originated from natural media and allowing the separation of e.g. the forest canopy signal from the total observed signal have been developed for active microwave (Sun & Ranson, 1995; Lin & Sarabandi, 1999; Liang, et al., 2005; Liu, et al., 2010), optical (Li, et al., 1995; Klein, et al., 1998; Vikhamar & Solberg, 2003; Salminen, et al., 2009; Niemi, et al., 2012) and passive microwave (Kruopis, et al., 1999; Pardé, et al., 2005; Langlois, et al., 2011) data. Yet, some of these models are very complex, requiring intricate prior knowledge on the simulated media (snow, soil, vegetation), and are computationally heavy. In real-time or near real-time mapping of wide areas, the preference is for simpler models requiring less ancillary information and processing power. More information regarding the existing models for simulating the effect of vegetation on the remote sensing signals can be

found in Publication 1. The model used in this work for simulating the remote sensing signals of forested terrain, is a simplified version of the HUT (Helsinki University of Technology) semi-empirical forest model (Pulliainen, et al., 1994; 1996; 1998), hereafter referred to as the zeroth order model. The zero of order in the context of radiative transfer models refers to the number of multiple scatterings within a random medium (in this case forest canopy) that are accounted for in a model (Ulaby, et al., 1986; Karam, 1997). The zeroth order model used in this thesis therefore considers the canopy as one effective layer/particle, attenuating the radiation passing through by absorption and single particle scattering, and acting as a source of emission (only passive microwave), thus ignoring multiple scattering within the canopy itself.

2.4 Forest floods

Floods are a well-known natural phenomena in Finland experienced almost every spring during the snowmelt season, causing damages to e.g. agriculture, the road network and buildings. Near real-time flood maps can help emergency personnel when operating during flood events, and they can be useful to land-owners and farmers in planning preventive or recovery actions. Flood maps can also be beneficial to private or public sectors for community, agriculture and forest planning, or they can be used by insurance companies when handling claims related to flood damages. The progress of the floods during the spring snow melting period could also be predicted more accurately based on flood maps of the previous years. (Marttila, et al., 2005)

Traditionally floods have been mapped with airborne optical instruments. This technique can provide maps with very high spatial resolution, works in almost all weather conditions, and allows temporal and spatial flexibility, provided that a pilot, airplane and the related equipment are available. Yet, the costs are high, and the spatial coverage is low compared to satellite imagery. The use of drones instead of airplanes can reduce costs, but the spatial coverage remains small. Space borne remote sensing techniques enable a relatively fast and cost-efficient mapping of floods for wide areas (Klemas, 2015; Refice, et al., 2018). Optical satellite data has been widely used for flood mapping (Huang, et al., 2018). However, they are not suitable for frequently clouded areas such as the boreal environments.

SAR techniques offer a good alternative, applicable in all weather conditions and enabling mapping even in spatial resolutions higher than one meter (Tsyganskaya, et al., 2018; Shen, et al., 2019). When using single polarization SAR data, the flooded areas can be separated from non-flooded areas based on backscatter differences. The backscatter of floods in open (non-forested) areas is considerably lower than the backscatter of non-flooded areas, due to the specular reflection occurring on the water surface. For floods under tree canopy, the scattering scheme is more complex, but typically the backscatter is higher than in dry forests, due to corner reflection between the water surface and the tree trunks (Engheta & Elachi, 1982; Richards, et al., 1987; Townsend, 2001; 2002). In operational algorithms based on SAR, the separation of floods and non-

flooded areas is usually carried out using backscatter thresholding methods (Brivio, et al., 2002; Matgen, et al., 2007; Martinis, et al., 2009). Finding the optimal threshold values is a critical step in flood detection algorithms. The optimal threshold value for differentiating flooded forests typically decreases with larger incidence angles (Townsend, 2001).

Fully polarimetric SAR can identify floods in vegetated areas, which are undetected by the more straightforward methods based on changes in backscattering intensity. For example, separation of double bounce effects, mainly caused by floods under tree canopy, from the other scattering mechanisms, are possible with different decomposition techniques (Wang & Davis, 1997; Brisco, et al., 2013; Schmitt & Brisco, 2013). However, fully polarimetric SAR imagery is currently not available in a scale required by operational flood monitoring.

Previous studies aiming at flood detection in forested areas with SAR show, that inundated areas under tree canopy can be well detected even when using relatively high frequency X-band SAR (Pulvirenti, et al., 2013; Voormansik, et al., 2014; Martinis & Rieke, 2015), in spite of the limited penetration of the signal through forest canopies. Concerning open (non-forested) areas, higher frequency C- and X-band are even favorable, because the lower frequency L-band signal can more easily mix between open water and other smooth surfaces (Drake & Shuchman, 1974; Martinis & Twele, 2010; Voormansik, et al., 2014).

The most common reason for spring floods in the boreal region is the increased water level in rivers and lakes, mainly caused by a combination of rapid snowmelt and frozen soil (Krasovskaia & Gottschalk, 2002). During typical spring floods, low elevation areas next to rivers and lakes are inundated, while higher elevation areas remain dry. The aim is therefore to identify the borderline between flooded and dry areas. Floods in boreal forests were mapped by Voormansik, et al., (2014), who concluded that additional testing of the X-band sensor should be carried out with more detailed information regarding tree species, stand age, height and density. ESA's Sentinel-1 satellite pair offers a valuable SAR data source suitable for monitoring flood conditions (Twele, et al., 2016; Clement, et al., 2018; Ruzza, et al., 2019; Tsyganskaya, et al., 2019; Uddin, et al., 2019), especially in northern latitudes due to nearly daily temporal resolution. However, the land areas are regularly imaged only with VV- and VH-polarizations, which are less useful for detecting floods under forest canopy compared to HH-polarization (see section 2.2)

2.5 Soil frost detection with SAR

More than half of the total land areas in the northern hemisphere experience seasonal soil freezing (Zhang, et al., 2003). A large portion of these areas are covered by boreal forests. As mentioned in chapters 1 and 2.1, microwave remote sensing methods are ideal for soil moisture detection, because higher soil water content increases the dielectric constant of the soil. Concerning active microwave Earth observation, soil freezing thus lowers the dielectric constant, causing higher penetration into the soil, leading to decreased backscatter. Soil

F/T estimates are generally more rigorous if the soil was wetter prior to freezing, because then the change in the dielectric constant is more prominent.

Several methods for detecting the F/T state of the ground surface with passive and active microwave instruments can be found in literature. Algorithms based on higher K- and Ka-frequency passive microwave instruments, such as the SSM/I (Special Sensor Microwave Imager) (Kim, et al., 2011) and AMSR-E (Advanced Microwave Scanning Radiometer Enhanced) (Zhao, et al., 2011) have been introduced; however, these methods acknowledge the interference of factors such as forest canopy and the presence of snow cover to the retrieved F/T state. Following the launch of SMOS and SMAP, methods for the detection of soil F/T state using L-band passive (Rautiainen, et al., 2016) and active (Xu, et al., 2016) microwave observations (Derksen, et al., 2017), less affected by the presence of vegetation, have been developed. The SMAP algorithm designed for the active sensor was tested for Aquarius L-band scatterometer observations (Xu, et al., 2016). The algorithm is based on a seasonal thresholding approach, where the soil's F/T state is estimated by comparing the observed backscatter with the backscatter representing freeze and thaw conditions. A product showing the soil surface state has also been developed for the ASCAT (Advanced Scatterometer) instrument (Naeimi, et al., 2012).

Studies regarding soil F/T detection with C-band SAR started with ERS-1 (Rignot & Way, 1994), and continued with Envisat (Park, et al., 2011). Soil freezing directly affects the dynamics of the polarimetric entropy and mean scattering alpha angle, enabling the detection of soil's F/T state using an eigen-based decomposition technique with fully polarimetric C-band data (Jagdhuber, et al., 2014). The availability of fully polarimetric SAR data is however not sufficient for continuous monitoring of the soil state. A recent study where Sentinel-1 data was combined with a semi-empirical dielectric constant model for agricultural areas located near Paris shows the potential of C-band SAR data for continuous monitoring of the soil F/T state (Baghdadi, et al., 2018).

Currently available methods for the detection of soil F/T state, which rely on single-polarization SAR data, do not explicitly take into consideration the influence of the forest canopies, and are therefore potentially less reliable for boreal forest regions. The challenge in using C-band SAR compared to lower frequency L-band, and moreover, VV-pol (available from Sentinel-1) compared to HH-pol, for the detection of soil freeze, is the limited penetration through forest canopies (Wang, et al., 1995; Townsend, 2002; Lang & Kasischke, 2008; Pierdicca, et al., 2013). Estimation of soil F/T state using observed values directly can therefore be difficult or even infeasible with these data. A similar model to the one presented in this study has been used in previous studies for retrieving the different backscatter components which form the total backscatter (Pulliainen, et al., 1994; 1999; Montomoli, et al., 2016). A numerical inversion of the model allows the retrieval of the different backscatter contributions, such as the ground backscatter, enabling e.g. the estimation of soil moisture. Similarly, the retrieved backscatter components could be used in the context of detecting the soil F/T state.

3. Materials and methods

This chapter first describes the methods applied in the more theoretical part of this thesis; applying a simple zeroth order model for simulating the effect of vegetation on the remote sensing signal of optical, SAR, and passive-microwave sensors. Then, the methods of the more practical part of this work; flood detection and soil F/T state estimation in boreal forests using SAR, are explained. In addition to investigating the backscatter contributions in flooded forests using the zeroth order model, the aim in Publication 2 was to define in which forest conditions regarding canopy closure and tree height, flood detection is feasible with HH-polarization X-band SAR. In Publication 3, the ground and the canopy backscatter retrieved from C-band SAR observations using the model were further utilized for soil F/T detection. Finally, section 3.5 describes which forest data was used in this study, and how the forests data was prepared.

Pre-processing of the space-borne SAR data in this thesis included calibration to sigma naught backscatter values (σ^0) and georeferencing while considering the terrain topography (terrain correction). Correction of the influence of the topography on the radiometry (terrain flattening) was not performed, as the areas of interest were relatively flat, however, the incidence angle was considered in the analyses. More detailed information about the performed SAR processing is given in Publications 1, 2 and 3.

3.1 Forest forward model

In this work, a simplified zeroth order model of the radiative transfer equation (Pulliainen, et al., 1994; 1996; 1998) was applied to simulate the influence of the forest canopy on the observed remote sensing signal. The model can be used to estimate the signal contributions of the ground and the canopy, despite the limited or even non-existent penetration of the signal through the forest canopy. This is done by utilizing remote sensing observations from various canopy conditions and by modeling the total observed signal as a function of a forest density parameter, e.g. canopy closure, stem volume or tree height. Due to sufficient accuracy and simplicity, this model enables a retrieval of the signal components for wide areas, and moreover, it can be applied for optical as well as microwave active and passive data. A similar approach has been previously applied in the case of active and passive microwaves (Pulliainen, et al., 1994; 1999; 2001; Luojus, et al., 2007; 2009; Koskinen, et al., 2010) and in the case of optical data (Metsämäki, et al., 2005; 2012; 2015; Pulliainen, et al., 2014). However, Publication 1 presented a unique study applying modified versions of the same model

to all sensor types over a single test site, and Publication 2 presented an enhanced version of the active microwave model (double bounce scattering included) for four different test areas. The model aims at distinguishing and quantifying the contributions of the main components on the total signal measured at the sensor. An important factor in the model is the canopy extinction coefficient which determines the transmissivity (t) of the electromagnetic signal through the forest canopy.

In Publication 1 the model was tested for three airborne and one space-borne dataset. The airborne datasets analyzed were: 1) The AISA (Airborne Imaging Spectrometer for Applications) optical dataset collected within the Airborne Imaging Spectroscopy Application and Research in Earth Sciences (AISARES) Graduate School during March 2010; 2) The SnowSAR SAR dataset collected within the Phase A studies of the proposed Cold Regions Hydrology High-Resolution Observatory (CoReH2O) mission, one of the candidates for the 7th Earth Explorer Core mission by ESA, during winter 2011-2012; 3) The Helsinki University of Technology Radiometer (HUTRAD) passive microwave data obtained in March 2011. The Analyzed space-borne dataset was a whole-winter time series of TSX acquisitions from winter 2011-2012, obtained within the CoReH2O study.

The ground surface and the forest canopy components forming a zeroth order forest model in the investigated sensor types are depicted in Figure 3. As seen in Figure 3a, the T_B components contributing to the total signal measured by the sensor, that are accounted in the model, are direct emission from the canopy and the ground, as well as canopy downwelling emission reflected from ground towards the sensor. Similarly, as shown in Figure 3b and in Figure 3c, the backscatter and the reflectance contributions respectively, from the total observed signal measured by the sensor, are the signals scattered from the canopy and from the ground surface. In all cases, depending on the forest transmissivity t , forest canopy dampens the signal coming from the ground surface towards the sensor.

In Publication 2 the model was tested using Cosmo Sky-Med Stripmap HH-polarization backscatter images acquired during spring flood events for four test sites across Finland; Kittilä, Kolari, Pudasjärvi and Evo. Figure 4 shows a scheme of the active microwave model applied in the case of flooded forests. In addition to the canopy and the ground backscatter contributions depicted in Figure 3b, this model also includes the double bouncing component, mainly caused by scattering between the tree trunks and the flood surfaces.

Figure 3. Different T_B (a), backscatter (b) and reflectance (c) contributions to the total radiation, which are considered in the models of the study of Publication 1, described by Equations (3.5), (3.6) and (3.7). Figure adapted from Publication 1.

Figure 4. Different backscatter contributions to the total radiation which are considered in the model of Publication 2, described by Equation (3.9): Canopy volume scattering, double bounce scattering between flood surface and tree trunks, and direct surface scattering from the ground/flood surface. Figure adapted from Publication 2.

The basic methodology and related equations explaining the model are presented in this chapter, but more specific explanations and equations regarding the different applications are given in Publications 1-3. Regarding the forest cover, it can be assumed that the one-way transmissivity of the forest canopy is exponentially related to the total extinction, so that

$$t_{one-way} = e^{-K_e FP / \cos \theta}, \quad (3.1)$$

where K_e is the canopy extinction coefficient, FP (forest parameter) is a parameter describing the physical properties of the forest canopy (canopy closure or stem volume in this study), and θ is the incidence angle. In the models applied for optical and SAR data, the radiation passes through the forest canopy twice; once when propagating from the sensor towards the ground, and again, when returning to the sensor after hitting the ground interface. Instead of one-way transmissivity, a two-way transmissivity is therefore used. In the active microwave model, the two-way transmissivity (Eq. 3.2) is defined as the one-way transmissivity (Eq. 3.1) to the second power, because the incoming and outgoing angles are the same (forest canopy conditions are considered equal for both propagation paths):

$$t_{two-way,SAR} = e^{-2K_e FP / \cos\theta}. \quad (3.2)$$

In the optical model, the incoming θ_{sun} and the outgoing θ_{sensor} angles are different, leading to a two-way transmissivity defined as:

$$t_{two-way,OPT} = e^{\frac{-K_e FP}{\cos\theta_{sun}} - \frac{-K_e FP}{\cos\theta_{sensor}}}. \quad (3.3)$$

The radiative transfer model for mixed open area and forested observations is expressed as:

$$\alpha_{total} = FF\alpha_{forest} + (1 - FF)\alpha_{ground}, \quad (3.4)$$

where the forest fraction (FF) represents the forest fraction within the sample area ranging between 0 and 1, α_{total} represents the total radiation measured at the sensor, α_{forest} represents radiation from forests and α_{ground} radiation from open areas. The presented model, however, considers a sample area as being entirely non-forested or forested with changing canopy closure or stem volume, hence, the forest fraction of a sample area is either zero (non-forested) or one (entirely forested). In the optical and the active microwave models this assumption is acceptable, because the pixel size was always smaller than 10 x 10 m. Yet, in the passive microwave model, where the footprint size was in the order of 40 x 80 m for 10 and 18 GHz, and 50 x 100 m for 36 GHz, the FF would often be between zero and one. In the passive microwave model, only samples with FF lower than 0.1 (non-forested) and higher than 0.7 (forested) were therefore included in the analysis.

The zeroth order models for optical (Eq. 3.5), active microwave (Eq. 3.6) and passive microwave (Eq. 3.7) observations are shown below. The first term in Equations (3.5), (3.6) and (3.7) determines the contribution of the ground surface, and the second term determines the contribution of the forest canopy on the observed signal. Ground surface here refers to the joint contribution of the ground itself together with the contribution of snow if exists. The third term in Eq. (3.7) determines the downwelling emission of the tree canopy which is re-

flected from the ground towards the sensor. Eq. (3.9) shows the active microwave model which includes the double bounce scattering mechanism (the third term) applied in case of flooded forests (Publication 2). Other possible multiple scattering contributions occurring within or between the atmosphere, vegetation and ground surface are neglected in this study, because their impact to the total radiation is relatively small. The aim of this work was to test and use a model suitable for practical mapping applications, and therefore, the added value in including multiple scattering components would have been minor compared to the disadvantages caused mainly by larger ancillary data needs and longer processing times. When applied for optical data, the zeroth order total reflectance ρ_{total} observed above the forest canopy can be expressed as:

$$\rho_{total} = t_{two-way,OPT}\rho_{ground} + (1 - t_{two-way,OPT})\rho_{canopy}, \quad (3.5)$$

where ρ_{ground} is the reflectance of the ground surface or the snow surface if exists, and ρ_{canopy} is the reflectance of the canopy. Applying an analogous model as presented in Eq. (3.5) for the case of microwave backscatter gives:

$$\sigma^0_{total} = t_{two-way,SAR}\sigma^0_{ground} + (1 - t_{two-way,SAR})\sigma^0_{canopy}, \quad (3.6)$$

where σ^0_{total} is the total backscatter, σ^0_{ground} is the backscattering coefficient of the ground layer and σ^0_{canopy} is the backscattering coefficient of the forest canopy. As said, two-way transmissivity is used in the optical ($t_{two-way,OPT}$) and SAR ($t_{two-way,SAR}$) models, as the radiation beam passes through the canopy layer twice.

For the passive microwave model, one-way transmissivity $t_{one-way}$ is used, as the radiation passes through the forest canopy only once. A third component is also added to the model; the emission of the canopy towards the ground, which is scattered from the ground to the sensor. The passive microwave model can be expressed as:

$$T_{B,total} = t_{one-way}T_{B,ground} + (1 - t_{one-way})T_{canopy} + (1 - t_{one-way})rt_{one-way}T_{canopy}, \quad (3.7)$$

where r is the reflectivity of the ground or snow, $T_{B,ground}$ is the T_B of the ground layer and T_{canopy} is the physical temperature of the forest canopy. The model does not include emission from the atmosphere, which contribution to the total measured T_B can be estimated as:

$$T_{B,atm} = T_{B,sky}t_{one-way}^2r. \quad (3.8)$$

Using model simulations (Liebe, 1985; Pulliainen, et al., 1993), the microwave emission of the atmosphere $T_{B,sky}$ in the analyzed frequencies and incidence angles ranges roughly between 10 and 30 K. According to Eq. (3.8), if $T_{B,sky}$ is assumed to be the maximum 30 K, the T_B contribution of the atmospheric emission in this study would be approximately on average 4.9 K for open areas and

1.6 K for forested areas where the stem volume is 100 m³/ha, corresponding to 1.94 % and 0.64 % from the total measured T_B respectively. Hence, the neglect of atmospheric emission in the passive microwave model (Eq. 3.7) did not produce considerable errors.

Eq. (3.9) shows the active microwave model where the first two terms represent the contribution of ground surface and forest canopy respectively, as presented in Eq. (3.6), and the third term represents the double bounce (corner reflection) scattering which is mostly originated from the scattering between tree trunks and water surface:

$$\sigma^0_{total} = t_{two-way,SAR}\sigma^0_{ground} + (1 - t_{two-way,SAR})\sigma^0_{canopy} + Bt_{two-way,SAR}N_{trees}RCS_{tree}/a. \quad (3.9)$$

B in Eq. (3.9) is a free constant to be optimized by the model. N_{trees} is the number of tree trunks in one resolution cell, which is assumed to be linearly proportional to the forest canopy closure divided by the surface area of a single tree estimated from the tree height. RCS_{tree} is the radar cross section of one tree trunk which is also estimated from the tree height, and a is the area size of one resolution cell on the ground. Publication 2 gives a more detailed explanation of the active microwave forest model used.

3.2 Retrieval method

A numerical inversion method was implemented to the forward models described in Eqs. (3.5)–(3.7) to retrieve the ground-level signal and the forest canopy signal in the case of optical reflectance, active microwave backscatter and passive microwave emissivity. The method exploits a large number of observations to iteratively fit the model against the most suitable parameters describing the vegetation properties. The free parameters in the optimization effectively yield the required parameters, i.e. the signal emanating from beneath the forest canopy and the signal emanating from the canopy itself. In this study, models were fit to the observational data using the method of least squares, minimizing the following cost functions:

$$\min \left\{ \begin{aligned} &\sum_{i=1}^N [\rho_{model,i}(\rho_{ground}, \rho_{canopy}, K_{e,OPT}, \theta, FP_i) - \rho_{obs,median,i}]^2 \\ &\sum_{i=1}^N [\sigma^0_{model,i}(\sigma^0_{ground}, \sigma^0_{canopy}, K_{e,SAR}, \theta, FP_i) - \sigma^0_{obs,median,i}]^2 \\ &\sum_{i=1}^N [T_{B,model,i}(T_{B,ground}, T_{canopy}, K_{e,PM}, \theta, FP_i) - T_{B,obs,mean,i}]^2 \end{aligned} \right\}, \quad (3.10)$$

where FP refers to the used forest parameter (canopy closure or stem volume) and i refers to the canopy closure or stem volume classes. The active microwave model written in Eq. (3.10) does not include the double bounce scattering component, but the retrieval principal of minimizing the difference between the modeled backscatter and the median observed backscatter is the same with or without the third component. Publication 2 gives more detailed information regarding the retrieval method which includes double bounce scattering. There

were three free parameters in each model given in Eq. (3.10), while the FP was obtained from ancillary data. The free parameters in the optical model were the contribution of open (non-forested) areas ρ_{ground} and canopy ρ_{canopy} to the total measured radiation, as well as the canopy extinction coefficient $K_{e,OPT}$. Correspondingly, the three free parameters in the SAR model were σ_{ground}^0 , σ_{canopy}^0 and $K_{e,SAR}$, and in the passive microwave model $T_{B,ground}$, T_{canopy} and $K_{e,PM}$. In Publication 1, the extinction coefficient K_e was replaced by the effective extinction coefficient κ'_e , incorporating the incidence angle which was nearly constant for all observations.

The focus in Publication 1 was to test and validate the proposed model for the three different sensor types. For this purpose, the observed signal from open areas was compared with the modelled one. The observed signal of open areas was obtained by calculating the median (optical and active microwave data) or mean (passive microwave data) value of all observations in areas where canopy closure or stem volume was zero. This inversion method is applicable providing that the ground surface and the vegetation transmissivity properties are considered to be constant over the area of interest. The area of interest in practical retrieval applications is a grid cell consisting enough observations from which a reliable model fitting can be achieved. An output product showing e.g. the retrieved ground backscatter would then consist of output grid cells, each one having a certain ground and canopy transmissivity properties. For instance, in Publication 3, the size of one output grid cell was 1000 x 1000 m, which consisted of more than 3800 possible observations with various forest properties. Land cover areas with a distorting effect on the signal were omitted, using land cover information extracted from the Finnish Corine Land Cover.

3.3 Mapping forest floods

In this study a simple flood detection algorithm based on a threshold value approach was applied for HH-polarization X-band SAR data in order to separate flooded from non-flooded areas. Two threshold values were used, one lower threshold value to separate open area floods from dry areas, and another higher threshold value to separate floods in forested areas from dry areas. The ability of the algorithm to detect floods in various forest conditions was assessed by comparing the flood detection results with reference flood information and forest properties.

Manual in situ information regarding the flood condition was collected at two test sites; Kolari and Evo, while automatic measurements of the river water level were utilized in the two other test areas; Kittilä and Pudasjärvi. The field data from Kolari and Evo consisted of flood boundary points which were collected using high accuracy Global Positioning System (GPS) and Global Navigation Satellite System (GNSS) receivers. The data points were collected temporally as close as possible to the satellite image acquisitions. In Kolari, the measurements and the photographs were taken during the same day, but in Evo, part of the campaign was delayed for four days due to a weak GPS signal in the first days. Fortunately, the flood surface level was stable during this time. If a clear line

between flooded and non-flooded areas could not be determined, square shaped areas representing homogeneous partly flooded terrain were defined. These were typically a mixture of wet ponds and non-flooded hummocks. Soil moisture was not measured quantitatively, but as typically during spring flood season, the soil was observed to be moist in all areas during the whole field measurement campaign.

In order to properly assess the accuracy of the SAR detection in forests, sufficient amount of ground truth information covering various forests conditions, defining the real flooded areas, was needed. During spring floods, the water level is typically very dynamic, and therefore, especially in the larger test areas of Kittilä and Pudasjärvi, it was not possible to conduct a ground measurement campaign covering enough areas on such a tight schedule. For the extraction of the reference areas, it was thus necessary to develop a reliable method based on remote sensing data. In addition to the SAR backscatter images, a high resolution digital elevation model (DEM), the LiDAR based forest maps and the available in situ data were utilized to manually digitize the flooded and non-flooded reference areas. Floods in open treeless areas and in most forests were well separated from non-flooded areas based only on the SAR backscattering image. This provided a good initial estimate for the reference areas. Each initial reference flooded area was then manually corrected if needed, and verified based on the high resolution DEM, and when available, based also on the in situ measurements. As said, manual in situ measurements were not conducted in Kittilä and Pudasjärvi, but instead, automatic in situ sensors of the Finnish Environment Institute (SYKE), measuring the water surface level along the rivers, were utilized in addition to the other ancillary data for determining the flood extent. The same SAR images were used for manually extracting the initial flood reference areas and for the flood detection algorithm.

In this study, the optimal threshold values for each test area were chosen manually by comparing the backscatter values inside training areas representing open floods, forest floods and non-flooded areas. The training areas were manually digitized by a visual interpretation of the SAR backscatter images. A lower threshold value separating floods in open areas from dry areas was calculated based on the observed backscatter inside the open floods and non-flooded training areas, as described in Eq. (1) of Publication 2. An upper threshold value separating flooded forests from dry areas was calculated based on the observed backscatter inside the forest floods and non-flooded training areas, as described in Eq. (2) of Publication 2.

3.4 Soil frost detection

A new approach for the estimation of soil F/T state with Sentinel-1 C-band SAR for boreal forests was presented in this work. The soil F/T state estimation was performed based on the two retrieved parameters; ground and canopy backscatter components, derived by applying the zeroth order backscatter model on the C-band SAR observations. The F/T soil state estimate was given in a 1 km grid cell size. The observed and retrieved backscatter values were first analyzed

against various forest and air temperature conditions. A classification to freeze, thaw or uncertain classes was then performed using a linear 2-D line calculated from the retrieved ground and canopy backscatter values representing freeze and thaw cases. Ground truth information regarding soil F/T state at the time of the satellite acquisitions was acquired from six in situ stations mounted in different locations across the test area, measuring soil temperature and permittivity at 5 cm depth and air temperature at the height of 110 cm. If the soil state based on the in situ measurements was not clearly frozen or thawed, it was flagged as uncertain. The soil state was flagged as uncertain also during the melting season, because in wet snow conditions, the SAR backscatter is mainly controlled by the wet snowpack and not by the underneath soil conditions. The wet snow period was recognized based on snow temperature close to zero together with decreased backscatter values during the spring months.

Following an analysis of the retrieved and observed backscattering signals with respect to forest properties and in situ observations, it was found, that the backscatter of the ground surface and the forest canopy allowed separating the freeze and thaw states using 2-D linear classification. Based on the in situ information, the retrieved backscatter contributions of the ground σ_{gr}^0 and the canopy σ_{can}^0 were classified to values representing frozen soil, thawed soil and uncertain values. A 2-dimensional linear classification line separating the retrieved values representing freeze and thaw conditions was then calculated using a least sum of square errors estimation method. The 2-D separation line $\mathbf{w}$ was defined as:

$$\mathbf{w} = (X^T X)^{-1} X^T \mathbf{y}, \quad (5.1)$$

where X is a matrix containing the 2-dimensional feature vectors (points) $\mathbf{x}_1 \dots \mathbf{x}_N$:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & 1 \\ \vdots & \vdots & \vdots \\ x_{N,1} & x_{N,2} & 1 \end{bmatrix} \quad (5.2)$$

The first column of matrix X contains the median value of the retrieved σ_{gr}^0 , each value representing one SAR acquisition. The second column contains the corresponding σ_{can}^0 values, and the third column provides a weighting factor of value 1 for all feature vectors. N is the number of all points, in this case, the number of SAR acquisitions used. Vector $\mathbf{y}$ is a discriminant vector corresponding to the feature vectors, where value 1 denotes frozen and -1 thawed. Points representing uncertain soil state were not considered in the calculation of the classification line.

F/T classification with the proposed method was first tested for the areas around each in situ station, by including only the backscatter observations from the nine nearest grid cells to an in situ station, while of course considering only the ground observations of that particular station. Then, the F/T classification was tested separately for different soil types found in the test area, by using all

available backscatter observations within each examined soil type, and information from all in situ stations for deriving the soil state. If all in situ stations indicated frozen soil, the soil was considered frozen, and if all stations indicated thawed, the soil was considered thawed. Otherwise, the soil state was considered uncertain. The test area included six major soil types: Coarse Haplic Podzol (CHP), Fine Haplic Podzol (FHP), Histosol, Umbric Gleysol (UG), Bedrock and Haplic Arenosol (HA). Table 1 describes the main soil types and their coverage in the test area of Sodankylä.

Table 1. The main soil types and their coverage in the Sodankylä test area. Table adapted from Publication 3.

Soil type	Coverage (%)	Description
Coarse Haplic Podzol	30.9	Typically forested mineral dry or semi dry soil with relatively large grain size
Fine Haplic Podzol	24.1	Same as coarse Haplic Podzol but with smaller grain size
Histosol	20.7	Organic wet soil, found in bogs and wetlands. Mostly devoid of trees.
Umbric Gleysol	8.7	Semi organic peat soil, typically forested
Bedrock	8.0	Found mainly on hill tops and on slopes. Incapable of holding water, and usually with no trees.
Haplic Arenosol	4.7	Typically forested fine sandy-loam soil found predominantly close to large rivers, particularly if the river channel has changed its shape, exposing old channel bed materials.

Histosol and Bedrock soil types were neglected. Histosol soils (bogs and wetlands) are mostly devoid of trees, thus they are out of the scope of this study, and Bedrock (rocky soil) is less relevant considering soil F/T state retrieval due to very low water holding capacity.

3.5 Forest data

One important factor in a successful retrieval of the forest canopy influence on the remote sensing signal is the quality of the forest data used. The model requires at least information regarding the canopy closure (CC) or the stem volume (SV) of the forest, and if double bounce scattering is included, also tree height (TH) information is needed. In Publication 1 and Publication 2, forest CC, TH and SV maps were generated from LiDAR point cloud data available through NLS. Corresponding MS-NFI datasets, generated by LUKE, were used for calibrating the LiDAR based SV, and validating the LiDAR based CC and TH maps. In Publication 3, only MS-NFI data was used for deriving forest information. The following paragraphs introduce the MS-NFI forest data generated by LUKE and give an overview on how the forest maps were generated from the LiDAR point clouds.

The MS-NFI products include various data describing the forest properties in Finland, freely available through a download service maintained by LUKE. The data are continuously being updated, and until now, versions from years 2006, 2009, 2011, 2013, 2015 and 2017 have been published. The MS-NFI is produced by assimilation of optical satellite data with in situ measurements and other digital spatial data. A k-nn estimation method using the 11th Finnish National Forest Inventory (NFI) field measurements, Landsat 8 OLI and Resourcesat 1 LISS-

III imagery, as well as other digital spatial data was used to generate the forest products (Katila & Tomppo, 2001; Tomppo, et al., 2008; 2011). The field data consisted of 58 046 forest reference plots measured during 2009–2013. Mäkisara et al. (2016) gives a detailed description of the MS-NFI 2013 products. In this thesis, MS-NFI forest datasets from versions 2011 and 2013 were utilized.

Airborne laser scanning (LiDAR) data from NLS was used to create CC and TH maps in 10 m spatial resolution. Vegetation height grids in 1 m and 2 m pixel size were first created from the point clouds by subtracting the ground level height (Digital Terrain Model) from the top of the vegetation (Digital Surface Model). The CC grids were then generated by 1) classifying pixels of the 1 m vegetation height grid to tree or no-tree; 2) calculating the ratio between tree pixels and all pixels inside a grid cell of 10 x 10 m; 3) applying a correction depending on the scanning angle. The TH grids were generated by 1) removing water and low vegetation areas from the 2 m vegetation height grid; 2) applying a circle shaped dilation (maximum) filter with a radius of 2 pixels (equivalent to 4 m on the ground) and; 3) calculating the mean vegetation height inside a grid cell of 10 x 10 m. Data was processed first with LAStools (Isenburg) and then with SAGA GIS (Conrad, et al., 2015) software. The evaluation showed good correlation between LiDAR based and MS-NFI based CC and TH data (see Publications 1 and 2). Table 2 shows the properties of the LiDAR data.

Table 2. Technical details and imaging geometry of the LiDAR measurements. Table adapted from Publication 1.

Point density	at least 0.5 points/m ²
Distance between points	~1.4 m
Mean vertical error	15 cm
Mean horizontal error	60 cm
Flight altitude	2 km
Footprint on the ground	50 cm
Wavelength	Infrared
Storage	Discrete return

SV was also retrieved indirectly from the LiDAR data, by multiplying CC by TH (CC x TH) and by comparing the product to SV from MS-NFI data (SV_{MS-NFI}). Figure 5 shows an example of the LiDAR based SV retrieval for the Sodankylä test area. A linear and a nonlinear exponential fitting of CC x TH to SV_{MS-NFI} was tested, and the nonlinear fit, expressed by the following fit curve (Eq. 3.11), in which a and b are constants optimized for each test area separately, was found to be better.

$$SV_{MS-NFI} = a(1 - e^{b \cdot CC \cdot TH}). \quad (3.11)$$

Figure 5. Modeling of SV from LiDAR CC and TH for the Sodankylä test area. The exponential fit had a better correlation, lower RMSE and smaller bias ($r^2=0.452$, RMSE=24.1, bias=3.95) compared to the linear fit ($r^2=0.428$, RMSE=29.0, bias=16.2). Figure adapted from Publication 1.

The MS-NFI forest data have been shown to underestimate the SV in forests with high SV (Katila, et al., 2000; 2006). Due to the empirical fitting of the LiDAR data to the MS-NFI SV estimates, the bias of the retrieved LiDAR based SV estimates is expected to have similar bias values as were found for the MS-NFI product itself. Therefore, also the LiDAR based forest SV data is expected to show underestimation in forests with high SV. Nevertheless, for remote sensing applications requiring up to date forest information with high spatial resolution and full national coverage, such as the ones demonstrated in this thesis, the MS-NFI is definitely the optimal reference forest data source.

4. Results

4.1 Application of the forest model – multi-sensor analysis

The results describing the statistical fit of the SAR forest backscatter model against the spread of observations with varying vegetation cover is presented in Figure 6. The retrieved estimate of the ground level signal was also compared to measurements over non-vegetated terrain. For all sensor types, the model inversion was performed against two forest parameters, namely canopy closure (CC) and stem volume (SV). As seen in Figure 6, the zeroth order model used was able to successfully simulate the backscatter of the forested terrain. Similar plots showing the model simulations for optical reflectance and microwave T_B data are presented in Publication 1.

Figure 6. Three examples of model estimates against TSX acquisitions. Median and STD of discretized observed values in decibel units as well as model fit are depicted. Median of the observed backscatter over non-forested areas, modeled effective extinction coefficient and coefficient of determination between the observations and the model are also given for each channel. 25.11.2011 (top row) represents the beginning of the winter, when the snow layer is thin. 10.2.2012 (center row) represents typical winter snow condition, when ground is covered with deep dry snow layer. 27.4.2012 (bottom row) represents melting season snow conditions when ground is covered with wet snow. VH-pol (left column) and VV-pol (right column). Figure adapted from Publication 1.

Results of the optical, SAR and passive microwave forest models are summarized in Table 3, Table 4 and Table 5, respectively, in terms of the root mean square error (RMSE), bias error and coefficient of determination (r^2) between

the model estimates and the observations, as well as the difference between the observed and the retrieved signal over open (non-vegetated) terrain. For all sensor types, the errors and correlations were about as high when using CC or SV as the forest parameter. Also, the differences between the retrieved and the observed reflectance, backscatter and T_B were similar when using CC and SV as the forest parameter.

Table 3. Model estimates against observations for the optical airborne AISA spectrometer: RMSE, bias and coefficient of determination between the estimated and the observed reflectance, as well as the difference between the estimated and the observed median reflectance in open areas, at four spectral bands (blue: 459–479 nm, green: 545–565 nm, red: 620–670 nm, NIR: 841–876 nm), when using CC and SV as the forest parameter. Table adapted from Publication 1.

Date	Band	CC				SV			
		RMSE	bias	r^2	$\rho_{\text{snow,obs}} - \rho_{\text{snow,mod}}$	RMSE	bias	r^2	$\rho_{\text{snow,obs}} - \rho_{\text{snow,mod}}$
18.3	Blue	0.123	0.0009	0.79	0.02	0.121	-0.0043	0.79	0.02
	Green	0.126	0.0016	0.78	0.02	0.123	0.0009	0.78	0.03
	Red	0.125	0.0022	0.76	0.02	0.123	-0.0021	0.77	0.02
	NIR	0.137	0.0011	0.62	0.02	0.134	0.0018	0.64	0.02
21.3	Blue	0.127	-0.0042	0.72	0.00	0.125	-0.0053	0.73	0.00
	Green	0.136	-0.0101	0.73	0.00	0.133	-0.0080	0.74	0.01
	Red	0.128	-0.0097	0.80	0.01	0.125	-0.0092	0.81	0.02
	NIR	0.119	-0.0142	0.71	0.00	0.114	-0.0071	0.73	0.02

Table 4. Model estimates against observations for the active microwave SnowSAR and TSX instruments: RMSE, bias and coefficient of determination between the estimated and the observed backscatter, as well as the difference between the estimated and the observed median backscatter in open areas, when using CC and SV as the forest parameter. All available TSX images between the 1st of Dec and 30th of Apr (when the ground was covered with snow) were considered when calculating the statistical averages. RMSE, bias and the difference between the estimated and the observed median backscatter in open areas were calculated using backscatter values in decibel units. Table adapted from Publication 1.

Sensor	Band	Pol	CC				SV			
			RMSE	bias	r^2	$\sigma_{\text{snow,obs}}^0 - \sigma_{\text{snow,mod}}^0$	RMSE	bias	r^2	$\sigma_{\text{snow,obs}}^0 - \sigma_{\text{snow,mod}}^0$
Snow-SAR	X	VV	2.80	-0.054	0.44	-0.36	2.84	-0.100	0.42	-0.36
	X	VH	2.50	0.435	0.41	-0.69	2.54	0.305	0.38	-0.69
	Ku	VV	2.75	-0.176	0.35	0.05	2.78	-0.184	0.33	0.05
	Ku	VH	2.03	0.079	0.48	0.00	2.09	-0.022	0.44	0.00
TSX	X	VV	1.85	-0.15	0.36	-0.74	1.82	0.030	0.35	-0.15
	X	VH	1.80	-0.11	0.43	0.75	1.80	0.097	0.41	-0.14

Table 5. Model estimates against observations for the passive microwave HUTRAD radiometer: RMSE, bias and coefficient of determination between the estimated and the observed T_B , as well as the difference between the estimated and the observed mean T_B in open areas, when using CC and SV as the forest parameter. Table adapted from Publication 1.

Band	Pol	CC				SV			
		RMSE	bias	r^2	$T_{B,\text{snow,obs}} - T_{B,\text{snow,mod}}$	RMSE	bias	r^2	$T_{B,\text{snow,obs}} - T_{B,\text{snow,mod}}$
10 GHz	V	1.33	-0.072	0.09	0.8	1.20	0.008	0.15	0.5
	H	2.21	0.008	0.72	-0.4	2.21	0.100	0.72	-0.7
18 GHz	V	1.89	-0.005	0.75	0.0	1.79	0.090	0.78	-0.1
	H	3.32	0.042	0.82	-0.1	3.21	0.141	0.83	-0.8
36 GHz	V	8.48	0.093	0.84	1.4	8.00	0.126	0.86	1.0
	H	10.54	0.116	0.84	1.9	10.00	0.154	0.86	1.2

A comparison between model estimates and remote sensing observations demonstrated that for the investigated sensor types and frequencies, a zeroth

order model can accurately estimate the signal behavior in boreal forests. Particularly, the correlation of the model estimates against HUTRAD passive microwave and AISA airborne optical data exhibited high values, with r^2 ranging between 0.7 and 0.9, depending on the day of observation and the spectral band (not including 10 GHz band in passive microwave and NIR band in optical). Moreover, for all investigated sensor types, the values observed over open terrain were very close to the retrieved model estimates for the signal at the ground/snow surface, beneath the forest canopy. This similarity indicates that the demonstrated methodology can successfully estimate the signal contribution of the surface beneath the forest canopy and compensate for the effect of the forest canopy on the total measured radiation, when investigating e.g. soil or snow cover properties.

Modeling against airborne passive microwave observations also exhibited high correlations of up to 0.9 for the two higher observed frequency bands of 18.7 and 36.5 GHz. For the lower 10.65 GHz frequency, correlation was lower, primarily due to the higher inherent insensitivity to vegetation. When using CC as the forest parameter, the model performed nearly as well as when using SV. CC, which is more easily derived from satellite observations, can therefore act as a good alternative to SV if the latter is not available.

In the active microwave model, small bias values indicated that the median of the observed backscatter in open areas was accurately estimated. However, larger variation of the observational data, typical for active microwave sensors, caused higher RMSE between model and observations. The larger variation led to lower correlation compared to the optical and passive microwave cases, especially for the SnowSAR airborne Ku- and X-band data. The analysis of the TSX time series showed that despite radical changes occurring in e.g. soil moisture, snow and canopy conditions, the backscatter of the ground/snow surface was still estimated accurately by the model, meaning that changes in canopy conditions were sufficiently addressed by the zeroth order model. r^2 values up to over 0.7 between model and observations were achieved during dry snow and early snowmelt seasons. The correlations were reduced to r^2 values of under 0.5 in the early snow season and under advanced snow melt conditions. As mentioned, the lower correlation reflects an overall larger variation of SAR observations compared to optical and passive microwave observations. These results demonstrate that the zeroth order models have the potential to well simulate the signal extinction properties in a boreal forest environment, without accounting for higher-order scattering effects.

4.2 SAR forest model in flooded terrain

The zeroth order model for the active microwave X-band HH-polarization backscatter data was tested for the case of flooded forests in Publication 2. This chapter deals only with the modelling of the backscattering signal of forests during flood events, and the rest of the results concerning the flood mapping study (Publication 2) are presented in chapter 4.3. As explained in section 3.1, in addition to the ground and canopy backscatter contributions that were accounted

in Publication 1 (Eq. 3.6), the applied model in Publication 2 included also the double bounce component, which is significant in flooded forests (Eq. 3.9). Flooded areas were analyzed for four test sites across Finland; Kittilä, Kolari, Pudasjärvi and Evo. The model was tested separately for each test site. The similarity of the modeled backscatter components and the observed values was the highest in Pudasjärvi, and then in Kittilä. The flood reference areas in these test sites were the most diverse, including a larger number of observations from different forest conditions such as floods in open, semi-forested and under denser and higher forests. Moreover, the total size of the reference areas was substantially larger in Kittilä and Pudasjärvi than in Kolari and Evo test sites. The modeling was also more difficult in Kolari and Evo, because they lacked continuous semi-forested or open flooded areas.

Figure 7. Analysis of X-band HH-polarization SAR data: Modeled σ^0 contributions of flood surface direct scattering, canopy volume scattering and the double bounce scattering components, as well as the observed σ^0 values as a function of canopy closure (CC) and tree height (TH). Figure adapted from Publication 2.

Figure 7 shows the modelled surface direct scattering, canopy volume scattering and the double bounce scattering components, as well as the observed total backscatter, as a function of canopy closure (CC) and tree height (TH), only for flooded areas in the investigated test sites. When CC and TH are zero to very small, the strongest, although weak, backscatter component, is the direct surface scattering occurring over the water surface. As CC and TH increase, the contribution of the direct surface scattering decreases, but both the contribution of the canopy volume scattering and the double bounce scattering increase. The

double bounce scattering increases more rapidly than the canopy volume scattering, as already a relatively small increase in CC and TH significantly increases the backscattering caused by the double bouncing between the tree trunks and the water surface. Even in dense forests, when flooded, the most prominent scattering component in is the double bouncing backscatter, and not the canopy volume scattering.

Figure 8. Analysis of X-band HH-polarization SAR data: Median of the modeled σ^0 in the flooded areas, median and STD of the observed σ^0 in the flooded and non-flooded areas (individual observations as points and median values as circles) in Pudasjärvi test area. σ^0 values as a function of canopy cover (CC) on the left, and σ^0 as a function of tree height (TH) on the right. The median of the modeled σ^0 is calculated for the same CC and TH intervals as the median of the observations. Figure adapted from Publication 2.

Table 6. Model performance and the retrieved model parameters for each test area. K_e is given in Nepers per stem volume unit and in decibels per stem volume unit. RMSE and bias were calculated between all observations of flooded forests and the corresponding modelled values, using backscatter values in decibel units. Table adapted from Publication 2.

Area	Model Performance		Model Parameters				
	RMSE	bias	$\sigma^0_{\text{flood surface}}$ [dB]	σ^0_{canopy} [dB]	K_e [Np/(m ³ /ha)]	K_e [dB/(m ³ /ha)]	B
Kittilä	3.08	-0.20	-15.7	-9.1	0.0167	0.0725	0.0131
Kolari	2.82	0.57	-15.9	-7.8	0.0222	0.0964	0.0311
Pudasjärvi	2.37	-0.17	-19.4	-11.5	0.0086	0.0373	0.0066
Evo	2.76	0.06	-11.3	-9.8	0.0056	0.0243	0.0044

The modeled and the observed total σ^0 of the flooded areas, and the observed σ^0 in the non-flooded areas as a function of CC and TH are shown in Figure 8 for Pudasjärvi test area. As expected, the total observed backscatter of flooded areas is low in open areas due to the specular reflection over flood surfaces. As CC and TH increase, stronger total backscatter is observed, mainly due to the increased double bouncing between flood surface and tree trunks. In denser forests with higher trees, the total observed backscatter slightly decreases, as the increasing amount of canopy decreases the penetration of the double bouncing signals more than what it increases the canopy volume scattering component. RMSE and bias between all backscatter σ^0 observations (pixels) of flooded forests and the corresponding modelled values, as well as the retrieved model parameters

are presented in Table 6. The best model performance was achieved in Pudasjärvi, where the RMSE between the modeled and the observed σ^0 was 2.37 dB. In Kittilä the RMSE was 3.08, in Kolari 2.82 and in Evo 2.76.

4.3 Mapping forest floods

4.3.1 Flood detection in various forest conditions

One of the main goals in this work was to define under which forest properties flood detection with X-band HH-polarization SAR data is feasible. The percentage of non-detected floods from the total flood reference areas as a function of canopy closure (CC) and tree height (TH) is presented in Figure 9. The results show that the simple threshold-based algorithm used detected less flooded areas in forests where the TH was low; over zero but under 4–5 m, or when the CC was low; over zero but under 20 %. Hence, in open areas where CC and TH were very close to zero, as well as in denser forests or/and forests with higher trees, the flood detection was more successful than in the semi-forested areas. TH seemed to have more influence on the capability of the algorithm to recognize the floods, at least in Kittilä, because relatively more floods were undetected in low TH areas than in low CC areas, and relatively more floods were detected in high TH areas compared to high CC areas. In Pudasjärvi, however, TH and CC seemed to have a similar impact on the capability of the algorithm to recognize floods.

Figure 9. The percentage of non-detected flood areas as a function of CC and TH in Kittilä and Pudasjärvi. Figure adapted from Publication 2.

Floods in low TH forests were harder to detect using solely X-band HH-polarized SAR backscatter information, because the tree trunks were too short and narrow to cause a sufficient amount of double bouncing signal together with the flood surface. Floods in low CC forests were also less well detected, because the small number of tree trunks causing double bounce scattering increased the

level of backscatter compared to open floods, but the backscatter was still not strong enough to be classified as forest floods.

As seen in Figure 10, a linear trend well describes the relationship between the derived optimal threshold values and the incidence angle. Both the upper threshold value separating flooded forests and the lower threshold value separating open floods from non-flooded areas are higher in steeper incidence angles. The threshold values derived for Evo test area are somewhat lower in relation to the retrieved linear trend.

Figure 10. A linear relationship between incidence angle and the optimal σ^0 threshold values (in linear scale) separating floods from non-flooded areas, for X-band SAR, using least squares fitting. "thr1" represents the σ^0 values separating open floods and "thr2" the values separating forest floods from non-flooded areas, as a function of incidence angle. Figure adapted from Publication 2.

4.3.2 Validation against manual in situ observations

The results of the SAR based flood detection were compared with flood areas observed and digitized during the ground measurement campaign in the Kolari test area. Ground observations included non-flooded, partly flooded and completely flooded areas, as well as if possible, flood boundaries. Figure 11 shows the flooded areas detected by the satellite marked with partly transparent purple color over the SAR backscatter image in the middle, and the observations on the ground with corresponding photographs taken from different locations. The comparison of satellite detection against in situ measurements from Kolari indicated that the floods were generally well detected. Floods were recognized in all areas where they were observed in situ, and the detected flood boundaries followed well the true boundaries observed on the ground. Most of the partially flooded areas, marked as red quadrilaterals in Figure 11, were also detected as floods, and all non-flooded areas, marked as green quadrilaterals, including peat bogs, were classified correctly as dry land by the flood detection algorithm. Although the ground was not completely covered with water in the partially flooded areas, the backscattering intensity was high enough to be classified as floods by the flood detection algorithm. On top of the corner reflection between the patchy water surface and the tree trunks, scattering between hummocks and water surface together with increased soil moisture probably contributed to the observed strong backscatter. Also in peat bogs (the yellow quadrilateral) the

presence of hummocks and the increased soil moisture somewhat increased the backscatter compared to other non-flooded areas. Yet, without corner reflection between flood surface and tree trunks, the backscatter was still not too high to be falsely classified as flooded by the satellite detection.

Figure 11. Satellite detected flood areas and ground observations from Kolari study area. Detected floods are shown in the middle in partly transparent blue color, on top of the SAR image (brighter values indicate higher σ^0). Georeferenced coordinates (in UTM) are on the left and upper side of the image. The distance in meters is shown on the right and bottom side of the image. Photos taken from dry, partly flooded, moist (peat bog) and flooded areas are presented next to the satellite image. Figure adapted from Publication 2.

4.4 Detecting soil frost/thaw

4.4.1 Backscatter vs. air temperature

An initial analysis showed that backscatter values during cold air temperature conditions can be well separated from backscatter values during warm air temperatures when using both canopy and ground backscatter information (Figure 12 a). The separation is visually more apparent when replacing canopy backscatter (in y-axis of Figure 12 a) with the difference between canopy and ground backscatter (Figure 12 b). This study found that air temperature in freezing conditions (below zero Celsius degrees) has influence on the canopy backscatter, and to a small extent also on the ground backscatter, as shown in images c and

d of Figure 12. As expected, the ground and canopy backscatter values increased during the end of the winter due to increased volume scattering in the snow layer (Figure 12 f and g).

Figure 12. The influence of air temperature on the retrieved and observed backscatter for the whole test period (a-e), for winter 2014-2015 (f), and for winter 2015-2016 (g). Retrieved σ_{gr}^0 in x-axis and σ_{can}^0 in y-axis (a) as well as σ_{gr}^0 in x-axis and σ_{diff}^0 (i.e. $\sigma_{can}^0 - \sigma_{gr}^0$) in y-axis (b), with respect to air temperature. Retrieved σ_{gr}^0 and σ_{can}^0 (c), observed σ_{open}^0 and σ_{forest}^0 (d) and the retrieved difference σ_{diff}^0 (e) in y-axis, with respect to air temperature in x-axis, together with linear trend lines and correlation coefficients for the whole test period and only for cold temperatures (air temperature under -2°C). A time series showing the retrieved σ_{gr}^0 , retrieved σ_{can}^0 , observed σ_{forest}^0 , air temperature at the time of the SAR acquisition, the maximum air temperature since the last SAR acquisition, and the snow depth for the winter periods (f-g). The retrieved and the observed σ^0 values shown in these plots represent the mean and the median values, respectively, of one SAR acquisition over the whole test site, excluding lakes, wetlands, rocky terrain and artificial areas. The air temperature was acquired from one of the in situ stations using the sensor located at 110 cm height. Figure adapted from Publication 3.

Based on the correlations in images c-e, the F/T state of soil could be fairly well estimated using either σ_{gr}^0 (Figure 12 c and d) or σ_{diff}^0 (Figure 12 e), however, as seen in Figure 12 b, if only σ_{gr}^0 or only σ_{diff}^0 would be used to differentiate between the retrieved values in negative and positive temperature conditions, the dynamic range of uncertain observations would in both cases be more than 1 dB. Instead, if a separation between the negative and the positive temperature conditions is done in a 2-D plane (Figure 12 b), the uncertain region can be reduced

to almost zero. Hence, even though the physical properties of the soil such as soil's F/T state do not directly have impact on the canopy backscatter, the results show that σ_{can}^0 can be helpful when estimating the soil F/T state. In very cold air temperatures of approximately under $-10\text{ }^{\circ}\text{C}$ and during the end of the winter, higher σ_{can}^0 will decrease the likelihood of false thaw classification. Otherwise, if relying only on σ_{gr}^0 , which also shows a slight increase in the cases mentioned above, estimation of the soil F/T state would be more difficult.

The main reason for the observed negative correlation between temperature and backscatter, mainly of the canopy, was most likely canopy freezing, which starts at temperatures below $-5\text{ }^{\circ}\text{C}$. Changes in the dielectric constant of ice/snow influencing the signal absorption can also lead to higher backscatter values in very cold temperatures. See chapter 5 or Publication 3 for more discussion regarding the influence of air temperature on microwave observations in sub-zero conditions.

4.4.2 Linear classification of F/T soil state

Figure 13 presents the median σ_{gr}^0 and σ_{can}^0 values and the F/T classification results for individual soil types. Each observation represents the median value of one SAR acquisition. SAR acquisitions with an incidence angle between 31° and 33° over the test area are shown on the upper row, while acquisitions with an incidence angle between 37° and 39° on the lower row. Uncertain points during the freezing and the melting seasons are marked with different colors. Classification of the soil F/T state based on σ_{gr}^0 alone would have caused large number of false detections, since there is a notable overlap (a range of up to 2 dB) in observations representing both frozen and thawed conditions. Taking into account also the retrieved σ_{can}^0 enables a separation of the frozen and thawed soil states more efficiently. The optimal linear classification line is depicted in the figures by dashed lines. The observations representing uncertain conditions during the autumn are mostly located in between the 'frozen' and the 'thawed' observations in the σ_{can}^0 σ_{gr}^0 space. Observations during the snowmelt season form a distinct group with notably low values of σ_{gr}^0 .

As seen in Figure 13, the F/T detection accuracy is dependent on the soil type, and is mostly determined by the ability of the soil to hold water. A visual interpretation of the plots in Figure 13 shows that thaw and frost point clusters were further away from each other, and thus better separable, for the Fine Haplic Podzol (FHP), Umbric Gleysol (UG) and Coarse Haplic Podzol (CHP) soil types, while for the Haplic Arenosol (HA) soil type the separation was harder. HA soil is typically very dry due to low water holding capacity and conversely a high infiltration rate, and therefore the contrast between frozen and thawed soil is low. For the wetter Haplic Podzol and UG soil types, the contrast between frozen and thawed observations is higher, and therefore the classification is easier. It also appears that the F/T state can be better determined for the finer grained FHP than for CHP, because FHP has a larger water holding capacity than its coarse grained counterpart. Nevertheless, the linear classification enables a clear separation of freeze and thaw conditions for all cases when performed individually for each soil type, reflected by the low number of false classifications.

Higher incidence angle led to slightly better classification accuracy for all soil types.

Figure 13. Retrieved median σ^0_{gr} and σ^0_{can} values, and F/T classification lines for the main soil types in the test area. Scenes with incidence angle of $31^\circ - 33^\circ$ over the test site area are on the upper row and $37^\circ - 39^\circ$ on the lower row. Figure adapted from Publication 3.

Table 7 shows the achieved accuracy of the F/T detection for the analyzed soil types in terms of the total number of observations classified as frost and as thaw, the number of false frost and thaw classifications, and the total classification accuracy.

Table 7. Classification accuracy statistics for each soil type and incidence angle, excluding autumn and spring uncertain conditions. Table adapted from Publication 3.

Soil type	Incidence angle	False frost	Total frost	False thaw	Total thaw	Total accuracy
CHP	$\sim 32^\circ$	2	22	0	12	94 %
	$\sim 38^\circ$	0	26	0	23	100 %
FHP	$\sim 32^\circ$	0	20	0	14	100 %
	$\sim 38^\circ$	0	26	0	23	100 %
UG	$\sim 32^\circ$	1	21	0	13	97 %
	$\sim 38^\circ$	0	26	0	23	100 %
HA	$\sim 32^\circ$	2	21	0	12	94 %
	$\sim 38^\circ$	1	26	1	23	96 %

4.4.3 Soil F/T maps

Figure 14 shows nine examples of the retrieved F/T state of the soil in a grid cell size of 1×1 km, for winter 2014-2015. The first six images (a-f) represent the freezing period, and the last three images (g-i) are from the melting period. White color refers to pixels outside the mapped area, excluded soil types (rocky terrain or wetlands) or steep terrain. The images are in a good agreement with

the snow/air and soil temperatures derived from the in situ station, shown below the example F/T images.

Figure 14. In the upper part of the figure; examples of the retrieved soil F/T state during freezing (a-f) and melting (g-i) periods of winter 2014-2015, at 1 x 1 km pixel size. Red indicates thawed and blue frozen soil. Dark green indicates artificial areas and light green water bodies. White represents other excluded areas; wetlands, rocky terrain, steep terrain, areas outside the mapped area, or grid cells with insufficient number of valid observations. The pixel value shows the distance from the classification line, in dB units. The classification lines for each soil type are depicted in Figure 13. In the lower part of the figure; soil temperature in 5 cm depth and snow/air temperature in 10 cm height measured at one of the in situ stations during autumn 2014 and spring 2015 are plotted. Snow temperature is measured when the sensor is covered, and air temperature when not covered with snow. The vertical dashed lines show the timing of the example SAR acquisitions. Figure adapted from Publication 3.

During the freezing period represented by images a-f (Figure 14), the soil state varied between thawed and frozen. On the 6th of October 2014 (a), the soil was mainly thawed, but after colder temperatures during the following days, on the

18th of October (b) the soil was mainly frozen. After the 22nd of October, the temperatures rose back to above zero degrees, and the soil was thawed on the 26th of October (c). The temperatures then decreased again, causing frozen soil state on the 7th of November (d). A short period of warmer temperatures changed the soil state, detected as partly thawed on the 11th of November (e). At the end of December (f) and onwards, the retrieval detected constantly frozen soil state until the melting period, which started approximately in mid-April. The image from the 24th of April (g) is a typical example of a retrieval result during the melting season with wet snow present on the ground. Dark blue color indicates absolutely frozen soil, however, the high pixel values are actually caused by very low σ_{gr}^o due to the wet snow. On the 13th of May (h), the soil temperature in 5 cm depth was close to zero, while the air temperature was much warmer. The top soil layer (above 5 cm depth) measured by the C-band signal, was therefore most likely correctly interpreted by the retrieval as thawed. On the 3rd of June (i), both soil and air temperatures were clearly above zero, and the soil state was correctly detected as thawed.

5. Discussion

In this chapter, the most relevant findings of this thesis are further addressed and discussed in light of related previous research and possible future plans. Various models simulating the observed signal from natural media have been presented in literature, concerning active microwave (Sun & Ranson, 1995; Lin & Sarabandi, 1999; Liang, et al., 2005; Liu, et al., 2010), optical (Li, et al., 1995; Klein, et al., 1998; Vikhamar & Solberg, 2003; Salminen, et al., 2009; Niemi, et al., 2012), and passive microwave (Kruopis, et al., 1999; Pardé, et al., 2005; Langlois, et al., 2011) sensor types. Some of these developed models are however complex, requiring plenty of ancillary information and heavy computational resources. The aim in this thesis was to develop simple methods with sufficient accuracy for near real-time monitoring of wide areas, thus enabling an efficient exploitation of the increasing satellite data availability. The presented model was able to well estimate the different signal components in boreal forests, and was found to be suitable for practical applications, such as soil F/T detection and flood mapping. Compared to the optical and the passive microwave models, the RMSE between the modelled and the observed values was relatively high in the active microwave model, due to larger variation in the observed values. The coefficient of determination (r^2) between the modelled and observed backscatter was moderate, around 0.4. Yet, the backscatter of the ground surface, which is usually the sought parameter in remote sensing applications of the Earth surface in the boreal region, was estimated rather accurately; the deviation between the observed and the modelled backscatter was on average 0.3 dB. This is highly encouraging, because as an example, the backscatter difference between frozen and thawed ground (Figure 12b; Figure 13; Figure 14) (Rignot & Way, 1994; Park, et al., 2011; Xu, et al., 2016; Baghdadi, et al., 2018) or between wet snow and ground after snowmelt (Koskinen & Hallikainen, 1997; Nagler & Rott, 2000; Luoju, et al., 2007), is typically over 2 dB. This means that the estimated ground backscatter using the relatively simple model is sufficiently accurate for common remote sensing application in the boreal region. Stem volume has previously been used when modelling the effect of forest canopy on the passive (Kruopis, et al., 1999; Langlois, et al., 2011) and active (Pulliainen, et al., 1994; 1999; 2001; Luoju, et al., 2007; 2009; Koskinen, et al., 2010) microwave signals. This study was the first one to show that canopy closure can be used instead of stem volume as the forest data source, when modeling the passive microwave frequency signatures, and Publication 1 together with Montomoli et al. (2016), were the first ones to demonstrate the same for active microwave data.

Previous studies have shown that even the relatively high frequency X-band SAR can be used to detect floods under tree canopies (Pulvirenti, et al., 2013; Martinis & Rieke, 2015), also in boreal forests (Voormansik, et al., 2014). This study was the first one to explicitly specify in which boreal forest conditions regarding tree height and density, flood mapping with HH-polarized SAR data is indeed feasible. It was found, that if relying only on the backscatter values, flood detection was problematic in forests where canopy closure is less than 15-20 % or tree height is under 4-5 m. These findings significantly contribute to operational flood mapping capabilities in boreal environments, because a large portion of areas are forested, including flood prone areas. Ancillary data sources such as a DEM, forest data and in situ observations can be used to complement the SAR backscatter information for estimating the flood extent in these problematic zones. Separation of floods from non-flooded areas in SAR-based operational detection algorithms is usually carried out using threshold methods (Brivio, et al., 2002; Matgen, et al., 2007; Martinis, et al., 2009). Previous studies show that optimal threshold values typically increase in steeper incidence angles (Townsend, 2001). Finding the optimal threshold values is a key step in flood detection algorithms, and therefore, pre-knowledge on these values can be helpful. For example, processing times can be significantly decreased by automating the selection of the appropriate threshold values based on pre-knowledge. When comparing the investigated flood cases of Kittilä, Kolari, Pudasjärvi and Evo, a decreasing linear dependency between the retrieved optimal threshold values separating floods from non-flooded areas and the incidence angle was found. The test areas represented typical riparian and non-riparian boreal forest environments, however, the presented results are more applicable for northern to middle-northern boreal forests, as these are covered by three test areas with notably different incidence angles. Evo test site was the only one representing southern boreal forest conditions, and moreover, it had considerably less samples than the other three sites. For more general and robust assumptions defining problematic canopy closure and tree height zones in the southern boreal forests, more test cases are therefore required.

This study presents a novel approach for detecting the soil F/T state in boreal forests using Sentinel-1 single polarization data. The zeroth order model is used to overcome the limited penetration of the C-band signal through forest canopies. Methods relying on the lower frequency L-band less sensitive to vegetation (Xu, et al., 2016) could be used, however, currently the availability of these data is not sufficient for continuous monitoring purposes. Therefore, in addition to the scientific novelty of this study, it can be beneficial to community and industry, e.g. in the estimation of terrain trafficability of heavy machinery in forested terrain. This study suggests, that when the retrieved canopy backscatter is taken into account, in addition to the retrieved ground backscatter, the soil F/T state can be better estimated, especially in very cold temperature conditions or during the end of the winter. It is obvious that canopy backscatter is not directly affected by the physical properties of the soil, however, backscatter sensitivity to e.g. snow properties or the freezing of canopy and bushy vegetation on the

ground, caused mostly by air temperature changes, can indirectly help to determine whether the soil is frozen or not. In this study, the retrieved canopy backscatter during very cold temperatures of approximately less than -10°C and during the end of the winter decreased the likelihood of false thaw classification, by compensating a similar or weaker increase in the retrieved ground backscatter. Otherwise, if relying only on the ground backscatter, the estimation accuracy of the soil F/T state would have been considerably lower.

The influence of temperature on the microwave backscattering signal from the ground and especially from forest canopies, in sub-zero conditions, has not yet been widely covered in the literature. According to previous studies, the negative correlation between air temperature and backscatter can be caused by the increase in snow volume scattering related to snow metamorphism (Naeimi, et al., 2012; Bergstedt, et al., 2018), or by the increased snow cover (Eckerstorfer, et al., 2017). Even though these assumptions are valid, they do not explain why after a cold temperature peak, the backscatter was reduced back to similar values observed before the cold peaks (Figure 12 f and g). Previous research also shows that temperature changes in sub-zero conditions alter the dielectric constant of snow and ice, affecting also the observed backscatter (Evans, 1965; Matsuoka, et al., 1996; Matzler, 1998; Fraser, et al., 2016). This study suggests that canopy freezing was the main reason causing the negative correlation between temperature and backscatter. Canopy freezes gradually starting from temperatures below -5°C , such that the freezing point is lower for drier canopy (Kärkkäinen, 1985). Canopy freezing can explain the steeper relationship between $\sigma^{\circ}_{\text{can}}$ and air temperature compared to the relationship between $\sigma^{\circ}_{\text{gr}}$ and air temperature (Figure 12 c and d). Mostly tree canopy, but also bushy vegetation on the ground, are expected to cause less attenuation of microwave radiation when frozen, increasing the total measured backscatter in colder temperatures. According to a recently published research conducted near Sodankylä, Finland, the attenuation caused by forests canopy in microwave signals at 10 – 37 GHz is considerably reduced in colder temperatures, regardless of the amount of snow on the canopy (Li, et al., 2019). The backscatter increase in colder temperatures (in sub-zero conditions) observed in this study is therefore most probably caused by 1) the freezing of canopy and bushy vegetation, decreasing the signal attenuation, as well as by 2) changes in the dielectric constant of ice and snow, decreasing the signal absorption.

Following the launch of Sentinel-1 satellites (a and b) in recent years, the availability of C-band data has significantly increased, currently providing nearly daily observations over northern Europe. Therefore, the proposed method has the potential to enable continuous near real-time monitoring of soil's F/T state. Moreover, it can be assimilated with existing methods relying on passive microwave L-band data (Rautiainen, et al., 2014; 2016; Derksen, et al., 2017), which have better temporal resolution and soil penetration depth, but coarser spatial resolution. An active-passive combined F/T product, utilizing C-band SAR to provide more detailed information regarding e.g. the onset of soil freezing and the variability of the soil state both in horizontal and vertical directions, is planned to be implemented in the future.

6. Summary and conclusions

The aim of this thesis was to investigate the influence of the forest canopy on the remote sensing signal for three different sensor types; SAR, optical and passive microwave. A simplified zeroth order model was used to simulate the measured signals over boreal forest environments. The focus was more on SAR measurements, for which the model was also applied in two practical remote sensing applications; flood detection and soil frost/thaw (F/T) estimation in boreal forests.

The applicability of the zeroth order model was first tested by fitting the observations to the model through optimization of the open parameters. Then, the main signal components, such as the ground and the canopy contribution to the total measured signal at the sensor, were extracted. A comparison between model estimates and observations demonstrated that the zeroth order model used can well estimate the extinction properties of electromagnetic signals in boreal forest canopy. The method thus allows to single out the sought signal component, typically the contribution of the ground beneath the canopy, from the other contributing factors. Compared to more complex analytical models, the presented model requires less ancillary data, and is therefore optimal for Earth observation applications covering wide areas. Furthermore, a single parameter or proxy value (either canopy closure or stem volume) describing the forest properties was shown to provide the necessary correlation with the observed signal for fitting the models to the observations. This also implies that forest canopy effects can be sufficiently accounted in retrieval algorithms even if multiple scattering effects are ignored. Also, simulation of canopy effects can be done with ancillary data already available or with data retrieved relatively easily from other remote sensing sources. The results are therefore highly relevant concerning practical applications for the retrieval of geophysical parameters from Earth observation satellites in northern forested regions.

As said, the model was applied in two practical applications using active microwave data; flood detection and soil F/T state estimation in boreal forests. Spring floods were detected with Cosmo Sky-Med HH-polarized SAR data in four different study areas across Finland, using a relatively simple threshold based algorithm built for open and forested terrain. The effect of varying forest properties in terms of canopy closure and tree height on the capability of the algorithm to recognize floods was assessed by utilizing high accuracy and resolution LiDAR based forest and ground elevation data. Reference flood areas were derived by combining the backscatter image with a high resolution DEM

and in situ observations collected during the flood events. Floods were recognized over open areas due to lower backscatter, and in forests due to higher backscatter, compared to the backscatter of non-flooded areas. However, flood detection was more difficult in semi-forested areas containing sparsely distributed or low trees. If tree height was below 4-5 m the tree trunks were too short and narrow to produce strong double bounce scattering with the flood surface, and if canopy closure was under 15-20 %, the number of tree trunks forming the double bounce scattering was not sufficient. This information is important regarding automatic or semi-automatic flood detection methods, because other available data such as a high resolution DEM and water level in situ measurements can be used to complement the SAR images and to gain better flood estimation accuracy in these problematic forest conditions. The forward model allowed to estimate the contributions of the surface scattering, double bounce scattering between flood surface and tree trunks, and canopy volume scattering.

The zeroth order model was also applied for Sentinel-1 C-band SAR data to estimate the ground and the canopy backscatter contributions. The observed and the retrieved backscatter values were analyzed against forest and air temperature data. The retrieved ground and canopy backscatter were then classified to observations representing freeze, thaw or uncertain conditions, using the in situ observations, and a line separating the freeze and thaw observations was calculated by a linear 2-d classification algorithm. Frozen and thawed ground under boreal forest canopy were detected for a variety of soil types present in the test area. The ability to separate frozen and thawed soil was considerably improved when taking into consideration the retrieved canopy backscatter σ_{can}^0 in addition to the ground backscatter σ_{gr}^0 , mainly in the following two cases: 1) An increase in σ_{can}^0 during colder winter temperatures, mainly caused by canopy freezing, but also by changes in the dielectric constant of ice and snow, helped compensating a similar but smaller increase in σ_{gr}^0 . 2) Due to snow metamorphosis during the end of the winter, stronger snow backscatter caused an increase in σ_{can}^0 , which compensated a similar increase in σ_{gr}^0 . An attempt to use solely σ_{gr}^0 as an input to the F/T classification in these both cases would have increased the likelihood of false thaw detection. Water holding capacity was the most relevant feature of soil affecting the accuracy of the soil F/T classification. F/T detection for the wetter Fine Haplic Podzol (FHP), Umbric Gleysol (UG) and Coarse Haplic Podzol (CHP) soil types was more successful than for the drier Haplic Arenosol (HA), due to the higher contrast between the backscatter of frozen and thawed terrain. Higher incidence angle provided slightly better classification results for all investigated soil types. FHP soil as well as UG and CHP soil at incidence angles of $\sim 38^\circ$ were classified with the highest accuracy of 100 %, while HA and CHP soil at $\sim 32^\circ$ incidence angle were classified with the lowest accuracy of 94 %.

A large portion of the boreal region is covered by forests, posing a challenge to satellite based mapping. This study shows, from theory to a practical level, that the zeroth order model used was able to simulate the remote sensing observations over boreal forest environments, thus enabling the extraction of different contributions to the total observed signal, such as the ground and the canopy

signal contributions. This study therefore increases the understanding on how forests influence the remote sensing observations and provides tools for exploiting satellite observation for the mapping and monitoring of common geophysical phenomena taking place in the boreal forest region. In particular, the findings and the developed methods in this work are important for successful flood mapping in open and forested areas, and they improve the monitoring capabilities of the soil F/T state.

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