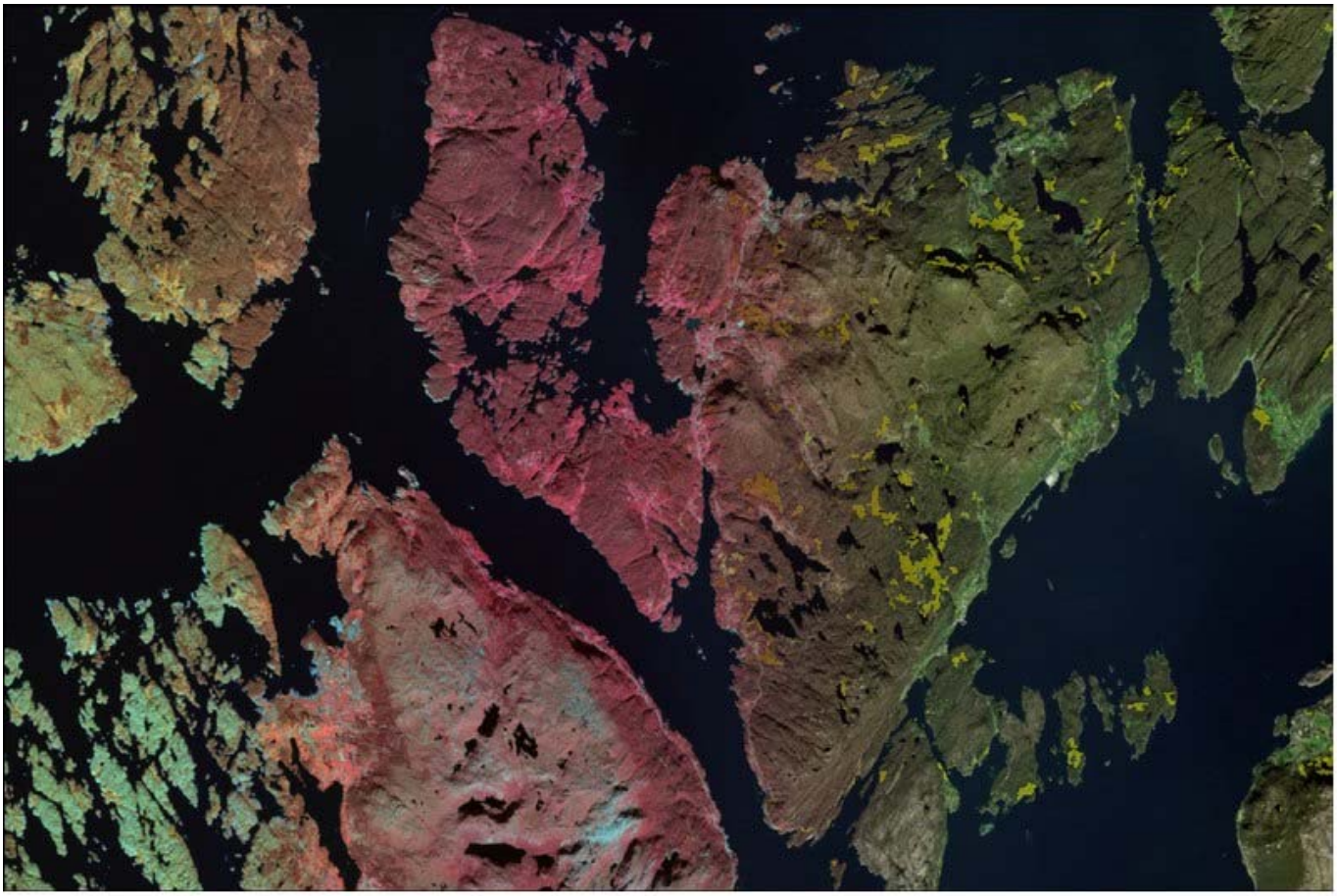
Norwegian University of Life Sciences
Faculty of Environmental Science and Technology
Department of Ecology and Natural Resource Management

2016
ISSN: 1891-2281

INA fagrapport 33

Use of remote sensing for mapping of non-native conifer species

Hans Ole Ørka & Marius Hauglin



Ørka, H.O. & Hauglin, M. 2016**. Use of remote sensing for mapping of non-native conifer species.** - INA fagapport 33. 76 pp.

Ås, Februar 2016

ISSN: 1891-2281

AVAILABILITY
Open

PUBLICATION TYPE
Digital document (pdf)

QUALITY CONTROLLED BY
The Research committee (FU), INA, NMBU

PRINCIPAL
Miljødirektoratet, Ref: M-490|2016, Contact person: Tomas Holmern (tomas.holmern@miljodir.no)

COVER PICTURE
Collage of Landsat 8 imagery visualized with different spectral bands and the produced non-native species map (yellow) over Tysnes, Norway. Illustration: Hans Ole Ørka

NØKKELORD
Fjernanalyse, fremmed treslag, utbredelseskart, satellitebilder, flybilder, flybåren laserscanning, treslagsklassifisering.

KEY WORDS
Remote sensing, non-native species, species distribution maps, satellite imagery, aerial imagery, airborne laser scanning, tree species classification.

Hans Ole Ørka (hans.ole.orka@nmbu.no) & Marius Hauglin (marius.hauglin@nmbu.no), Department of Ecology and Natural Resource Management, Norwegian University of Life Sciences, P.O.Box 5003, NO-1432 Ås.

Preface

The work presented in this report is the result of the project “Bruk av fjernmåling til kartlegging av fremmede bartrær” (Use of remote sensing for mapping of non-native conifer species). The project was funded by the Norwegian Environment Agency and conducted from November 2014 to November 2015. The project consisted of four parts.

The first part in the report present the current literature on the use of remote sensing for species identification and classification, with an emphasis on non-native and invasive species. It includes a discussion of available remote sensing platforms, sensors and general methods for identification.

In the second part, we derive species distribution maps for Norway spruce and Scots pine using existing literature and national remote sensing based forest maps. We then use the same forest maps and the derived species distribution of Norway spruce to create a non-native species map, and demonstrate how such a non-native species map can be used to provide statistical sound estimates of the area dominated by non-native tree species. We conclude this second part by evaluating the consistency between our map and other available sources of non-native species locations and we demonstrate how such a map can be used to compute coverage and proximity to important natural areas.

In the third part, we develop models and evaluate the performance of different remote sensing data to discriminate between Norway spruce and Sitka spruce. These two species occur in the same areas, and there is a need to discriminate between them in order to map and monitor the spread of the non-native Sitka spruce. The remote sensing data we evaluated were single scene and multi-temporal data from the Landsat 8 satellite, as well as remote sensing data acquired on a regular basis in Norway. These include the three dimensional information from airborne laser scanning, and orthophotos created from aerial imagery acquired through the national aerial photo campaigns (omløpsfotografering).

In the fourth and last part, we summarize our results, and discuss a possible establishment of a mapping and monitoring program for non-native tree species in light of the current knowledge.

Table of Contents

Summary

Non-native species are by many considered a threat to local biodiversity. In Norway, conifer species have been introduced in order to find species with better timber production than the native species. Several of these introduced species have been considered to be invasive, and put on an official «blacklist». Thus, from a management perspective, more information about the extent, occurrences and potential dispersal are important information. To gather such information solely based on field surveys are time-consuming and costly, and it has therefore been suggested to develop methods based on remote sensing. In this report we review different types of remote sensing data and how these can be used to map and monitor non-native species.

Natural species distributions of Norway spruce and Scots pine were created based on available literature and existing remote sensing-based forest maps. The same maps were used to create a non-native species map, i.e. a map of areas where spruce occur outside its natural distribution. We evaluated the accuracy of the map by photo-interpretation, and assessed the consistency with other occurrence data. We further estimated the area of non-native species on a county and national level in Norway. The area covered by non-native species outside the natural distribution of spruce was estimated to be 1200 $km^{2,}$ with a standard error of 275 km^2.

A specific challenge when using remote sensing for mapping of non-native species in Norway is to separate species of the same genera. We therefore conducted a study in Fusa and Tysnes municipalities where we evaluated the ability to discriminate between Norway spruce and Sitka spruce using different types of remote sensing data. Data from Landsat 8 satellite images, aerial imagery and airborne laser scanning were tested. Slight to moderate ability to separate between the two species were found, with a best overall accuracy of 78%. The results suggest that Landsat 8 imagery can be used to discriminate between stands dominated by Norway spruce and Sitka spruce. Additional data from airborne sensors contributed not substantially in this case.

Based on our own analyses and a review of relevant literature we discuss a possible establishment of a national mapping and monitoring programme for non-native tree species.

Sammendrag

Fremmede arter blir av mange betraktet som en trussel mot det biologiske mangfoldet. I Norge har flere bartrearter blitt innført med tanke på å bedre produksjonspotensialet i skogen, og flere av disse artene finnes nå på den offisielle «svartelista». For forvaltningen er det derfor et økende behov for kunnskap om utbredelse og potensiell spredning av disse artene. Det er både tidkrevende og kostbart å samle denne informasjonen utelukkende basert på feltundersøkelser, og det er derfor foreslått å utvikle metoder basert på fjernmåling for kartlegging og overvåkning. I denne rapporten har vi gjennomgått ulike typer fjernmålingsdata med hensyn på potensiale for kartlegging og overvåking av fremmede bartrær.

Vi har videre etablert utbredelsekart for vanlig gran og furu basert på gjennomgang av eksisterende litteratur samt nasjonale skogkart fra fjernmålingsdata. De eksisterende skogkartene ble også bruk til å etablere et kart over fremmede bartrær, dvs. grantrær utenfor sin naturlige utbredelse. Nøyaktigheten av utbredelseskartet ble evaluert ved hjelp av fototolkning. Videre undersøkte vi hvordan kartet stemte overens med andre tilgjengelige kilder om lokaliteter av fremmede treslag, og estimerte arealet med fremmede bartrær på fylkes- og landsnivå. Arealet av fremmede bartrær utenfor den naturlige utbredelsen til gran i Norge ble estimert til 1200 km^2, med en standardfeil på 275 km^2.

En spesifikk utfordring i fjernmåling av fremmede bartrær er å skille mellom arter av samme slekt. Vi etablerte en test i Fusa og Tysnes dere vi vurderte potensialet for å skille mellom vanlig gran og sitkagran med ulike typer fjernmålingdata. Fjernmålingsdata som ble testet var satellittbilder fra Landsat 8, flyfoto fra omløpsfotograferingen og flybåren laserskanning. Vi fant en svak til moderat evne til skille mellom de to artene. Den beste totale nøyaktigheten var på 78%, dvs. at 78% av lokalitetene var riktig bestemt. Testen indikerer at Landsat 8 bilder kan brukes til å skille mellom bestand med vanlig gran og sitkagran og at resultatene ikke bedres vesentlig ved bruk av flybårne sensorer.

Basert på en litteraturgjennomgangen og våre analyser diskuterer vi en mulig etablering av et kartleggings- og overvåkingopplegg for fremmede treslag.

Abbreviations and terms

Airborne	Carried by an aircraft.
ALS	Airborne laser scanning. Range measurements using lidar.
GIS	Geographical Information System.
kappa	Measure of overall classification accuracy. Suitable for comparison of performance of different models on the same classification problem.
lidar	Range measurements using laser light (LIght Detection and Ranging).
Orthophoto	Orthorectified aerial images, i.e. images that have the same scale in all parts of the image.
Pixels size	Is the smallest addressable element in a image or raster dataset. In remote sensing the size is given in real world scale, also referred to as the ground sampling distance.
Producer accuracy	Measure of classification accuracy. The probability that an entity in a given class is classified as belonging to this class.
Random forest	A machine learning technique used for classification.
Spaceborne	Carried by a satellite (or space shuttle).
Spatial resolution	Typically referring to the resolution of remote sensing data as observed on the ground. Pixel size in the case of imagery, or points per m^2 for ALS data.
Spectral resolution	Referring to the number of spectral bands in an image. An ordinary digital colour image is called multispectral: it contains information in three bands – from the red, green and blue part of the spectrum. Hyperspectral images typically contain information in more than 100 narrow bands. In addition to the visible light, also the near-infrared and the infrared radiation is commonly used in remote sensing.
SVM	Support Vector Machine. A machine learning technique used for classification.
UAV	Unmanned Aerial Vehicle (drone).
User accuracy	Measure of classification accuracy. The probability that a classified entity really belong to this class.

Part 1: Remote sensing and species identification

Introduction

Non-native species are by many considered a threat to local biodiversity. The spread of non-native – and potentially invasive – species is typically caused by human activity; either through deliberate introduction of species or as a consequence of transportation of biological matter in for example ballast water or wood materials. In the forestry sector in Norway the previous use of tree species from around the world is an example of a purposive introduction of non-native species. The purpose was in this case to find species with potential for better timber production than the native species, especially in areas at the west coast. Sitka spruce (*Picea sitchensis*), Contorta pine (*Pinus contorta)*, Silver fir (*Abies alba)*, Western hemlock (*Tsuga heterophylla*) and different varieties of Larch (*Larix spp.*) have been planted in Norway. A hybrid between White spruce (*Picea glauca*) and Sitka spruce called Lutz spruce (*Picea × lutzii)* has also been introduced. Of these, several have been considered to be invasive, and put on an official «blacklist» (Gederaas et al. 2012). The direct spread of non-native species will typically occur within a given distance from an initial location, with the distance determined by characteristics of the specific species, wind and other factors. From a management perspective, it is desirable to map occurrences of non-native species, and to establish systems to monitor further expansion. Reliable mapping of such scattered occurrences through field surveys can be time-consuming and costly, it is therefore suggested to develop methods using remote sensing data.

To be able to identify non-native species through remote sensing it is required that there exist features which distinguish the non-native vegetation apart from the native vegetation, and that these features are directly or indirectly present in the remote sensing data. One typical – and important – example is spectral information; how vegetation reflects light and other types of electromagnetic radiation depends on a range of factors, including species or species composition (Turner et al. 2003). Spectral data from aerial or satellite imagery can therefore be used to map vegetation. Imagery with low resolution can be used to analyse vegetation communities, whereas a finer resolution can be used to map and identify individual vegetation elements, such as single trees. Three-dimensional remote sensing data – such as lidar data – contains information on the spatial structure of the vegetation and can further contribute to a discrimination between species or vegetation types. In the case of non-native species this could for example mean to be able to identify species with a diverting crown shape, or which form stands with an atypical spatial structure.

From the 2000s and onward there have been several studies on detection of non-native and

invasive species using remote sensing data. There have also been studies which use similar methods to map and classify different native species and vegetation types. A detailed introduction and discussion of the use of remote sensing data for identification of invasive trees and plants can be found in Bradley (2014) and Huang and Asner (2009).

Several remote sensing technologies and platforms can be relevant; airborne laser scanning (ALS), aerial or satellite multispectral or hyperspectral imagery as well as data collected with unmanned aerial vehicles (UAV). These remote sensing technologies and platforms have different advantages and disadvantages when used to map and monitor tree species in general, which also apply to the more special case of mapping and monitoring non-native species. In the next section, we will review and discuss these remote sensing technologies and their strengths and challenges related to tree species mapping and classification. We treat medium and high spatial resolution spaceborne sensors separately. These sensors are typically passive, and the main difference between them will be the spatial resolution. Differences due to spectral, temporal and radiometric resolution will in most cases play a minor role. Lastly, we discuss high spatial resolution airborne technologies. The airborne sensors include passive multispectral and hyperspectral sensors as well as the active lidar sensors used in ALS.

Medium spatial resolution spaceborne sensors

The use of spectral data from medium spatial resolution satellite imagery has a high potential for mapping and monitoring of non-native species. This is mainly due to easy access and the temporal resolution of these data. The most common sensors/satellites available are Landsat 8 and the upcoming Sentinel 2 missions, which was lauched in June 2015 and a second satellite planned for lauch in mid-2016. These sensors typically have a spatial resolution of 10 - 60 m, a spectral resolution of 8 - 13 bands and cover large geographical areas. Landsat 8 has a revisit time of 16 days and Sentinel will achieve 2-3 days revisit times at mid-latitudes with two satellites operational. Thus – for monitoring purposes – these satellites will provide repeated measurements which will increase the number of cloud free images and further facilitate multi-temporal analysis.

Medium spatial resolution satellite imagery is typically combined with field inventory data from national forest inventories to develop national forest maps (Gjertsen 2007; Tomppo et al. 2008). Beyond this application for production of national forest maps, medium spatial resolution satellite imagery is rarely used in operational forest inventories due to insufficient accuracy (Holmgren and Thuresson 1998; Mäkelä and Pekkarinen 2004).

Carter et al. (2009) used multispectral (Landsat 5) and hyperspectral (Hyperion) medium spatial resolution images acquired to classify Tamarisk (*Tamarix spp.*) in North-America. They

concluded that the high spectral resolution of Hyperion gave an increase in accuracy of 8 percentage points over the multispectral alternative. The accuracies obtained for this classification were between 80 and 88% in terms of overall accuracy, but commission (false positive) errors were also high at 62-83%.

Classification can also be enhanced by acquiring remote sensing data at specific phenological stages where the non-native species can be separated from native vegetation. For example, Resasco et al. (2007) evaluated Landsat imagery from different time periods over the year and found better classifications of under-story shrub using leaf-off imagery from a specific time period.

A limitation with medium spatial resolution data is that a single pixel represent a mix of species. Thus, they are only suitable for mapping of patches or stands of non-native species. Early detection of occurrences of non-native trees is desirable from a management point of view, but the resolution of the remote sensing data will determine at what scale detection of non-native species is possible. Using satellite imagery with a spatial resolution of e.g. 30 m it is unlikely that identification of single non-native trees will be successful. However, such coarse resolution might on the other hand be sufficient for identification of forest stands dominated by non-native species. For example, it has been demonstrated that in pure Sikta spruce plantations in United Kingdom mean height can be predicted from medium resolution satellite imagery (Donoghue et al. 2004; Huang and Asner 2009).

High spatial resolution spaceborne sensors

High spatial resolution spaceborne sensors typically have a spatial resolution of 5 m or less, however usually a lower spectral resolution than the medium resolution satellites. The revisit time is often higher because the sensors can adjust the image acquisition angle. The costs are typically moderate and a relatively large area can be covered with one scene. This gives more homogeneous image quality than with multiple aerial images.

High resolution satellite imagery has been used for species identification (Carleer and Wolff 2004; Mora et al. 2010). Mora et al. (2010) also discriminated between spruce species – black spruce (*Picea mariana*) and white spruce (*Pica glauca*). One suggested application of high resolution imagery is to support large-area sample-based forest inventories in remote areas (Falkowski et al. 2009).

In a study which aimed at classifying the invasive species Tamarisk four-bands multispectral imagery with 2.5 m spatial resolution was preferred over 220-bands hyperspectral imagery with 30 m spatial resolution (Carter et al. 2009). Fuller (2005) used spectral features derived from

multispectral satellite images with a spatial resolution of 4 m to detect areas dominated by melaleuca (*Melaleuca quinquenervia*) – an invasive tree species – in Florida. The results showed that large and dens stands of the invasive species were reliably detected, whereas the method and data were to a lesser extent suitable for detection of smaller groups or single trees. This demonstrates the important relationship between data resolution and the size of detectable objects. Bradley (2014) notes – based on results from reviewed studies – that "detection of more heavily invaded areas seems to be most promising". Successful detection and classification of for example single trees does require a resolution of the remote sensing data such that a tree crown spans multiple pixels. It is suggested by Hengl (2006) that the minimum size of objects detectable in imagery must have a size greater that four pixels. Thus, for a spatial resolution of 4 m the the smallest object recognizable is 64 m^2.

High resolution spatial resolution airborne sensors

Data from airborne sensors are typically expensive to acquire but do have a very high spatial resolution.

In operational forest inventories data from airborne sensors are preferred over data acquired from satellites. This is mostly due to higher spatial resolution. Data from aerial imagery are typically photointerpreted to obtain information about species in operational forest inventories (Magnusson et al. 2007). However, aerial imagery has also been used to classify important tree species (Brandtberg 2002). Today, aerial imagery is commonly used in combination with ALS in operational forest inventories. The three-dimensional data from ALS have a high correlation with important forest attributes such as timber volume and tree height. ALS can also be used to delineate and identify single trees, allowing for recognition of species on an individual tree level. A review of the use of ALS for species classification are provided by Vauhkonen et al. (2014) Although, most of the ALS species classification studies are based on individual trees, area-based approaches have also been tried out. For example, Donoghue et al. (2007) separated plantations of Lodgepole pine (*Pinus contorta*) and Sitka spruce using only ALS data. They pointed out intensity, variation in height and percentages of ground returns as important variables.

ALS has however limitations in more complex forest with many species and species within the same genera. Thus, it is suggested that ALS is combined with spectral information when forest conditions are more diverse (Vauhkonen et al. 2014). Alternatively, multispectral ALS data as recommended by Vauhkonen et al. (2014) are now becoming available. Fusion of multispectral imagery and ALS have been used to obtain species information either on an area-basis, or at a single-tree level (Ørka et al. 2013; Dalponte et al. 2012). Estimation of species-specific tree volume

using data from a combination of multispectral imagery and ALS are becoming operational in Finland (Packalén and Maltamo 2007; Packalén et al. 2009). Singh et al. (2015) did however not find any improvement by adding spectral data when classifying an invasive understory plant using ALS.

In detection of non-native species some studies also use multiple data sources, such as the combination of ALS data and hyperspectral imagery. The digital imagery yields in that case spectral or textural information from the surface of the vegetation, whereas the ALS data provide information on the three-dimensional spatial structure. Asner et al. (2008) combined data from ALS and hyperspectral imagery to identify an invasive tree species (*Morella faya*) in Hawaii. In that study, they found that the spectral signature of the non-native species differed from the native vegetation. This enabled an identification of areas with occurrences of the invasive species.

Hyperspectral sensors are not frequently used in operational forest inventories. This is because of the limitations in commercial availability of such sensors, together with the large amounts of data delivered by such systems. With respect to forest inventory information data from hyperspectal airborne sensors have been found to be superior to multispectral imagery (Dalponte et al. 2013; Dalponte et al. 2009; Ørka et al. 2013).

The body of literature on the use of airborne spectral imagery for species recognition is dominated by the use of hyperspectral images. The high numbers of continuous narrow bands in hyperspectral imagery increase the ability to describe and distinguish between the spectral responses from different species. The list of studies using hyperspectral imagery to detect invasive species are long, and includes species such as leafy spurge (*Euphorbia esula*) (Lawrence et al. 2006), spotted knapweed (*Centaurea maculosa*) (Lass et al. 2002; Lawrence et al. 2006), iceplant (*Carpobrotus edulis*); jubata grass (*Cortaderia jubata*) (Underwood et al.2003), Brazilian waterweed (*Egeria densa*) (Hestir et al. 2008) and pepperweed (*Lepidium latifolium*) (Andrew and Ustin 2008).

Remote sensing with Unmanned Aerial Vehicles (UAV)

The availability of easily operated UAVs has increased the last 5 years. Using imagery acquired by UAVs together with structure from motion algorithms and photogrammetric principles provide data for estimation of forest attributes with high accuracy (Puliti et al. 2015). The use of UAVs for species monitoring is however restricted by limitations regarding the size of the area which is practical to cover, as well as legal aspects regarding autonomous operation of UAVs.

Some relevant studies do however use data from UAVs, for example Reid et al. (2011) captured images from a UAV to classify vegetation and single species. The classification of areas

with different vegetation was carried out using spectral and textural features extracted from automatically delineated segments. Textural features can be used to detect non-native species if these have shape or form patterns that distinguish them apart from the native vegetation. Rapid technological development and low costs of UAVs can make this platform a suitable alternative for data acquisition. The use of UAVs is however only feasible for data acquisitions in areas of limited size.

A table with information for some relevant studies related to this section is given as an appendix, (Table A-1).

Concluding remarks

All the above-mentioned remote sensing technologies may be used for mapping and monitoring of non-native species. The spatial resolution is important because it determines the size of the objects that can be detected on the ground, whereas other parameters mostly influence the obtained accuracy. The choice of remote sensing technology should be based on an analysis of total inventory cost, available budget, desired accuracy and the value of information. If for example the value of information is small, the use of freely available satellite imagery and a limited amount of field data could be a viable solution.

Part 2: Non-native and native species distributions

Introduction

An important requirement for mapping non-native species on large scales is to have information on the geographical distribution of the native species. Distribution maps are crucial in management of non-native species, since they, based on the current regulation, define whether a species is native or not. However, the details of existing distribution maps – such as those found in international geodatabases[1] – are often too coarse to be used in management and monitoring of non-native species.

During the last two decades remote sensing has been used to develop consistent national forest maps or vegetation maps in many countries (Tomppo et al. 2008; Gjertsen 2007). Such maps have often information on species distributions in terms of stem volume per hectare or similar attributes. Thus, these maps have information about the current species distribution and accounts for alpine, oceanic and arctic tree-lines. However, in cases where these maps do not distinguish between individual species or between native and non-native species from the same genera, additional information is needed to establish a map of the native species distribution. One example is at the west coast of Norway where different spruce species occur in the same areas. Most of these spruce species are non-native, but one species, Norway spruce, also occur as native (Lid and Lid 2007). Norway spruce has also frequently been planted outside its native habitat in these regions. In order to separate the areas where Norway spruce occur natively, from where it is introduced outside its native habitat and where other non-native spruce species occur, a more detailed distribution map is needed. Although DNA methods are available (Tollefsrud et al. 2015), the most readily available information of the native species distribution in Norway is found in existing literature. Thus, combining a current distribution map created from available national maps and a literature-based native species distribution map seems to be the most viable solution to provide more detailed and updated native distribution maps.

A current distribution map at the genera level can include both native and non-native species. Such a map can be used to estimate the area covered by non-native species, and to assess the impact in – and proximity to – specific areas of high natural value. In the case of area estimation, rigorous statistical methods beyond a mere summary of map areas should be used to obtain estimates of non-native species, as well as uncertainty measures and standard errors for these estimates. The simplest methods of obtaining area estimates from classified maps is to use the error matrix obtained from a sample (Stehman 2013). However, in both area estimation and in impact

1 e.g. http://www.euforgen.org/distribution-maps/

assessment the accuracy of the underlying map product will be highly influential. Using already existing maps may be a cost efficient way to obtain the information compared to organizing and conducting separate remote sensing campaigns to produce an updated non-native species map. However, it is likely that the designated remote sensing campaigns will provide higher accuracies than national available map products. Thus, evaluating the application and the accuracy that can be obtained by using non-native species distribution maps derived from national available vegetation and forest maps would support future decisions on how to obtain maps of non-native species.

In the current part of this project our aim was to produce digital maps of the native species distributions for Norway spruce and Scots pine in Norway, based on national available maps. Based on these maps, distribution maps for non-native conifer species were then created, and we investigated the applicability and accuracy obtained for such maps in area estimation and impact assessment. The specific objectives of the current part were to:

1. Create national maps of the native distribution of Scots pine and Norway spruce.
2. Create a national non-native spruce species map and estimate the area dominated by non-native spruce species.
3. Examine the relationship between the non-native species map and established databases, i.e. species occurrence data and the current risk assessment of protected areas.
4. Mapping the coverage and distances to important natural areas.
5. Creating maps indicating potential expansion from locations with non-native species.

Materials

Study area

The analyses was carried out in two steps at two different spatial scales. First, the distribution maps was created on national scale. In the second step, the area defined to contain non-native species was analysed in more detail.

Forest map

The map product named SAT-SKOG (Gjertsen 2007) was used as a source of information for tree species and forest extent. The map is based on Landsat imagery and field observation from the Norwegian national forest inventory, and is created by the Norwegian institute of bioeconomy research (NIBIO). The map contains information that include species proportions for pine, spruce and broadleaved trees. SAT-SKOG is the only map product providing this information for large areas in Norway. The map do however lack information in some areas (Figure 2-1). The main impact on the results produced in the current project is that information from Finnmark county was

missing.

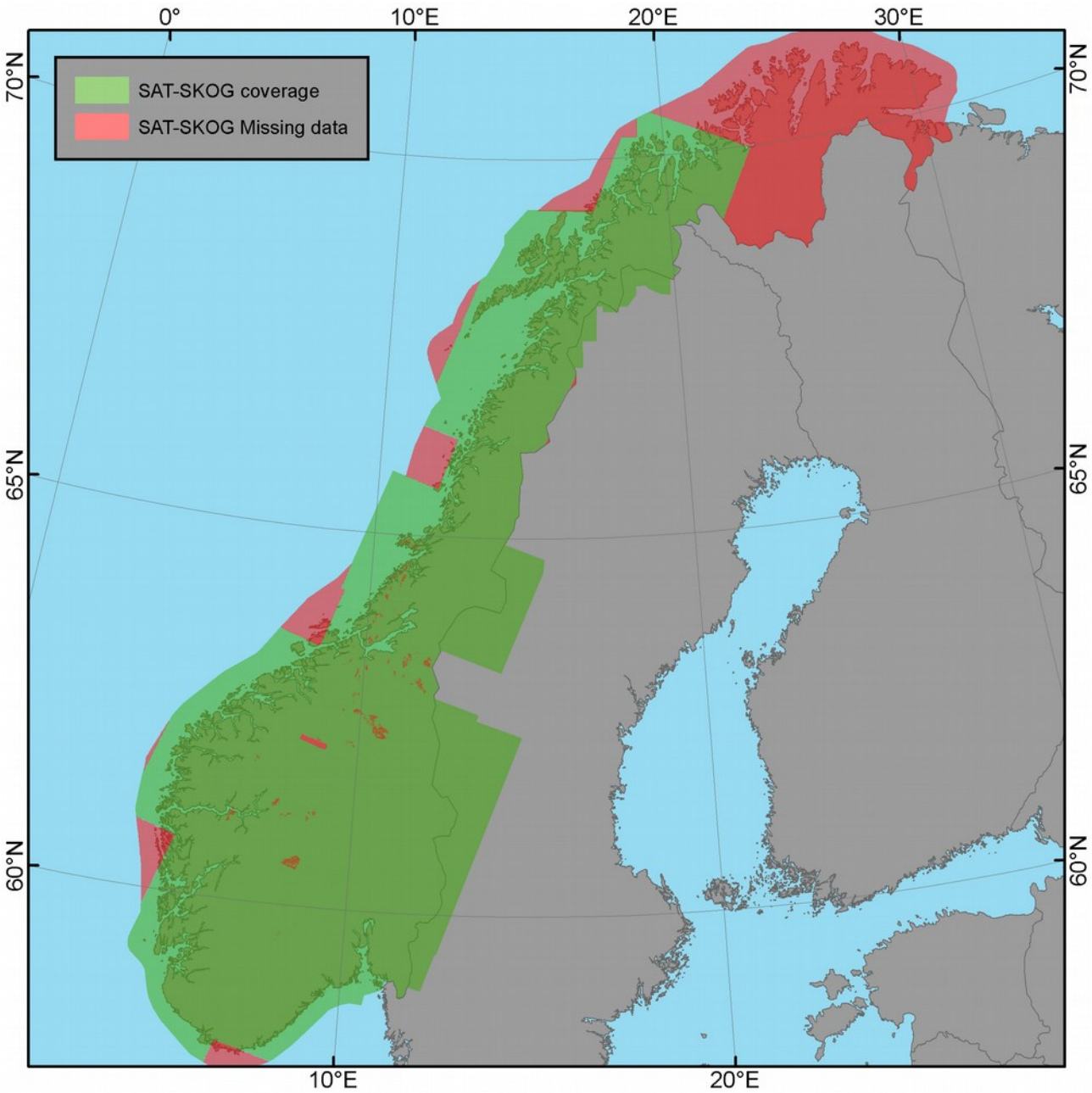


Figure 2-1: Coverage and missing information in the national forest map (SAT-SKOG). SAT-SKOG is a map product from NIBIO based on Landsat satellite imagery.

Validation data – species occurrence maps

We assessed the consistency between the non-native species map and other sources of occurrence data. Occurrence data on spruce (*Picea sp.*) found outside the native distribution area for spruce was downloaded from the Species Map Service provided by Norwegian Biodiversity Information Centre

and Global Biodiversity Information Facility Norway[2] (Artsdatabanken). Only data with a coordinate precision better than 100 m was considered, which resulted in a total of 2157 observations. Of these 1566 had a coordinate precision better than 30 m. This level of accuracy corresponds to the pixel size of SAT-SKOG, not including the positional error of the pixels themselves which is typically considered to be half the pixel size. The majority of the species in the downloaded observations were Norway spruce (1512) and Sikta spruce (492), the remaining observations were of Lutz spruce (77), white spruce (26), Serbian spruce (*Picea omorika*) (4), blue spruce (*Picea pungens*) (3) and other species (5).

Impact assessment – protected areas and selected nature types

The coverage of non-native species and the distance to non-native species were mapped for selected natural areas. The natural areas considered were protected areas, selected nature types and INON-areas (areas without major infrastructure). Spatial datasets of these areas were downloaded from the Norwegian Environment Agency[3]. The selected nature types considered were: i) "Slåttemark", ii) "Slåttemyr", iii) "Kalksjøer", iv) "Kalk-lindeskog", v) "Hule eiker", and vi) "Kystlynghei".

Methods

Natural species distribution

A native species distribution map was created based on existing literature and the species information in SAT-SKOG. First, two different species distribution maps were created, one representing the current species distribution based on SAT-SKOG and the other based on existing literature and administrative boundaries. The two maps were merged to create a current native distribution map of Norway spruce and Scots pine.

Current species distribution maps of spruce and pine were created based on the information provided by SAT-SKOG. The maps were produced through a GIS analysis: First all polygons with species proportions of more than 0 percentage for either of the two conifer species (i.e. spruce or pine) were selected. Other threshold levels were considered, but all thresholds will be subjective and thus introduce other types of errors in the final maps. Next, all polygons within a distance of 250 m was added to the first selection (i.e. the spruce or pine polygons). On the selected polygons a dilation operation using a 500 m filter (a buffer of 500 m) followed by an erosion operation with a filter of 450 m (a negative buffer of 450 m) was applied to remove small polygons. This procedure resulted in a map of the current species distribution.

2 http://artskart.artsdatabanken.no/

3 Downloaded on September 4, 2015.

The administrative native species distribution was established based on the description in the Norwegian flora (Lid and Lid 2007) and was created as a geographical layer using an official map of municipalities and counties. The administrative natural species distribution for Norway spruce and Scots pine are tabulated in Table 2-1. Scots pine have a natural distribution according to Lid and Lid (2007) for most of Norway and are only absent in parts of Finnmark. Norway spruce occurs on Sørlandet from Lyngdal, on Østlandet and Trøndelag and in Nordland, north to Rana, with some spontaneous locations north of Saltfjellet. On the west coast, Norway spruce occurs in Ryfylke, Hardanger, Voss, Modalen and Indre Sogn (Lid and Lid 2007).

The administrative natural species distribution seems most uncertain for Norway spruce. The counties and municipalities mentioned in Lid and Lid (2007) fit well with one of the oldest references and descriptions of the distribution of spruce in Norway (Gløersen 1884). There is however some uncertainty related to if localities mentioned by Gløersen are natural spontaneous locations or if they are introduced by humans. In the current analysis we used the description by Lid and Lid (2007) as the source for the native distribution, including areas where the species occurs less frequent, i.e. areas with spontaneous locations. There is also a current hypothesis that Norway spruce may have survived in ice-free refugia in Scandinavia during the last glaciation e.g. on the west coast of Norway (Parducci et al. 2012). NIBIO has also located sites with potential natural spruce occurrence based on earlier literature descriptions of sites, orthophotos and 3D data (Tollefsrud et al. 2015). These sites could possibly be evaluated in more detail to understand the immigration history of spruce and the current native distribution of spruce in Norway.

The detailed natural distribution map was derived by clipping the current species distribution map with the map based on the administrative native species distribution. The level of detail in this map is high because it includes detailed boundaries towards the alpine areas and the coastline. We did therefore also create a simplified version. In this version, all inner holes (e.g. lakes, urban areas and mountain tops) were included in the native distribution, and all individual polygons with a size less than 1 km^2 were removed or merged.

Non-native spruce species map

Data were extracted from SAT-SKOG for all areas outside the administrative native distribution of spruce defined above. From SAT-SKOG the areas dominated by spruce, defined as areas where spruce had the highest proportion of timber volume were created and defined as the non-native species distribution map. This non-native species map covered 4 counties on the west coast, namely Rogaland, Hordaland, Sogn og Fjordane and Møre og Romsdal. Nordland and Troms in northern Norway were also included. The non-native species map was used to:

1. Estimate the area of non-native species.
2. Evaluate the consistency of the map to other sources.
3. Map coverage and distance to natural areas.
4. Establish risk maps.

The steps in the process described above are outlined in Figure 2-2.

Table 2-1: Native distribution of Norway spruce and Scots pine on an administrative level.

Nr	County	Norway spruce	Scots pine
1	Østfold	all	all
2	Akershus	all	all
3	Oslo	all	all
4	Hedmark	all	all
5	Oppland	all	all
6	Buskerud	all	all
7	Vestfold	all	all
8	Telemark	all	all
9	Aust-Agder	all	all
10	Vest-Agder	Lyngdal, Lindesnes, Mandal Søgne, Kristiansand, Vennesla, Songdalen, Marnadal,Audnedal, Hægebostad, Åseral	all
11	Rogaland[a]	Sauda, Suldal, Hjelmeland, Forsand	all
12	Hordaland[b]	Voss, Modalen, Kvam, Jondal, Granvin, Ulvik, Eidfjord, Ullensvang, Odda	all
14	Sogn og Fjordane[c]	Aurland, Lærdal, Årdal	all
15	Møre og Romsdal	Rindal	all
16	Sør-Trøndelag	all	all
17	Nord-Trøndelag	all	all
18	Nordland[d]	Rana, Hemnes, Hatftfjelldal, Grane, Vefsen, Vevelstad, Brønnøy, Bindal, Gildeskål, Beirarn, Saltdal	all
19	Troms	none	all
20	Finnmark	Sør-Varanger, Kautokeino, Karasjok	Kvalsund, Porsanger, Sør-Varanger

Lid and Lid (2007) description "inst i fjordar og dalføre i Ro Ryfylket" (Ro = Rogaland) defined as municipalities with a county border. Thus, the other municipalities in Ryfylke (Kvitsøy, Rennesøy, Finnøy and Strand) are not included.

[b] All municipalities in Hardanger in addition to Modalen and Voss.

[c] All municipalities in Indre Sogn

[d] Lid and Lid (2007) description "og nordover til No Rana, med nokre spreidde bestandar i Gildeskål (omlag utgått), Beiarn og Saltdal" (No = Nordland).

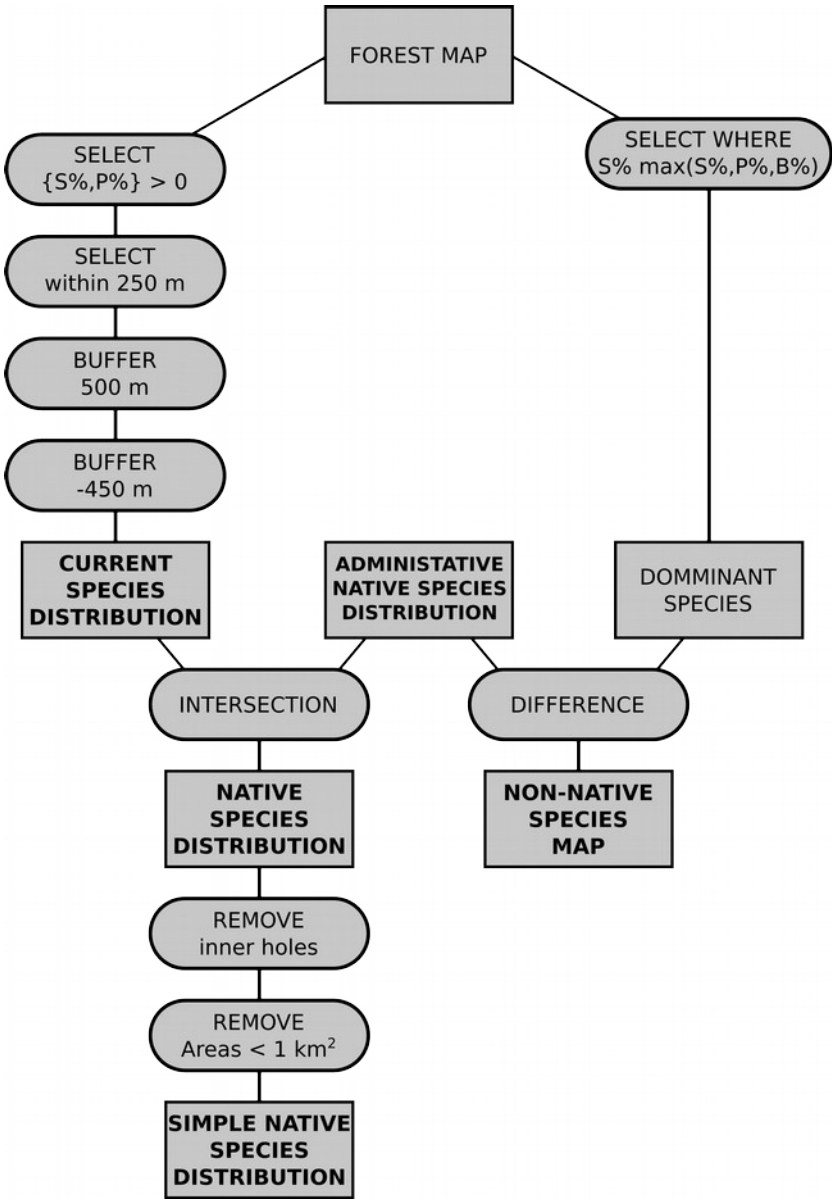


Figure 2-2. Outline of the process of creating the map products described in part 2 of the current project (S% = proportion of spruce, P% = proportion of pine and B% = proportion of broadleaved species).

Estimating area of non-native species

To estimate the area covered by non-native species we implemented a strategy based on an error matrix (Stehman 2013; Olofsson et al. 2014). For each of the 6 counties an equal number of reference locations were created, and tree species interpreted from available orthophotos[4]. In each county the reference sample was created by overlaying the map with a 1 x 1 km grid, and randomly drawing 80 observations from the grid locations that fell in areas where the map showed non-native

4 From wms.norgeibilder.no.

tree species (i.e. spruce) to be dominant. Similarly, 40 observations were drawn randomly from the grid locations outside areas being mapped as dominated by spruce. From the interpreted reference data a population error matrix was created:

$$\hat{p}_{ij} = n_{ij} / n_{i.}$$

Here *p* is a population error matrix, *n* is an error matrix, *i* is map class (row) and *j* is reference class (column). Estimated values are indicated by adding a hat symbol. From the population error matrix standard error matrix features such as producer accuracy (*P*) and user accuracy (*U*) as well as overall accuracy (*O*) and their respective variances (*V*) were calculated:

$$O = \sum_{j=1}^{q} p_{jj}$$

$$\hat{V}(\hat{O}) = \sum_{i=1}^{q} W_i^2 \hat{U}_i (1 - \hat{U}_i) / (n_i - 1)$$

$$U_i = p_{ii} / p_{i.}$$

$$\hat{V}(\hat{U}_i) = \hat{U}_i (1 - \hat{U}_i) / (n_i - 1)$$

$$P_j = p_{jj} / p_{.j}$$

$$\hat{V}(\hat{P}_j) = 1 / \hat{N}_{.j}^2 \left[\frac{N_{j.}^2 (1 - \hat{P}_j)^2 \hat{U}_j (1 - \hat{U}_j)}{n_{j.} - 1} + \hat{P}_j^2 \sum_{i \neq j}^{q} N_{i.}^2 \frac{n_{ij}}{n_{i.}} \left(1 - \frac{n_{ij}}{n_{i.}} \right) / (n_{i.} - 1) \right]$$

Here *q* is the number of reference observations. The area of non-native species (*y*) and its variance (*v*) were estimated based on the population matrix and the total area mapped in each class (*W*):

$$\hat{y} = \hat{p}_{.j} = \sum_{i=1}^{q} W_i \frac{n_{ij}}{n_{i.}}$$

$$\hat{v} = V(\hat{p}_{.k}) = \sqrt{\sum W_i^2 \frac{\frac{n_{ik}}{n_{i.}}\left(1 - \frac{n_{ik}}{n_{i.}}\right)}{n_{i.} - 1}}$$

The county level estimates ($\hat{y}_j(\hat{v}_j)$) was summarized to larger areas representing regions or the county level ($\hat{Y}(\hat{V})$) using standard formulas, here *k* is county:

$$\hat{Y} = \frac{\sum(W_k * \hat{y}_k)}{\sum(W_k)}$$

$$\hat{V} = \sum_k (\hat{v}_k * W_k^2)$$

The square root of the variances (*V*) provided the standard errors and a 95 % confidence interval was obtained by multiplying the standard errors with 1.96.

Consistency with spruce observations and protected areas

The agreement between the non-native spruce species map and the species occurrence observations from Artsdatabanken and the assessment of the protected areas (Miljødirektoratet) was evaluated through GIS analyses. From the point observations of species occurrence data the distances to the nearest polygon with non-native spruce were calculated. We also recorded the spruce proportion from SAT-SKOG at each point location. For the protected areas the proportion of the area covered by non-native polygons and the distance to the nearest polygon in the non-native map were created.

Coverage and distance to natural areas

Proportion of non-native species and distance to nearest polygon in the non-native species map were calculated for the selected natural areas. The distances was summarized and analysed according to the relevant categories in the data sources.

Risk maps

A risk map was created by buffering the non-native map with 2 and 5 km, corresponding to the seed dispersal zones suggested by Sandvik (2012).

Results and discussion

Native species distribution

Native species distribution maps were created combining the native administrative distribution and the current distribution obtain from SAT-SKOG. The maps created include a native administrative distribution, natural current distribution and a simplified native current distribution (Figure 2-3, 2-4). It can be discussed if municipalities with only some small patches of spruce should be included or not in a species distribution map. Such patches could have been introduced to by humans. We will however argue that using the most up-to-date reference literature on the Norwegian species distribution and include areas with enclaves of most likely native spruce, is a good foundation for further work on non-native tree species.

Non-native species map

The non-native species map indicated a cover of 1.3% of the land area outside the natural distribution of spruce (Figure 2-6). However, the area estimates need to be adjusted based on the map errors (see next section). Detailed non-native spruce species maps for selected areas are included as an appendix (Figure A-2 – A-11).

Estimated area of non-native spruce species

The area dominated by non-native spruce species outside the native spruce distribution (excluding Finnmark county) was in the current project estimated to be 1200 km^2, with a standard error of 275 km^2 and a corresponding 95% confidence interval of [661 km^2, 1739 km^2]. This estimate constitutes approximately 9.1% of the productive forest area, and is higher than the 595 km^2 estimate for non-native spruce species reported by Øyen et al. (2009) (note that we have excluded pine and non-spruce conifer species from the area reported by Øyen et al. by using their reported per-species figures). Øyen et al. derived this estimate from the number of seedlings delivered by forest nurseries in the period 1875 –2005. Using data from the Norwegian national forest inventory the area dominated by any non-native species were estimated to be 570 km^2 (Øyen et al. 2009). Øyen et al. also derived from a third source an estimate of 2900 km^2 of forest planted in Norway through the so-called “skogreisning”. Most of this occurred in areas in which the planted trees would be non-native, but some of these “skogreisning”-areas are located inside what we have considered the native distribution of spruce – for example in Hardanger – and is therefore not included in our estimate.

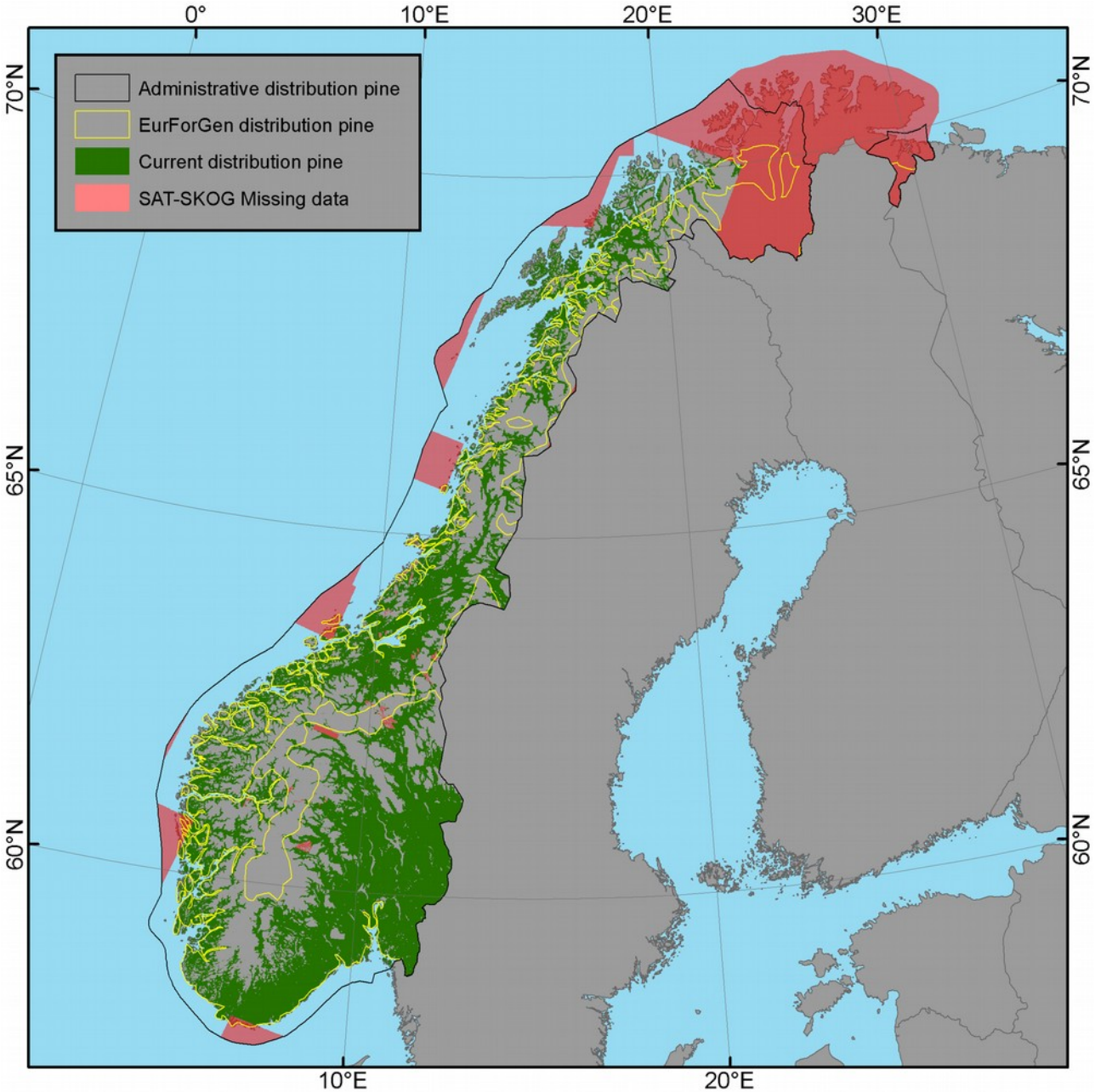


Figure 2-3. Natural species distributions maps for pine (simplified map in figure A-1). The map shows different sources of information on the native distribution of pine in Norway. The current distribution is derived from a combination of a literature-based administrative distribution, and conifer dominated pixels from the SAT-SKOG map product.

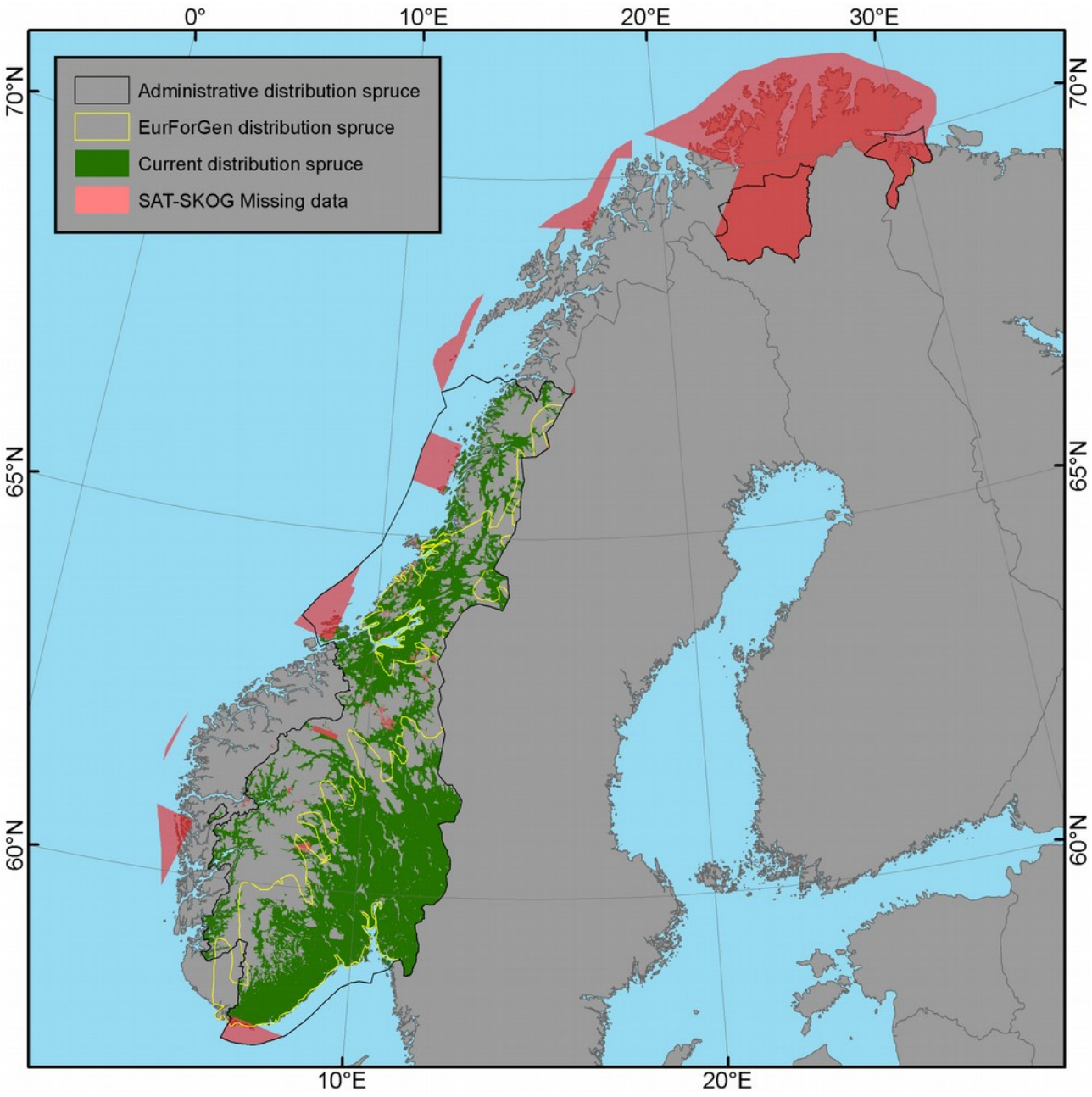


Figure 2-4. Natural species distributions map for spruce (simplified map in figure A-2). The map shows different sources of information on the native distribution of spruce in Norway. The current distribution is derived from a combination of a literature-based administrative distribution, and conifer dominated pixels from the SAT-SKOG map product. Some additional adjustments and decisions have been taken to arrive at the depicted current distribution. See text for details.

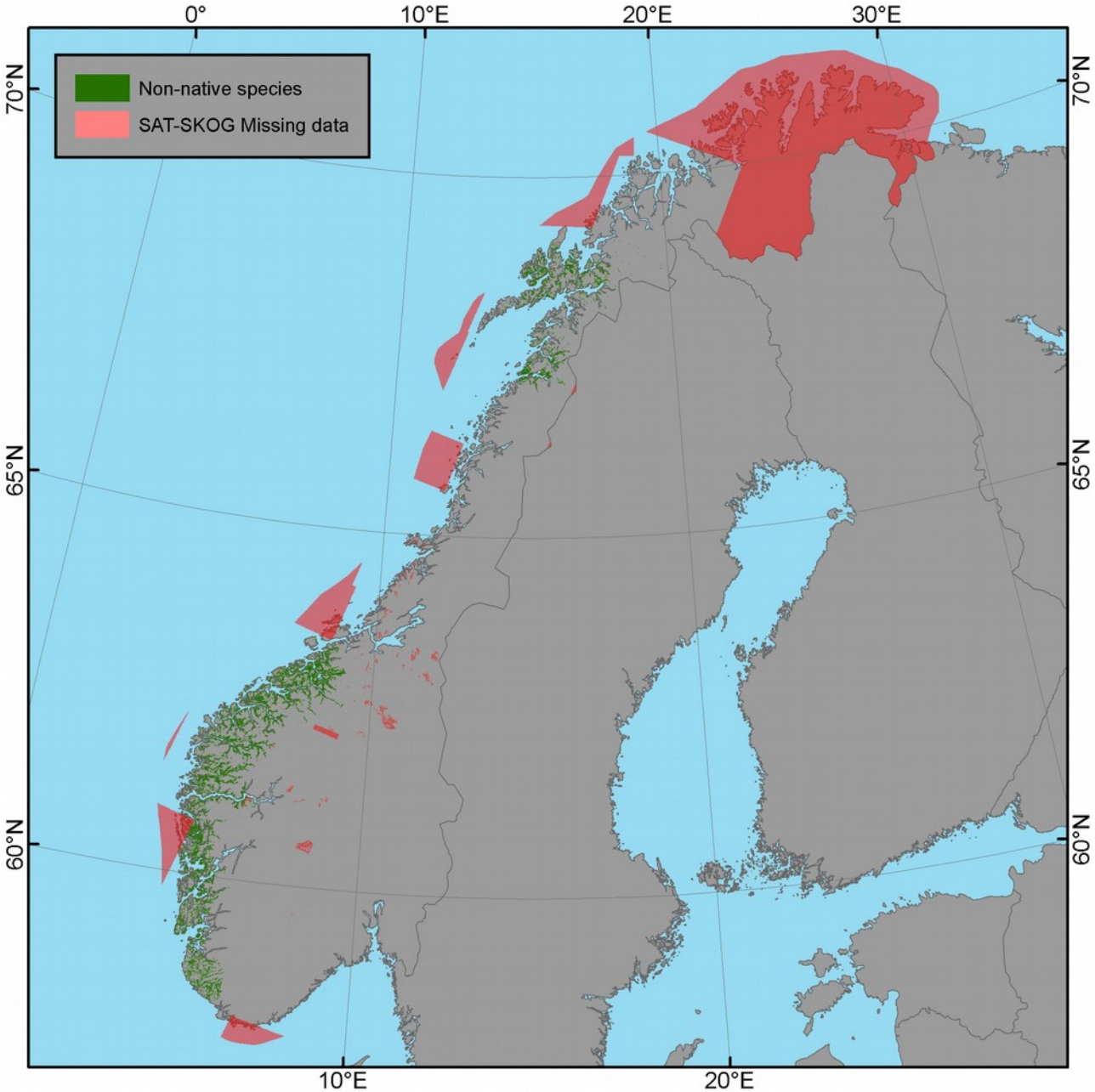


Figure 2-5. Non-native spruce species map. (Note that due to the included outlines of the green non-native polygons, the map do not represent the true area of these). The map shows the distribution of areas that are mapped as being dominated by non-native spruce species. The map is created by identifying pixels from SAT-SKOG which are dominated by spruce species, which occur outside the native distribution of spruce (see text for details).

The difference between these estimates from Øyen et al. and the results in the current project can partly be explained by the fact that the two first estimates from Øyen et al. do not include Norway spruce as a non-native species, even outside its native distribution. All three estimates from Øyen et al. do however include occurrences of non-native spruce species from all regions of Norway, also regions within the native distribution of Norway spruce, which were not considered in the current project. Øyen et al. did not provide any standard errors for their area estimates. It is therefore not possible to test statistically if these estimates in fact do differ from the results in the present project.

Area estimates were carried out for counties (Rogaland, Hordaland, Sogn og Fjordane, Møre og Romsdal, Nordland and Troms) and regions (Vestlandet and Nord-Norge). The largest areas dominated by non-native spruce species are at the west coast of Norway, particular in Sogn og Fjordane and Møre og Romsdal counties (Figure 2-7, 2-8 and Table 2-2).

Table 2-2. Productive forest area and estimates of area dominated by non-native spruce species.

County / region	Productive forest area [a] (km^2)	Non-native (km^2)	Non-native of productive forest area (%)
Rogaland	1053	194	18.4
Hordaland	2136	278	13.0
Sogn og Fjorande	2329	296	12.7
Møre og Romsdal	3027	329	10.9
Nordland	1753	35	2.0
Troms	2934	14	0.5
Vestlandet	8544	1160	13.6
Nord-Norge	4687	49	1.0
Norway	13232	1210	9.1

[a] Derived from the AR50 map product.

Figure 2-6. Area estimates (km^2) and confidence intervals of non-native spruce species dominance in different regions. The adjusted area is the area from the non-native map adjusted for the errors of this map obtained from photo interpretation of the stratified random reference sample.

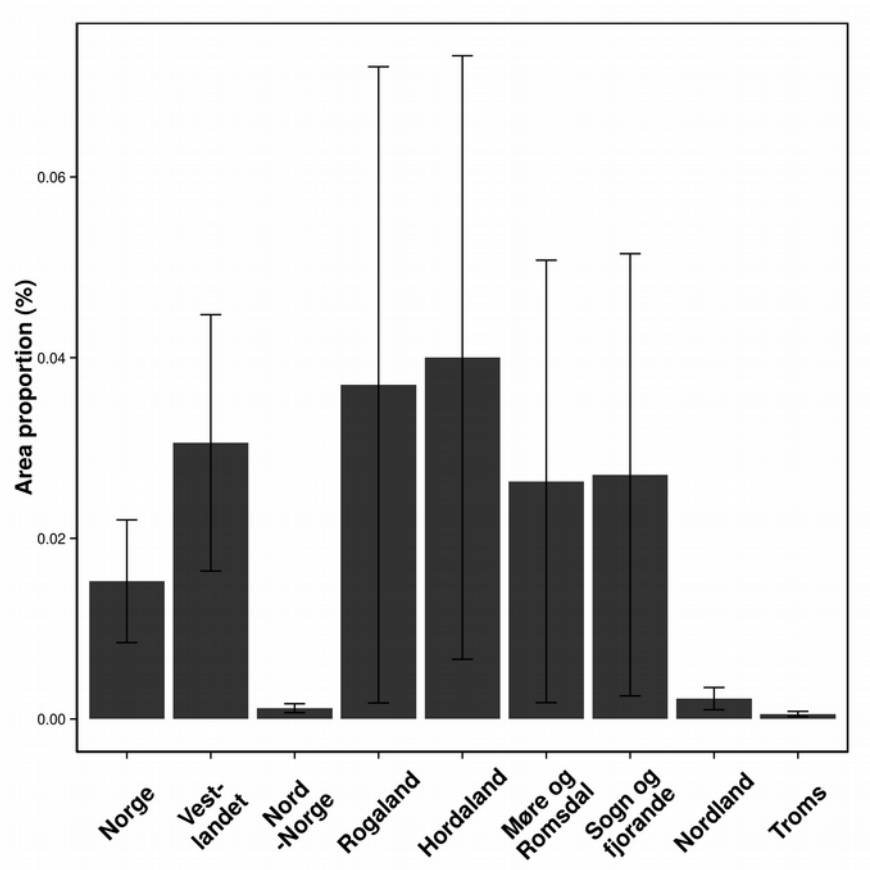


Figure 2-7. Area proportion estimates and confidence intervals of non-native spruce species dominance in different regions.

The non-native spruce species map has relatively high producer and overall accuracies, but the user accuracy are quite low because many of the locations classified as non-native spruce species are in reality dominated by native pine or broadleaved species. Especially in Nordland and Troms county the errors are high and many areas with non-native species in the map are other forest types or non-forest when checked in orthophotos. In these areas, the number of reference plots in the national forest inventory is lower and that has most likely also influenced the accuracy of the forest map, i.e. SAT-SKOG. These errors are accounted for in our final area estimates, which means that our area estimates are unbiased. The standard errors of these estimates are however relatively large, and vary from 21% to 48% of the area estimates. They can potentially be reduced by adding additional reference samples. The reference samples can be identified in available orthophotos with high confidence at most locations. Another method to improve the estimates is to fit a model to the reference samples (the photo-interpreted locations) and the data in the forest map. This will improve the accuracy of the map, but an independent validation is needed.

Table 2-3: Error matrices for the photo-interpreted reference points.

	Native	Non-native	Sum	Producer's accuracy
Rogaland				
Native	75	2	77	97.4
Non-native	15	25	40	62.5
Sum	90	27	117	
User's accuracy	83.3	92.6		
Overall accuracy				85.5
Hordaland				
Native	79	2	81	97.5
Non-native	11	29	40	72.5
Sum	90	31	121	
User's accuracy	87.8	93.5		
Overall accuracy				89.3
Sogn og Fjordane				
Native	78	1	79	98.7
Non-native	12	28	40	70.0
Sum	90	29	119	
User's accuracy	86.7	96.6		
Overall accuracy				89.1
Møre og Romsdal				
Native	78	1	79	98.7
Non-native	16	26	42	61.9
Sum	94	27	121	
User's accuracy	83.0	96.3		
Overall accuracy				86.0
Nordland				
Native	80	0	80	100.0
Non-native	30	10	40	25.0
Sum	110	10	120	
User's accuracy	72.7	100.0		
Troms				
Native	82	0	82	100.0
Non-native	29	11	40	27.5
Sum	111	11	122	
User's accuracy	73.9	100.0		
Overall accuracy				76.2

Table 2-4: Population error matrices, accuracy measures and area estimates in km$^{2.}$ (SE = standard error).

	Native	Non-native	Map area (km^2)	Adjusted area(km^2)	Adjusted area (SE)(km^2)	Adjusted proportion	Proportion (SE)	Producer's accuracy	SE Producer's	Overall accuracy	SE Overall
Rogaland											
Native	0.96	0.03	5159	5061	94	0.96	0.018	0.99	0.003	0.97	0.035
Non-native	0.01	0.01	97	194	94	0.04	0.018	0.31	0.299		
Total	0.96	0.04	5255	5255	189	1.00	0.036				
User's accuracy	0.97	0.63									
SE User's accuracy	0.04	0.15									
Hordaland											
Native	0.95	0.02	6804	6678	119	0.96	0.017	0.99	0.003	0.97	0.033
Non-native	0.01	0.02	152	278	119	0.04	0.017	0.40	0.333		
Total	0.96	0.04	6956	6956	237	1.00	0.034				
User's accuracy	0.98	0.73									
SE User's accuracy	0.03	0.14									
Sogn og Fjordane											
Native	0.97	0.01	11032	10959	141	0.97	0.012	0.99	0.003	0.98	0.024
Non-native	0.01	0.01	223	296	141	0.03	0.012	0.53	0.491		
Total	0.97	0.03	11255	11255	281	1.00	0.025				
User's accuracy	0.99	0.70									
SE User's accuracy	0.03	0.14									
Møre og Romsdal											
Native	0.96	0.01	14165	14116	181	0.97	0.012	0.99	0.004	0.98	0.024
Non-native	0.01	0.02	344	392	181	0.03	0.012	0.54	0.49		
Total	0.97	0.03	14508	14508	362	1.00	0.025				
User's accuracy	0.99	0.62									
SE User's accuracy	0.03	0.15									
Nordland											
Native	0.99	0.00	15392	15498	10	1.00	0.001	0.99	0.001	0.99	0.001
Non-native	0.01	0.00	140	35	10	0.00	0.001	1.00	0		
Total	1.00	0.00	15533	15533	19	1.00	0.001				
User's accuracy	1.00	0.25									
SE User's accuracy	0.00	0.14									
Troms											
Native	1.00	0.00	25821	25859	4	1.00	0	1.00	0	1.00	0
Non-native	0.00	0.00	53	14	4	0.00	0	1.00	0		
Total	1.00	0.00	25874	25874	8	1.00	0				
User's accuracy	1.00	0.28									
SE User's accuracy	0.00	0.14									

Consistency with other sources

The percentage of non-native spruce species observations from Artsdatabanken with a distance of less than 100 m (corresponding to the accuracy of the coordinates reported) from areas in our map classified as dominated by non-native spruce species, was 32.7%. A similar proportion was found when only considering locations with a higher precision, greater or equal to 30 m (31.2%). The average distance from a non-native spruce observation from Artsdatabanken to a spruce dominated area was 584 m, with 75% of the observations within 540 m and a median distance of 203 m. Furthermore, nearly half (1038 of 2157) of the locations from Artsdatabanken did not have any presence of spruce in SAT-SKOG, and only 101 of the locations had a spruce proportion of more than 50% according to data from SAT-SKOG (Figure 2-9).

Although the coordinate precision for many of the observations were reported to be of sufficient quality to be related to the SAT-SKOG product there are little consistency between these two sets of data. The main reason is that many of the records in the database are observations of single trees, which will not be visible in the 30 m resolution satellite imagery used to produce SAT-SKOG. It seems like the used of the species occurrence data from Artsdatabanken is of little use as calibration or validation data due to lack of the required level of accuracy. Another aspect is that the occurrence data are not representatively distributed in the landscape (Figure 2-10). Such clustering of observations will violate the assumptions for accuracy assessment, where random or systematic sampling are typically required. Thus, it is a clear recommendation not to rely on this occurrence data as field reference for remote sensing based estimation. We also consider it to be very likely that accuracies reported to be better than 1 – 5 m in Artsdatabanken are actually considerably lower. Use of survey-grade high precision GPS equipment in forested areas has been shown to have errors of up to 3 m with logging times of 15 minutes (Næsset and Gjevestad 2008) and consumer-grade GPS equipment have accuracies of around 10 m (Andersen et al. 2009; Wing et al. 2005).

The number of protected areas outside the native distribution of spruce was 158. Of these 55 intersected with the non-native spruce species areas. The average distance from these protected areas to a non-native spruce species area was 4437 m. However, the median value was 140 m, and 75% of the areas were within 1068 m from a non-native spruce dominated stand. Taking into account the suggested risk zones of 2 and 5 km nearly 90% of all the protective areas were within these distances: 143 (91%) and 139 (88%), respectively. Relating the protected areas directly to the forest map revealed that 30% of the protected areas outside the native distribution of spruce were dominated by spruce (> 50%) and 58% of the protected areas had a proportion of spruce of > 10% (Figure 2-9). Thus, there is a limited consistency between the threat assessment and the non-native species map.

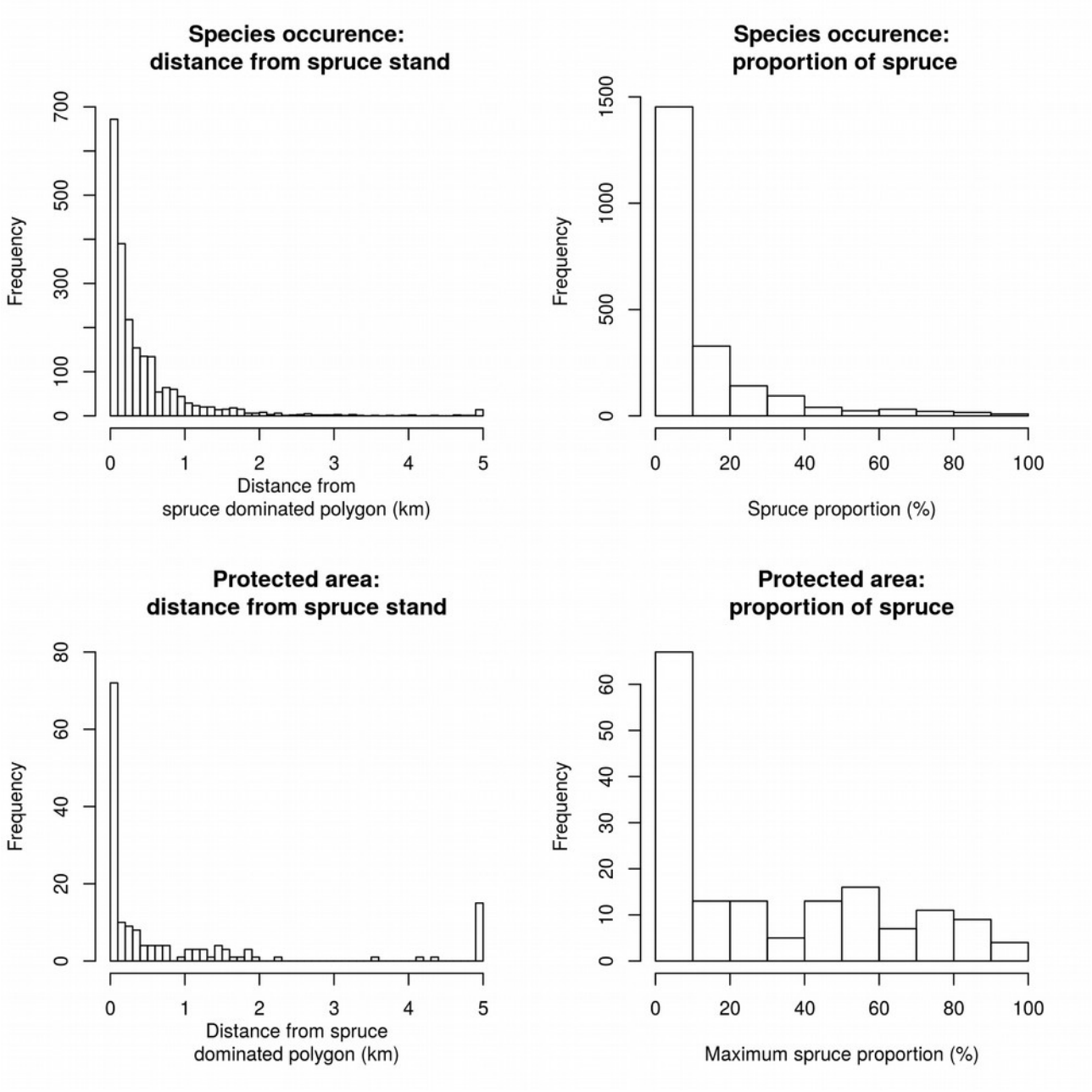


FIGURE 2-8. Distance between spruces occurrence data and the non-native species map polygons (upper left) and spruce proportion from SAT-SKOG on species occurrence locations (upper right). Distance between threatened protected areas and the non-native species map polygons (lower left) and the maximum spruce proportion from SAT-SKOG inside the threatened protected areas (lower right).

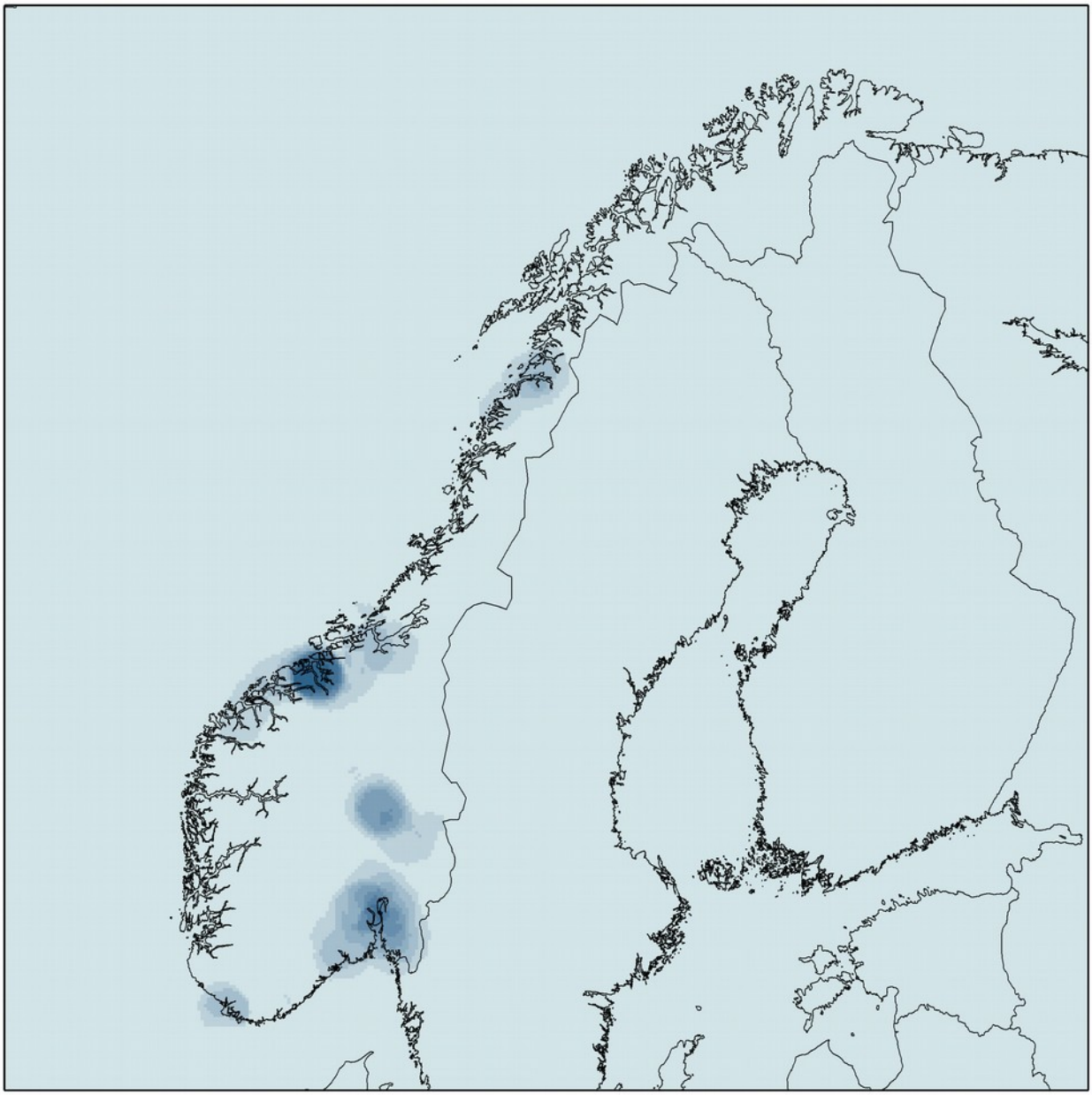


Figure 2-9: Density of spruce occurrence recording in Artsdatabanken provided by Norwegian Biodiversity Information Centre and Global Biodiversity Information Facility Norway. In total the density map is based on the 2157 observation (of Picea sp.) where the coordinate precision was better than 100 m.

Non-native species in protected and natural areas

Approximately half of the protected areas had some cover of non-native spruce species based on the created map. However, the coverage of areas dominated by non-native spruce species within the protected areas was usually low. On average, the area coverage was 2%, and 82 of the of the protected areas (13%) had a coverage between 5% and 10%. Only 12 protective areas had a

coverage of areas dominated by non-native spruce species of more than 10%. The median distance

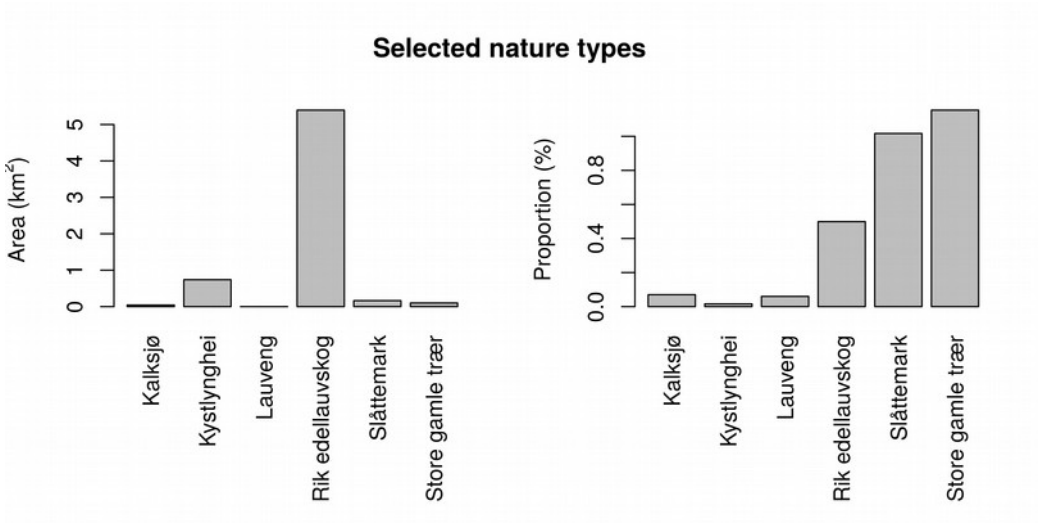


Figure 2-10. Overlap between the non-native species map and selected nature types. The area of the individual nature types dominated by non-native spruce species (left). Proportion of the individual nature types dominated by non-native spruce species (right).

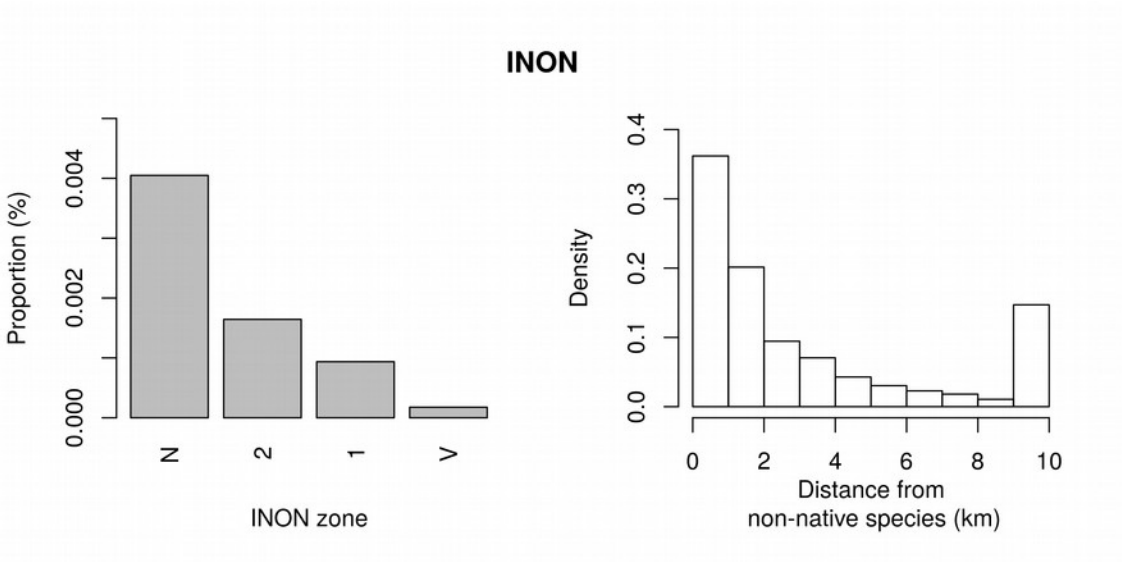


Figure 2-11. Coverage and distance from INON areas to locations mapped as dominated by non-native spruce species. Proportion of the area of each INON zone that are dominated by non-native spruce species (left) (N = Areas newly removed from INON, 2 = between 1 and 3 km from technical installation etc., 1 = 3 – 5 km from technical installation, V= Wilderness areas .

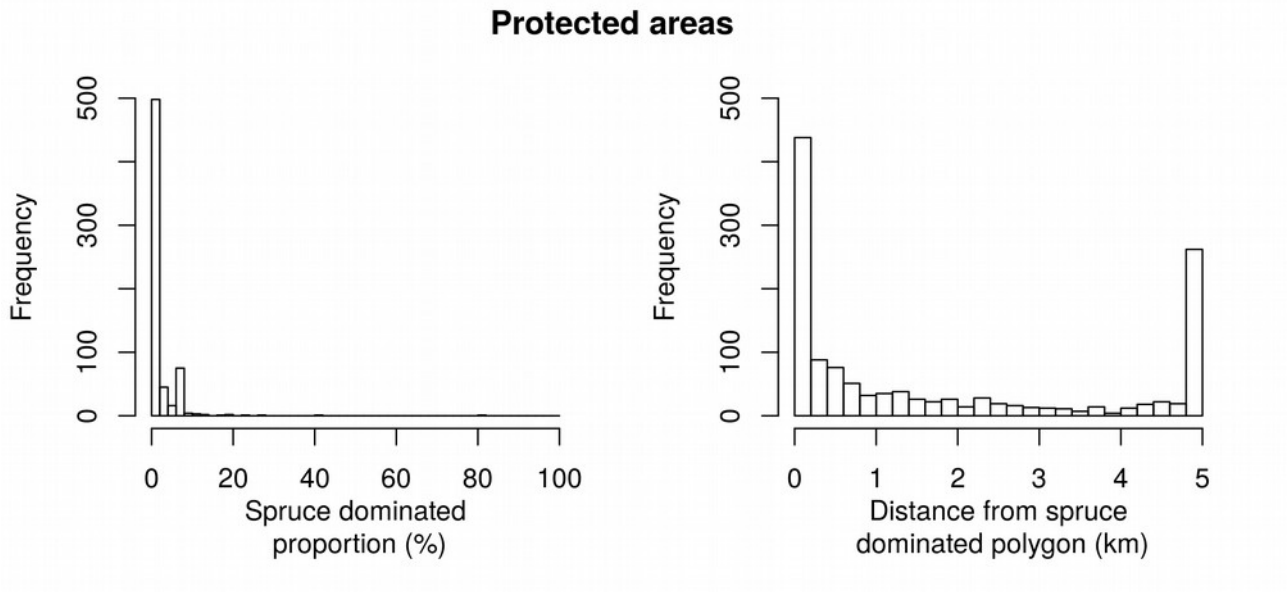


Figure 2-12. Coverage and distance from protected areas to locations mapped as dominated by non-native spruce species. Number of protected areas plotted against the percentage of the area that are mapped as dominated by non-native spruce species (left). Number of protected areas related to their distance from the nearest non-native spruce dominated polygon (right).

from a non-native polygon to a protected area was 793 m. However, 64% and 82% percent of the combined area of the individual protected areas were within the dispersal risk distance of 2 and 5 km (Figure 2-13).

All the selected nature types intersected with an area dominated by non-native spruce species. The median cover and the average cover within the areas were 2.6% and 9.5%, respectively. The coverage was highest in “Rik edelløvskog” (5.0% of the area) “Slåttemark” (10.2% of area) and “Store gamle trær” (11.5% of area). However, in terms of total area “Edellauvskog” and “Kystlynghei” were the types with the largest coverage of non-native species (Figure 2-11).

Only 6% of the INON polygons outside the administrative native distribution of spruce had some coverage of non-native species. The total area coverage with non-native species in the INON area according to the map was approximately 50 km^2. The coverage of non-native species are largest in zones closest to technical installations (Figure 2-12).

We would like to emphasize that the results presented above should be interpreted in light of the accuracy obtained for the non-native species map.

Risk maps

We created a risk map by applying the seed dispersal distances suggested by Sandvik (2012) to the non-native species map (Figure 2-14). These risk zones cover large parts of the land in the analysed areas. Thus, when a more detailed invasive species map is obtained, topography and wind directions should also be considered when producing such risk maps.

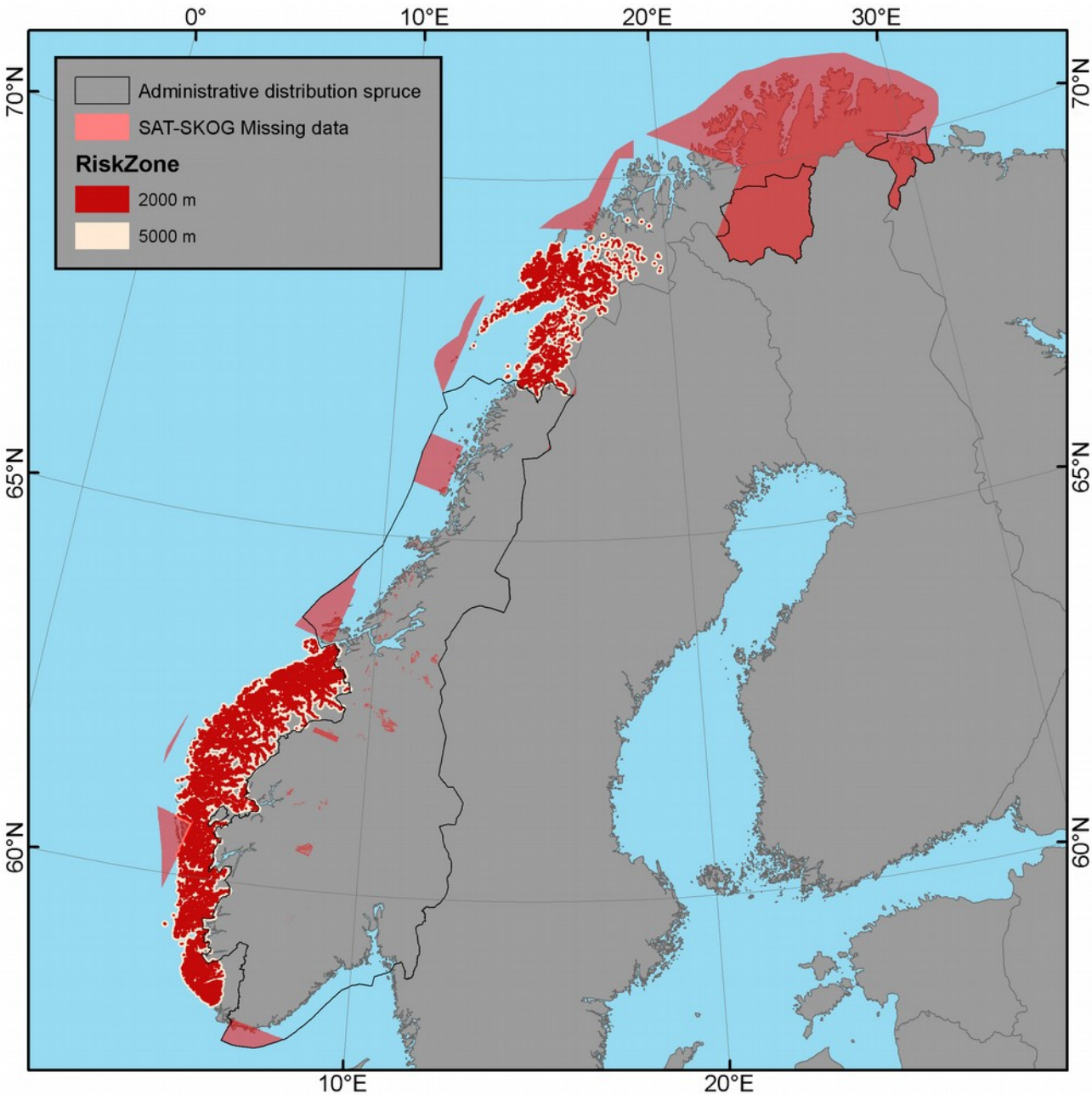


Figure 2-13. Risk zone map based on 2 and 5 km dispersal range from the non-native spruce map. The map shows the non-native spruce polygons with a 2 and 5 km buffer, i.e. the areas indicated in the map are within a distance of 2 or 5 km from locations with non-native spruce.

Part 3: Classification of spruce species

We have in this part of the project tested and validated methods to discriminate between Sitka spruce and Norway spruce, using remote sensing data.Both airborne and spaceborne remote sensing data have been used to map and classify vegetation. The main advantage of spaceborne remote sensing data is the availability both in terms of coverage and costs. Satellite imagery such as the Landsat products are freely available, and covers most areas of the globe with multiple acquisitions annually. The disadvantage of satellite imagery of this type is a resolution that is typically too course for some applications. With a spatial resolution of 30 m it is for example not possible to identify individual vegetation elements, which could be achieved using airborne remote sensing. Airborne sensors are flown closer to the ground and thus typically are able to provide data with a much higher resolution. Some sets of data from airborne sensors – such as the aerial imagery from the Norwegian mapping authorities – are freely available for governmental bodies, but the use of other types of airborne remote sensing data can involve acquisition costs.

We have tested and compared three sources of remote sensing data in the present part of the project, namely Landsat 8 satellite imagery, orthophotos created from aerial imagery, and data from ALS. Whereas the former two are imagery from passive spectral sensors, the latter is acquired using a lidar sensor. ALS is based on and active sensors, sending out and recording then reflections of pulses of laser light. The data product from ALS is typically a three-dimensional point cloud representing the points where the laser pulses were reflected from the vegetation and the ground. Laser echoes from the ground can be identified using specialized algorithms, which in turn enables calculations of above-ground heights for laser echoes reflected from the vegetation. This principle is central in the application of ALS for estimation in forestry. A thorough introduction to principles and application of lidar for vegetation mapping is outside the scope of this rapport. An introduction to the principle behind ALS can be found in Wehr and Lohr (1999). A more comprehensive introduction to the application of ALS in forestry can be found in Maltamo et al. (2014).

Materials

Study area

The data used in this part of the project were collected within Fusa and Tysnes municipalities on the western coast of Norway. The forest are naturally dominated by Scots Pine and deciduous species, mainly birch (*Betula pubescens*). From the 1940s and throughout the second part of the twentieth century regeneration using non-native tree species, mainly Norway spruce and Sitka spruce was common in this region at the west coast of Norway. The productive forest area is about 260 km^2 and

the species composition is approximately 13% spruce, 66% pine and 20% deciduous forest.

Field data

Three sets of field observations were utilised in the present part of the project, with observations from a total of 240 individual locations. All locations were situated in spruce dominated forest, and the proportions of Sitka spruce and Norway spruce were recorded for all locations. Two of the sets were initially collected as a part of the data acquisition in other research and forest inventory projects. The three datasets are described in the following:

Forest inventory plots

Sample plots with the main purpose of being used to create forest management plans were measured during the summer of 2012. These circular sample plots had a size of 250 m^2. The sample plots were clustered, with a 250 m spacing between sample plots in the cluster. From this initial set of plots, a sub-sample of 57 plots dominated by either Norway spruce or Sitka spruce was used in the present project.

Research plots

A second set of field observations was from sample plots measured during the autumn of 2013. These circular sample plots had a size of 250 m^2 and were laid out in clusters of three in a triangular design. The internal distances between plots within the clusters were 20 m. A total of 93 plots dominated by Norway spruce or Sitka spruce were used from this set in the present project.

Additional Sitka spruce plots

Field measurements with the main purpose of increasing the number of observations from locations dominated by Sitka spruce were carried out during the summer of 2015. From an initial set of all forest stands in the study area dominated by Sitka spruce, 30 stands were subjectively chosen for measurements. With an initial goal of having the observations evenly spread out in the study area, the selection was ultimately guided by accessibility from e.g. forest roads. The selection of the 30 stands were carried out prior to visiting the stands in the field, with the exception of a few occasions in which a nearby stand was measured instead, due to severe storm felling in the originally chosen stand. Within the selected stands, three locations were subjectively chosen, guided by these criteria: the locations should be evenly spread out in the stand, and should preferably not be close to stand borders. At each of the three locations, the proportions of the basal area of Sitka spruce versus other species were recorded using a relascope.

Plot positioning

For the first two datasets, the plot centers were positioned using survey-grade GPS+GLONASS equipment. The forest inventory plots were positioned using real time kinematic GPS+GLONASS using DPOS from the Norwegian Mapping Authorities (reported accuracy from processing < 0.20 m), and the research plots using differential GPS+GLONASS (reported accuracy from processing < 3.2 m). with post-processing. In the post-processing the three closest base-stations operated by the Norwegian mapping authority were used. A hand-held GPS receiver was used to record the position for additional Sitka spruce plots (accuracy ~10 m).

Remote sensing data

Airborne laser scanner data

Airborne laserscanning data was acquired using two Optech ALTM Gemini instruments mounted in a PA31 Piper Navajo fixed-wing aircraft. The data acquisition was carried out from 5th of June to 7th of August 2010. The initial processing of the ALS data was carried out by the contractor (Blom Geomatics, Norway) according to standard procedures. Echo heights were normalized using a triangular irregular network (TIN) created from ground echoes identified using the progressive TIN densification algorithm (Axelsson 1999; 2000).

Aerial imagery – orthophoto

Norway has a system for acquiring aerial images on a routinely basis. The orthophotos produced from these images are made readily available on the internet for end-users. The orthophotos used in the current project have a resolution of 0.25 m and were created from imagery acquired in July 2013 as part of the campaign “Vestlandet 2013”.

Landsat 8

A search restricted to images in the period from February 11, 2013 to August 31, 2015 with less than 30% cloud coverage returned 30 potential images covering the study area. Of these seven were selected for further use, based on manual inspection of the distribution of the cloud cover. The Landsat 8 data were downloaded[5], and had a pixel size of 30 m. The acquisition dates for the seven Landsat images were:

#1: 2013-07-10, #2: 2013-07-26, #3: 2014-09-15, #4: 2013-11-06,
#5: 2014-03-30, #6: 2014-04-15, #7: 2014-05-01.

5 From http://libra.developmentseed.org/

Methods

Variable extraction

For all the field reference locations numerical features were extracted from the remote sensing data, and these features – or *variables* in a modelling context – are described for each of the three datasets in the following:

Landsat 8

Field reference data were with the Landsat 8 data coupled with the pixel from the satellite images which contained the recorded field position. From this pixel, spectral values from the bands of the Landsat image were extracted. We also computed normalized difference vegetation index (NDVI) and three indices derived with a so-called tasseled cap transformation. Coefficients for the tasseled cap transformation were taken from Baig et al. (2014), where these indices also are further described. An overview of the variables extracted from the Landsat images is presented in Table 3-1.

Table 3-1. Variables derived from the Landsat satellite imagery and the corresponding band(s) used for calculating the variable.

Variable	Band(s)
Red	4
Green	3
Blue	2
Near infrared (NIR)	5
Short wavelength infrared (SWIR) 1	6
SWIR 2	7
NDVI	4 and 5
Brightness	2 – 7 (tasseled cap transformation)
Greenness	2 – 7 (tasseled cap transformation)
Wetness	2 – 7 (tasseled cap transformation)

Airborne laser scanning data

Laser echoes were extracted from 250 m^2 circular areas centred at the field measured plot centers, corresponding in size to the forest inventory plots. Note that this size also was used for the locations with relascope measurements. Within these circular areas above-ground heights of the laser echoes were extracted and percentiles and order statistics were obtained from the height distribution. This

type of height-derived variables have been used in estimation for forest inventories, and have been shown to be well correlated with e.g. timber volume (Næsset 2002). To use these height metrics for classification they were normalized to the maximum echo height (See Table 3-2). In addition to an accurate position, each recorded laser echo is also associated with an intensity value, giving the intensity of the reflected laser light. Previous studies show that these intensity values might hold information that can be used to discriminate between different tree species (Ørka,et al. 2009; Korpela et al. 2010). We therefore included variables describing the distribution of intensity values, corresponding to the variables derived from the height distribution. The variables were computed by the R-package *lasR*[6], developed by the authors, in the statistical software R (R Development Core Team 2011) . A summary of the variables derived from the ALS data is given in Table 3-2.

Table 3-2. Variables derived from the ALS data.

Variable	**Description**
Hmean	Mean echo height relative to the maximum echo height
Hsd	Standard deviation of the echo height distribution
Hcv	Coefficient of variance for the echo height distribution, relative to the maximum echo height
Hkurt	Kurtosis of the echo height distribution
Hskewness	Skewness of the echo height distribution
H10, H20 … H90	the 10th ,20th , … 90th percentile of the height distribution of the laser echoes, relative to the maximum echo height
d0, d1, …. d10	Density variables. Number of echoes above equally spaced height intervals.
imax	Maximum echo intensity
imean	Mean echo intensity
isd	Standard deviation of the echo intensity distribution
icv	Coefficient of variance for the echo intensity distribution
ikurt	Kurtosis of the echo intensity distribution
iskewness	Skewness of the echo intensity distribution
i10, i20 … i90	the 10th ,20th , … 90th percentile of the intensity distribution of the laser echoes.
i0, i1, …. i10	Number of echoes above equally spaced height intervals in the echo intensity distribution.

6 https://github.com/hansoleorka/lasR

Aerial imagery - Orthophoto

Pixels within 250 m^2 field plots were extracted from the aerial images, and variables were derived from the distribution of spectral values. All variables were derived separately for the red, green and blue bands. The distribution of spectral values was captured as percentiles of the value distribution (see Table 3-3). Texture is commonly used in different image analysis tasks, and we included textural variables derived using co-occurrence matrices (Haralick et al. 1973). The glcm R-package (Zvoleff 2015) was used to calculate the textural variables. Textural variables derived with co-occurrence matrices were calculated for each pixel, and the value depends on a predetermined window size, which gives the number of neighbouring pixels to include in the calculations. We calculated two distinct sets of textural variables: 1) a set with the values of the textural features from the single center pixel at each field reference location. In this case, the side of the window was equal to the diameter of the 250 m^2 field plot, which means that the pixels included in the calculations approximately corresponded to the pixels within the circular field plot. 2) Another set of textural variables derived by averaging the values for all pixels within the plot. In this latter case, the window size was reduced in order to limit the number of pixels outside the circular plot that were included in the calculations. The window side was in this case set to correspond to the radius of the 250 m^2 circular field plots. Both these approaches will lead to some pixels outside the plot being included in the calculation of textural variables. An overview of the variables derived from the orthophotos is presented in Table 3-3.

Modelling – classification algorithms

Three distinct types of classification models were used and compared in the present project: random forest, support vector machine (SVM) and logistic regression. Random forest is a machine learning classification algorithm and is based on multiple binary classification trees, grown with bootstrap samples of the data. It was introduced by Breiman (2001), and is used for classification and regression. SVM is another widely used machine learning classification algorithm based on constructing optimal separating hyperplanes in transformed versions of the data. Classification with random forest, SVM and logistic regression is further described by Hastie et al. (2013).

The classification was carried out using a leave-three-out cross-validation procedure. Three observations were held back as validation data, and the remaining 237 observations were used to build the classification models. The observations were grouped according to the clusters in the field data, which ensured that all observations from the same cluster or stand were in the same group, and thus not occurred in the modelling and validation set at the same time. The procedure was repeated 80 times, until all groups of three observations had been used for validation once. The predictions

for each validation iteration were recorded, and accuracy statistics computed.

The classification with the random forest algorithm was in the present project carried out using the *randomForest* package in R (Liaw and Wiener 2002). Default values for adjustable parameters were used. Classification with SVM was carried out using the *svm* function from the *e1071* package in R (Meyer et al. 2015). Default values for adjustable parameters were used for the SVM models. The logistic regression models were fit with the *glm* function in R, using the *step* function to do a stepwise variable selection. The stepwise procedure was carried out using Bayesian information criterion (BIC) for selection. Both forward and backward selections were enabled, with an empty model as the initial model. Finally the *glmulti* function in the *glmulti* package (Calcagno 2013) in R was used to select the best model from all possible subsets of the variables selected through the stepwise selection procedure. In this final model selection BIC was used as criterion, and only models with less than six variables were considered.

We derived the predicted classes from the logistic regression by using a cut-off value of 0.5, i.e. observations with a modelled probability of > 0.5 were classified as dominated by Sitka spruce.

Table 3-3. Variables derived from the orthophotos.

Variable	Description
P10_red, P20_red … P90_red P10_green, P20_green … P90_green P10_blue, P20_blue … P90_blue	10th ,20th , … 90th percentiles of the distribution of the red, green and blue spectral values, respectively.
Textural variables	
mean	The textural variables were calculated separately for the red, green and blue band. The variables are further described in Haralick et al. (1973).
variance	
homogeneity	
contrast	
dissimilarity	
entropy	
second moment	
correlation	

Accuracy assessment

The classification performance for each model was assessed by computing the overall accuracy, user and producer accuracy for the Sitka class, as well as the kappa statistic. The user accuracy corresponds in this case to the probability that a location classified as being dominated by Sitka

spruce really belong to this class. Conversely, the producer accuracy is the probability that a location dominated by Sitka spruce is in fact classified as such. The kappa statistic – also referred to as the Cohens kappa – is a measure of the overall accuracy, and is well suited for comparison of different models solving the same classification problem. There are several ways of interpreting the kappa value – Landis and Koch (1977) consider 0-0.20 as slight, 0.21-0.40 as fair, 0.41-0.60 as moderate and 0.61-0.80 as substantial, and 0.81-1 as almost perfect.

Results and discussion

The overall results from the cross-validation procedure show slight to moderate ability to discriminate between locations dominated by each of the two spruce species, using the remote sensing data. The resulting kappa values varied between 0.106 and 0.556 for the tested combinations of remote sensing data and classification methods (Table 3-4).

In terms of classification accuracy, the combination of Landsat image #1 and orthophoto images performed in the present study best, with a kappa value of 0.556 and a corresponding overall classification accuracy of 78% (Table 3-4). When inspecting the results from using data derived from single Landsat images it is evident that the accuracies vary, with kappa values ranging from 0.228 to 0.522. Models with data from Landsat images #1 and #3 performed best, with kappa values of 0.522 and 0.465, respectively. The best model using data from Landsat image #4 on the other hand, had a kappa value of 0.228. This indicates that the inherent information that reveal differences between Norway spruce and Sitka spruce is not present to the same degree in all seven Landsat images. Using a single Landsat image for this kind of classification is in other words sensitive to the selection of the image, and it could therefore be beneficial to use multitemporal Landsat imagery. The results could suggest that satellite imagery acquired in the summer yields a better classification, but a thoroughly investigation of possible differences due to acquisition season was not carried out in this project. It could be subject to further research.

Compared to the models based on data from the two airborne sensors, the satellite imagery performed in this comparison well, despite a lower spatial resolution. Using data with a lower spatial resolution does however restrict the possible spatial levels for predictions.

Combination of data from different sources did not yield predictions with considerable higher accuracy in this comparison. Adding data from ALS or orthophotoes did however slightly improve the classification accuracy as compared to the use of Landsat imagery alone. Also in this case, using data with a higher spatial resolution will also enable predictions at a finer spatial scale.

Three types of classification methods were tested in the present project, with logistic regression yielding the best results. The logistic regression was however implemented with a

variable selection procedure which was not used for the other two approaches. Any conclusions drawn from the performance of the different models should incorporate this, and future research could reveal if the two machine learning procedures would benefit from the use of a variable selection procedure with this type of data.

There are few directly comparable studies, but the accuracy obtained in the present project seems to be within the range of accuracies obtained in some related studies (see Table A-1 in the appendices). Carter et al. (2009) used imagery from Landsat 5 to classify an invasive tree species in Colorado (US), and obtained an overall accuracy of 80%. Higher accuracies than in the present study were obtained in some studies using satellite imagery with a higher resolution, such as Asner et al. (2008) and Fuller (2005). The classification accuracies in those studies were also higher than the accuracies obtained with high resolution orthophotos and ALS in the present project. One reason could be that the spectral and structural differences between Sitka spruce and Norway spruce are too small, or of such a nature that they are not well captured in the remote sensing data.

Vauhkonen et al. (2014) notes that the task of inter *genera* separation of species is challenging, and in species classification studies using remote sensing the species are typically from different *genera*.

Overall, the results from this part of the project suggest that Landsat 8 imagery can be used to discriminate between stands dominated by Norway spruce and Sitka spruce. Slight to moderate ability to separate the two species were found, with a best overall accuracy of 78%. Using additional data from airborne sensors did not yield considerable higher classification accuracies. The accuracy when classifying Norway spruce and Sitka spruce in an operational setting will however also rely on the ability to discriminate between spruce dominated forest and other vegetation and land cover types. The experience from the use of SAT-SKOG data in part 2 of this project suggest that errors must be expected, so how the final accuracy is influenced by these should be further evaluated.

Table 3-4. Accuracy statistics from the cross-validation of the classification models. User and producer accuracy for the Sitka class. The table is sorted according to the kappa value, i.e. the models with best performance appear at the top of the table. For Landsat the # indicate the image number used. (The terms used in the table are further described in the Terms and abbreviations section).

Overall accuracy	kappa	User accuracy	Producer accuracy	logistic regression	SVM	random forest	Orthophoto	Landsat	ALS
0.779	0.556	0.778	0.743					#1	
0.767	0.529	0.777	0.708					#1	
0.763	0.522	0.764	0.717					#1	
0.746	0.491	0.724	0.743					#1	
0.742	0.484	0.711	0.761						
0.733	0.465	0.717	0.717					#3	
0.729	0.458	0.703	0.735						
0.725	0.449	0.701	0.726					all	
0.717	0.430	0.706	0.681						
0.713	0.425	0.683	0.726						
0.708	0.414	0.694	0.681						
0.704	0.404	0.702	0.646					#2	
0.704	0.405	0.694	0.664					all	
0.700	0.396	0.695	0.646					all	
0.700	0.397	0.685	0.673					#1	
0.696	0.388	0.685	0.655					#3	
0.675	0.347	0.658	0.646						
0.663	0.320	0.651	0.611					#2	
0.654	0.304	0.642	0.602					#6	
0.646	0.289	0.625	0.619					#7	
0.642	0.275	0.642	0.540					#1	
0.642	0.284	0.610	0.664					#5	
0.642	0.287	0.603	0.699					#5	
0.638	0.272	0.616	0.611					#3	
0.638	0.259	0.671	0.451					#1	
0.629	0.259	0.598	0.646					#7	
0.629	0.255	0.607	0.602					#7	
0.625	0.248	0.600	0.611					#2	
0.621	0.234	0.610	0.540					#6	
0.617	0.215	0.644	0.416						
0.617	0.213	0.657	0.389					#1	
0.617	0.228	0.600	0.558					#4	
0.617	0.234	0.585	0.637					#5	
0.613	0.216	0.604	0.513					#6	
0.613	0.217	0.602	0.522					#1	
0.596	0.175	0.603	0.416						
0.592	0.182	0.564	0.584					#4	
0.571	0.128	0.557	0.434						
0.554	0.106	0.526	0.531					#4	

Part 4: Recommendations for non-native species mapping

Introduction

The words mapping, inventory and monitoring are by many used as synonyms, but they are not. The use of the words do also differ slightly between disciplines. Some authors consider an inventory to be a complete census for a specific area (Pokorny et al. 2006), but inventories may also be sample based, due to high costs of complete inventories. One example of a sample based inventory is the Norwegian national forest inventory. Ground survey data can be used alone to produce inventory information using appropriate statistical estimators, or it can be used as reference data for an remote sensing-based inventory. A map can be produced as part of this process, which could be referred to as an inventory (complete census) or a mapping. Usually, when the term inventory is used, the map are combined with the ground references to produce estimates, as in Part 3 of this report. Monitoring is typically considered as repeated inventories or surveys. This part of the report will mainly focus on how inventories of non-native conifer species can be conducted in Norway. Establishing monitoring programmes to obtain information on the spread of non-native species is also discussed.

Considering objectives and goals

Before one establishes an inventory system targeting non-native species the aims should be clear. There might be demands for statistics and maps, identifying threatened areas, and to establish a monitoring programme aiming at detecting the spread of non-native species. To meet these demands, several aspects should be considered. In Part 2 of this report, we establish statistics and maps for the presence of non-native spruce species in parts of Norway based on available sources. This map can be established at a relatively low cost. However, there were a lot of false positives, meaning that a some of the areas mapped as dominated by non-native species are miss-classified and do in fact contain only native trees. Thus, this approach are most likely only suitable for production of mean statistics, where by increasing the number of references points it its possible to decrease the standard errors of these estimates. Other more detailed methods are needed if the aim of the inventory or monitoring programme is early detection of new occurrences of non-native species.

Before establishing an inventory and a subsequent monitoring programme targeting non-native tree species in Norway some insight can be gained from the current project as well as available literature. Firstly, medium spatial satellite imagery has several advantages and thus seems like a suitable remote sensing data source. In the current project, the accuracies obtained with such

imagery were among the best. The limitations in the tested classification methods are that only mature forest was included in the data material, but it is likely that younger forest also could be separated to some degree, although this have to be tested. Nevertheless, the youngest development classes and occurrences of single non-native trees can not be detected using medium satellite imagery. The size of the minimum detectable object in such imagery is 3.6 ha, and at best 0.4 ha if the highest resolution of Sentinel 2 can be used alone. Thus, the objective of using such imagery should be restricted to mapping areas or forest stands dominated by non-native species.

To monitor spread of non-native species the use of medium resolution satellite imagery from archives may provide a rough indication on the large scale spread during the last, say, 30 years. However, even if the species composition is relatively stable over time, it would be difficult to validate such maps using present field observations, and the obtained accuracy will most likely not be very high. To monitor spread of non-native tree species more detailed methods could therefore be considered. Areas selected for monitoring are probably best located based on maps produced by medium resolution satellite imagery. The areas could be placed subjectively or in accordance with predetermined guidelines. This will depend on if the objectives are to monitor specific areas – such as a protected area – or if the objective is to produce national- or county-wise estimates with standard errors.

To decide which species to include in a non-native tree species inventory some guidance can be taken from the estimate that nearly 60% of the conifer non-native species are Sikta spruce (Øyen et al. 2009). This will also affect the selection of areas. An inventory and monitoring implementation could be carried out as a stepwise process and improved as more information are obtained. Therefore, it seems advisable to consider one or more of the counties which have areas outside the native spruce distribution in Norway first. However, an inventory should include all non-native tree species.

The scope of the inventory is also important. If only national statistics are aimed for, the use of data from the national forest inventory are most likely enough. However, if county-wise estimates are needed, additional sources of data should be considered. If the aim is to obtain estimates on a stand – or even single tree level – yet more detailed data and methods must be used.

Field survey considerations

A field survey should be designed to provide a statistical estimate of areas which are dominated by, or have presence of, non-native tree species. Data from a field survey could also be used as reference data for remote sensing, provided that this is incorporated in the design of the survey. One important requirement for field observations to be coupled with remote sensing data is sufficient

accuracy and rigour in the georeferencing of the field plots. With an accurate coupling of field observations and remote sensing data, the remote sensing data can be used as auxiliary information and improve the field based area estimates.

Field data are essential in remote sensing analysis. They typically also represent a substantial cost. For example, the field inventory that was used in the current project had a price of approximately 2000 NOK per field plot. If the distance between plots increases, the inventory costs will also increase. In order to use meaningful statistical estimators, sample plots should be located following predetermined and specific rules.

The area covered by non-native species in Norway is – according to the findings in the present project – less than 2%, and less than 6% in the counties with the highest proportions. Planning sampling surveys for populations occupying only some percentages of the area is a challenging task (Kalton and Anderson 1986). It seems natural to base as inventory of non-native tree species on the Norwegian national forest inventory. Today, the Norwegian national forest inventory uses a 3 × 3 km grid in all counties except for Finnmark where a grid of 9 × 9 km is used. This inventory can provide data on the national level but additional field data are needed to provide more detailed estimates.

Compared to other variables, such as biomass and tree height, species composition is more stable over time. It could therefore be possible to utilise collected field data over a longer time period. If a field sample is established now, it could be possible to use the field data together with the Landsat archives to estimate species distribution back in time. Conversely, field data collected today could be used as reference data for future acquisitions of Landsat images. Thus, this might reduce inventory costs. This should however be tested.

Remote sensing data

The costs, spatial resolution and coverage for different satellite-borne and airborne remote sensing techniques are listed in Table 4-1. As mentioned above these specifications have to be consider jointly together with the objectives of inventory.

Medium resolution satellite imagery has a spatial resolution of 10 – 30 m, resulting in a minimum mapping unit of approximately 0.4 – 3.6 ha. Combining Landsat with other airborne data sources slightly improved the classification of Sitka spruce and Norway spruce in the current project. For the separation of the two species alone the addition of airborne data is not important, but when considering also other land cover classes it could be important. Use of additional ALS data will for example provide a very useful dataset for separation of forested and non-forested areas.

Table 4-1: Overview of satellite-borne and airborne remote sensing data sources.

Type	Examples	Spatial resolution	Approx. costs	Coverage
Spaceborne:				
Medium satellite imagery	Landsat, Sentinel	10 – 30 m	Free	35000 km^2
High resolution satellite imagery	RapidEye Ikonos GeoEye	1 – 5 m	10-16 NOK/km^2 80 – 130 NOK/km^2	500 – 3500 km (6000)
Airborne:				
Aerial imagery (Multispecktral)	Ultracam	0.1 – 0.5 m	300-520 NOK/km^2	60 – 4000 km^2
LiDAR	Optech	0.5 – 10 p/m2	500-2000 NOK/km^2	60 – 4000 km^2
Hyperspectral	HySpex	0.5 – 1.5 m	1000 – 1500 NOK/km^2 (5000 NOK/km^2)	0 – 4000 km^2
UAV	eBee	2 – 4 cm	7200 NOK km^2	0.5 - 2.5 km^2

If the aim of a remote sensing campaign is to cover specific smaller areas, technologies with a higher spatial resolution should be considered. A combination of ALS and hyperspectral imagery has been pointed out to be efficient (Huang and Asner 2009). Another, possibility is to use data derived from photogrammetric point clouds (White et al. 2015; Gobakken et al. 2014). These have lower cost compared to ALS and since most of Norway already have or will have an ALS based terrain model they could a viable alternative. Photogrammetric point clouds can also be created from imagery acquired by UAVs. A choice between airborne or UAV-borne sensors should be defined by the size of the target area, data acquisition costs and desired point cloud accuracy.

Remote sensing data is typically used with a full data coverage in the study area. It can however also be used with a sampling approach, in which data from only selected parts of the area are acquired. This reduces both the cost and time consumption associated with the data acquisition. One could with this approach apply additional high spatial resolution remote sensing in a sampling framework for the target area, and thus increase the level of detail and at the same time provide statistical based estimates of the desired properties. Such designs have been proposed for both high resolution satellite imagery (Falkowski et al. 2009), ALS (Wulder et al. 2012) and it is used in the "Norwegian land cover and land resource survey of the outfields" (Strand 2013). Prediction maps produced with this approach will still have to rely on data with full coverage.

Both Landsat 8 and Sentinel 2 will provide data with a temporal resolution that will enable the use of multi-temporal imagery. The variation between classification accuracies observed for

different Landsat images in part 3 of the present project suggests that data from multiple images could be used to ensure more stable results. Multi-temporal data can also be further utilised, giving possibilities for detection of invasive plants with growth that differs from the native vegetation over a given time period. Huang and Geiger (2008) successfully detected Lehman lovegrass (*Eragrostis lehmanniana*) – an invasive plant in desert grasslands in North America – by using inter-annual satellite imagery. Bradley (2014) noted that invasive species have an advantage in competition with native species, and that "phenological patterns could provide opportunities for remote detection". Methods requiring multi-temporal remote sensing data might pose restrictions on possible data sources, and also increase cost and complexity of the data acquisition process.

Suggestions for implementation of a full scale inventory

Implementation of a full-scale monitoring system for non-native tree species in Norway could be beneficial. We do however recommend to first establish a pilot inventory in a smaller area, prior to a large-scale implementation. We suggest the following phases in such a pilot:

1. Establish goals for the non-native inventory, mapping and monitoring system.
2. Select a test area.
3. Do preliminary analysis based on available data in the selected area.
4. Select and establish sampling design and field reference protocol.
5. Acquire field and new remote sensing data.
6. Data management, modelling, analysis and reporting.

Based on the discussion above, the following objectives and goals can be formulated:

1. Derive full coverage maps and area estimates of areas dominated by non-native conifers at the county level.
2. Derive estimates of early dispersal of non-native species on county level.
3. Obtain detailed maps of a specific area, such as a protected area.

This list of objectives is not intended to be complete, but facilitates three different approaches that can be illustrated with different solutions based on remote sensing. The suggested use of remote sensing in relation to these three objectives will be:

1. Use Landsat 8 or Sentinel 2 data with a design-based field inventory, e.g. a systematic field

inventory. This will give relatively detailed maps of areas dominated by non-native species where the trees are higher than, say, 10 m, or where the crown coverage is high. Furthermore, based on a probabilistic field sample, area estimates with standard errors can be produced. The cost of this approach will be related to the field inventory and the data processing.

2. In order to use remote sensing for detection of early dispersal, high spatial resolution techniques are needed. A combination of airborne lidar and hyperspectral imagery is probably a good choice (Huang and Asner 2009). The high resolution data should then be acquired in selected areas of the county based on principles from sampling surveys (Falkowski et al. 2009). Field reference data must be acquired for some of these areas. The costs are in this approach related to acquisition of both field and remote sensing data, as well as data processing.
3. The third possible objective listed above is an example of estimation with field and remote sensing data acquired for a smaller area. In this case lidar data and aerial imagery available through the national mapping authorities may be used. Costs are here related to field reference data and processing.

One reasonable and realistic objective could be to obtain a highest possible accuracy at a low cost. The result from such a monitoring system should be maps and area estimates of non-native tree species. The area estimates should be based on statistical sound estimators and thus include estimated standard errors. This corresponds to #1 in the list above. We do suggest doing a pilot inventory in one selected county, where Landsat 8 and Sentinel-2 data are used to map non-native species. We will discuss the suggested phases of such an implementation in the following:

Phase 1: Preliminary work

The first phase in this phase should be to select a study area. We suggest to select one of the counties on the west coast (Vestlandet). It should include the challenge of separating Norway spruce and Sikta spruce, as well as having Norway spruce natively present in large parts of the county. Therefore, Rogaland, Hordaland or Sogn og Fjordane counties seems most relevant.

The initial work with the selected study area should include analyses similar to those carried out in the current project. In this first phase one should acquire relevant satellite data, map data and available field data (field data could possibly be derived from the national forest inventory). It should also be considered if an initial photo-interpretation should be carried out. These data can then be used to create initial maps of land-cover, including main genera of trees. The initial maps

can be based on map data as the forest map used in the current study, and then calibrated based on observations or classified satellite imagery.

Phase 2: Establishing sampling design and field inventory protocol

Based on the available information establish in phase 1 one should evaluate different sampling designs and sampling intensities in order to establish an efficient field protocol. This process should be done by simulating different scenarios based on the available data. In this phase where decisions on the sampling design are carried out, specific considerations regarding rare non-native species have to be considered. Establishing a sampling design are important in order to provide statistical sound estimates and standard errors. The locations selected through this phase should then be visited in the field.

In this phase one should also evaluate the number of field reference observation needed. In part 2 of this study we used 120 reference plots and in part 3 we used 240 reference observations. Similar numbers might also be relevant for a pilot study, but we recommend to record additional reference observation. This will enable an evaluation of the effect of the number of field reference locations.

A complete field inventory protocol should also be established during this phase. It must be decided if the species proportions should be recorded in terms of biomass, stem volume, number of stems, basal area etc. The cost of travelling to a location will most likely be a considerable part of the total cost in the field work, and recording some additional information when the field personnel are at the location will probably add only a minor cost.

Measurement of additional field locations independent of the sampling design to increase the number of observations used for classification should be considered. These locations may be subjectively placed and cannot be used as part of the statistical area estimation, but might improve the classification accuracy and the overall accuracies.

Phase 3: Field inventory

Survey-grade GPS equipment is commonly used in operational forest inventories. The high positional accuracy obtained by this equipment might not be required if observations of e.g. species composition within larger stands are to be coupled with Landsat imagery. We did use a hand-held recreational GPS receiver for the addition Sitka spruce locations in the current project, because we aimed at a stand level classification. It is however important that field locations are georeferenced.

A benefit of recording species information is that the species present at a forest location are relatively stable over time, which means that information can be recorded throughout the whole

growing season.

With good training of field personnel, the field inventory protocol should be easily adopted by persons with without forestry background. Personnel from Statens Naturoppsyn may for example be responsible for the field data acquisition.

Phase 4: Analyses and reporting

When all data are collected and processed, updated maps and area estimates should be produced and reported. It might also be possible to use the data and the developed classification models to create maps of non-native species based on historical imageries from the Landsat archives, and thus analyse development over time.

Conclusions

Using remote sensing data to map, inventory and monitor non-native conifer species seem to be possible. The present project showed that the use of existing maps to produce statistics provided unbiased estimates of the area covered by non-native species, but standard errors were high.

Separation of Sitka spruce and Norway spruce using remote sensing data resulted in moderate accuracies. The use of Landsat 8 satellite imagery or aerial imagery gave the highest accuracies, so these data sources should be considered further. One available data source that might improve the separation of these two species from the same genera are hyperspectral data. This was not tested in the present project.

For a full scale mapping, medium spatial resolution data such as satellite imagery from Landsat 8 or Sentinel-2 should be considered. This will however only provide information at a stand level – at best – with no chances of early detection of single occurrences of non-native trees. Such data do however have the advantage that time series will be available in the future (for Landsat it already exist).

Data acquired with high-resolution techniques – typically using airborne sensors – may provide an ability to early detect dispersal of non-native tree species. However, the potential of these techniques has to be investigated. It can also be applied for detailed mapping and inventories in targeted smaller areas. High spatial resolution data may also be applied in a sampling design, allowing for more accurate estimates of for example proportion of non-native tree species. This will however not yield full coverage data for e.g. predictions.

Establishing an inventory or monitoring program for non-native tree species using remote sensing data must facilitate accurately positioned field reference plots, distributed according to a

sampling design with known estimators. Objectives and goals of the inventory should be clearly stated before any decisions on the design are made. When the objectives and goals are known we suggested to carefully design the inventory – in accordance with the stated aims – and to test it in a defined region. This could for example be a county or one or some protected areas, depending on the stated objectives.

Acknowledgements

This project was funded by the Norwegian Environment Agency (Miljødirektoratet). We will like to thank Mr. Adrian Rasmussen for assistance with GIS processing and Dr. Endre Hofstad Hansen for assistance with photo-interpretation in part 2 of the project. We will further like to thank Dr. Liviu Ene for advice on statistical issues, and Dr. Kari Klanderud for advice regarding the native distribution of spruce.

References

Andersen, H.-E., Clarkin, T., Winterberger, K., & Strunk, J. (2009). An Accuracy Assessment of Positions Obtained Using Survey- and Recreational-Grade Global Positioning System Receivers across a Range of Forest Conditions within the Tanana Valley of Interior Alaska. *Western Journal of Applied Forestry*, *24*(3), 128–136.

Andrew, M. E., & Ustin, S. L. (2008). The role of environmental context in mapping invasive plants with hyperspectral image data. *Remote Sensing of Environment*, *112*(12), 4301–4317.

Asner, G. P., Knapp, D. E., Kennedy-Bowdoin, T., Jones, M. O., Martin, R. E., Boardman, J., & Hughes, R. F. (2008). Invasive species detection in Hawaiian rainforests using airborne I maging spectroscopy and LiDAR. *Remote Sensing of Environment*, *112*(5), 1942–1955.

Axelsson, P. (2000). DEM generation from laser scanner data using adaptive TIN models. *International Archives of Photogrammetry and Remote Sensing*, *33*, 111–118.

Axelsson, P. (1999). Processing of laser scanner data - algorithms and applications. *ISPRS Journal of Photogrammetry and Remote Sensing: Official Publication of the International Society for Photogrammetry and Remote Sensing* , *54*, 138–147.

Baig, M. H. A., Zhang, L., Shuai, T., & Tong, Q. (2014). Derivation of a tasselled cap transformation based on Landsat 8 at-satellite reflectance. *Remote Sensing Letters* , *5*(5), 423–431.

Bradley, B. (2014). Remote detection of invasive plants: a review of spectral, textural and phenological approaches. *Biological Invasions*, *16*, 1411–1425.

Brandtberg, T. (2002). Individual tree-based species classification in high spatial resolution aerial images of forests using fuzzy sets. *Fuzzy Sets and Systems. An International Journal in Information Science and Engineering*, *132*(3), 371–387.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*, 5–32.

Calcagno, V. (2013). glmulti: Model selection and multimodel inference made easy.

Carleer, A., & Wolff, E. (2004). Exploitation of very high resolution satellite data for tree species identification. *Photogrammetric Engineering and Remote Sensing*, *70*, 135–140.

Carter, G., Lucas, K., Blossom, G., Lassitter, C., Holiday, D., Mooneyhan, D., … Griffith, J. (2009). Remote Sensing and Mapping of Tamarisk along the Colorado River, USA: A Comparative Use of Summer-Acquired Hyperion, Thematic Mapper and QuickBird Data. *Remote Sensing*, *1*(3), 318–329.

Dalponte, M., Bruzzone, L., & Gianelle, D. (2012). Tree species classification in the Southern Alps based on the fusion of very high geometrical resolution multispectral/hyperspectral images

and LiDAR data. *Remote Sensing of Environment*, *123*, 258–270.

Dalponte, M., Bruzzone, L., Vescovo, L., & Gianelle, D. (2009). The role of spectral resolution and classifier complexity in the analysis of hyperspectral images of forest areas. *Remote Sensing of Environment*, *113*(11), 2345–2355.

Dalponte, M., Ørka, H. O., Gobakken, T., Gianelle, D., & Næsset, E. (2013). Tree Species Classification in Boreal Forests With Hyperspectral Data. *IEEE Transactions on Geoscience and Remote Sensing*, *51*, 2632–2645.

Dimitriadou, E., Hornik, K., Leisch, F., Meyer, D., & Weingessel, A. (2008). *e1071: Misc Functions of the Department of Statistics (e1071)*. TU Wien.

Donoghue, D. N. M., Watt, P. J., Cox, N. J., & Wilson, J. (2007). Remote sensing of species mixtures in conifer plantations using LiDAR height and intensity data. *Remote Sensing of Environment*, *110*, 509–522.

Donoghue, D. N. M., Watt, P. J., Cox, N. J., Dunford, R. W., Wilson, J., Stables, S., & Smith, S. (2004). An evaluation of the use of satellite data for monitoring early development of young Sitka spruce plantation forest growth. *Forestry*, *77*(5), 383–396.

Falkowski, M. J., Wulder, M. A., White, J. C., & Gillis, M. D. (2009). Supporting large-area, sample-based forest inventories with very high spatial resolution satellite imagery. *Progress in Physical Geography*, *33*(3), 403–423.

Fuller, D. O. (2005). Remote detection of invasive Melaleuca trees (Melaleuca quinquenervia) in South Florida with multispectral IKONOS imagery. *International Journal of Remote Sensing*, *26*, 1057–1063.

Gederaas, L., Moen, T. L., Skjelseth, S., & Larsen, L. K. (2012). Fremmede arter i Norge--med norsk svarteliste 2012. *Artsdatabanken, Trondheim*, *20*, 2012.

Gjertsen, A. K. (2007). Accuracy of forest mapping based on Landsat TM data and a kNN-based method. *Remote Sensing of Environment*, *110*, 420–430.

Gløersen, A. T. (1884). *Vestlands-granen og dens indvandrings-veie*. MALLINGSKE BOG TRYKKERI.

Gobakken, T., Bollandsås, O. M., & Næsset, E. (2014). Comparing biophysical forest characteristics estimated from photogrammetric matching of aerial images and airborne laser scanning data. *Scandinavian Journal of Forest Research*, 1–14.

Haralick, R. M., Shanmugam, K., & Dinstein, I. H. (1973). Textural features for image classification. *IEEE Transactions onSystems, Man and Cybernetics*, 610–621.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: data mining, inference, and prediction (Second Edition)*. New York: Springer.

Hengl, T. (2006). Finding the right pixel size. *Computers & Geosciences*, *32*(9), 1283–1298.

Hestir, E. L., Khanna, S., Andrew, M. E., Santos, M. J., Viers, J. H., Greenberg, J. A., … Ustin, S. L. (2008). Identification of invasive vegetation using hyperspectral remote sensing in the California Delta ecosystem. *Remote Sensing of Environment*, *112*, 4034–4047.

Holmgren, P., & Thuresson, T. (1998). Satellite remote sensing for forestry planning—A review. *Scandinavian Journal of Forest Research* , *13*(1-4), 90–110.

Huang, C.-Y., & Asner, G. (2009). Applications of Remote Sensing to Alien Invasive Plant Studies. *Sensors* , *9*, 4869–4889.

Kalton, G., & Anderson, D. W. (1986). Sampling rare populations. *Journal of the Royal Statistical Society. Series A* , 65–82.

Korpela, I., Ørka, H. O., Maltamo, M., Tokola, T., Hyyppä, J., & Others. (2010). Tree species classification using airborne LiDAR - Effects of stand and tree parameters, downsizing of training set, intensity normalization, and sensor type. *Silva Fennica*, *44*(2), 319–339.

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159–174.

Lass, L. W., Thill, D. C., Shafii, B., & Prather, T. S. (2002). Detecting Spotted Knapweed (Centaurea maculosa) with Hyperspectral Remote Sensing Technology. *Weed Technology: A Journal of the Weed Science Society of America*, *16*(2), 426–432.

Lawrence, R. L., Wood, S. D., & Sheley, R. L. (2006). Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (randomForest). *Remote Sensing of Environment*, *100*(3), 356–362.

Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. *R News*, *2*, 18–22.

Lid, J., & Lid, D. T. (2007). *Norsk flora*. (R. Elven, Ed.) (Vol. 7). Oslo: Det Norske Samlaget.

Magnusson, M., Fransson, J. E. S., & Olsson, H. (2007). Aerial photo-interpretation using Z/I DMC images for estimation of forest variables. *Scandinavian Journal of Forest Research / Issued Bimonthly by the Nordic Forest Research Cooperation Committee* , *22*, 254–266.

Maltamo, M., Næsset, E., & Vauhkonen, J. (2014). *Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies*. (M. Maltamo, E. Næsset, & J. Vauhkonen, Eds.). Springer Netherlands.

Mora, B., Wulder, M. A., & White, J. C. (2010). Identifying leading species using tree crown metrics derived from very high spatial resolution imagery in a boreal forest environment. *Canadian Journal of Remote Sensing*, *36*(4), 332–344.

Mäkelä, H., & Pekkarinen, A. (2004). Estimation of forest stand volumes by Landsat TM imagery and stand-level field-inventory data. *Forest Ecology and Management*, *196*(2–3), 245–255.

Næsset, E., & Gjevestad, J. G. (2008). Performance of GPS Precise Point Positioning Under Conifer Forest Canopies. *No.*, *5*, 661–668.

Næsset, E. (2002). Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sensing of Environment*, *80*, 88–99.

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, *148*, 42–57.

Ørka, H. O., Næsset, E., & Bollandsås, O. M. (2009). Classifying species of individual trees by intensity and structure features derived from airborne laser scanner data. *Remote Sensing of Environment*, *113*(6), 1163–1174.

Ørka, H. O., Dalponte, M., Gobakken, T., Næsset, E., & Ene, L. T. (2013). Characterizing forest species composition using multiple remote sensing data sources and inventory approaches. *Scandinavian Journal of Forest Research*, *28*(7), 677–688.

Øyen, B.-H., Andersen, H. L., Myking, T., Nygaard, P. H., & Stabbetorp, O. E. (2009). Økologiske egenskaper for noen utvalgte introduserte bartreslag i Norge. *Viten Fra Skog Og Landskap*, *1*.

Packalén, P., & Maltamo, M. (2007). The k-MSN method for the prediction of species-specific stand attributes using airborne laser scanning and aerial photographs. *Remote Sensing of Environment*, *109*, 328–341.

Packalén, P., Suvanto, A., & Maltamo, M. (2009). A two stage method to estimate species-specific growing stock. *Photogrammetric Engineering and Remote Sensing*, *75*, 1451–1460.

Parducci, L., Jørgensen, T., Tollefsrud, M. M., Elverland, E., Alm, T., Fontana, S. L., … Willerslev, E. (2012). Glacial survival of boreal trees in northern Scandinavia. *Science*, *335*(6072), 1083–1086.

Pokorny, M. L., Dewey, S. A., & Radosevich, S. R. (2006). Getting started: fundamentals of nonindigenous plant species inventory/survey. *Survey Methods for Nonindigenous Plant Species*.

Puliti, S., Ørka, H., Gobakken, T., & Næsset, E. (2015). Inventory of Small Forest Areas Using an Unmanned Aerial System. *Remote Sensing*, *7*(8), 9632–9654.

R Core Team. (2015). *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.

Reid, A., Ramos, F., & Sukkarieh, S. (2011). Multi-class classification of vegetation in natural environments using an Unmanned Aerial system. In *Robotics and Automation (ICRA), 2011 IEEE International Conference on* (pp. 2953–2959). ieeexplore.ieee.org.

Resasco, J., Hale, A. N., Henry, M. C., & Gorchov, D. L. (2007). Detecting an invasive shrub in a deciduous forest understory using late-fall Landsat sensor imagery. *International Journal of Remote Sensing*, *28*(16), 3739–3745.

Sandvik, H. (2012). Kunnskapsstatus for spredning og effekter av fremmede bartrær pa biologisk mangfold. DN-utredning.

Singh, K. K., Davis, A. J., & Meentemeyer, R. K. (2015). Detecting understory plant invasion in urban forests using LiDAR. *International Journal of Applied Earth Observation and Geoinformation*, *38*, 267–279.

Stehman, S. V. (2013). Estimating area from an accuracy assessment error matrix. *Remote Sensing of Environment*, *132*, 202–211.

Strand, G.-H. (2013). The Norwegian area frame survey of land cover and outfield land resources. *Norsk Geografisk Tidsskrift - Norwegian Journal of Geography*, *67*(1), 24–35.

Tollefsrud, M. M., Kvaalen, H., & Grundt, H. H. (2015). Vestlandsgrana – interessant både historisk og genetisk. *Norsk Skogbruk*, *4*, 32–34.

Tollefsrud, M. M., Latałowa, M., van der Knaap, W. O., Brochmann, C., & Sperisen, C. (2015). Late Quaternary history of North Eurasian Norway spruce (Picea abies) and Siberian spruce (Picea obovata) inferred from macrofossils, pollen and cytoplasmic DNA variation. *Journal of Biogeography*, *42*(8), 1431–1442.

Tomppo, E., Olsson, H., Ståhl, G., Nilsson, M., Hagner, O., & Katila, M. (2008). Combining national forest inventory field plots and remote sensing data for forest databases. *Remote Sensing of Environment*, *112*(5), 1982–1999.

Turner, W., Spector, S., Gardiner, N., Fladeland, M., Sterling, E., & Steininger, M. (2003). Remote sensing for biodiversity science and conservation. *Trends in Ecology & Evolution*, *18*, 306–314.

Underwood, E., Ustin, S., & DiPietro, D. (2003). Mapping nonnative plants using hyperspectral imagery. *Remote Sensing of Environment*, *86*(2), 150–161.

Vauhkonen, J., Ørka, H. O., Holmgren, J., Dalponte, M., Heinzel, J., & Koch, B. (2014). Tree Species Recognition Based on Airborne Laser Scanning and Complementary Data Sources. In *Forestry Applications of Airborne Laser Scanning* (pp. 135–156). Springer Netherlands.

Wehr, A., & Lohr, U. (1999). Airborne laser scanning - an introduction and overview. *ISPRS Journal of Photogrammetry and Remote Sensing: Official Publication of the International Society for Photogrammetry and Remote Sensing* , *54*, 68–82.

White, J., Stepper, C., Tompalski, P., Coops, N., & Wulder, M. (2015). Comparing ALS and Image-Based Point Cloud Metrics and Modelled Forest Inventory Attributes in a Complex Coastal

Forest Environment. *Forests, Trees and Livelihoods*, *6*(10), 3704–3732.

Wing, M. G., Eklund, A., & Kellogg, L. D. (2005). Consumer-Grade Global Positioning System (GPS) Accuracy and Reliability. *Journal of Forestry*, *103*(4), 169–173.

Wulder, M. A., White, J. C., Nelson, R. F., Næsset, E., Ørka, H. O., Coops, N. C., … Gobakken, T. (2012). Lidar sampling for large-area forest characterization: A review. *Remote Sensing of Environment*, *121*, 196–209.

Zvoleff, A. (2015). glcm: Calculate textures from grey-level co-occurrence matrices (GLCMs) in R.

Appendices

Simplified national non-native species maps

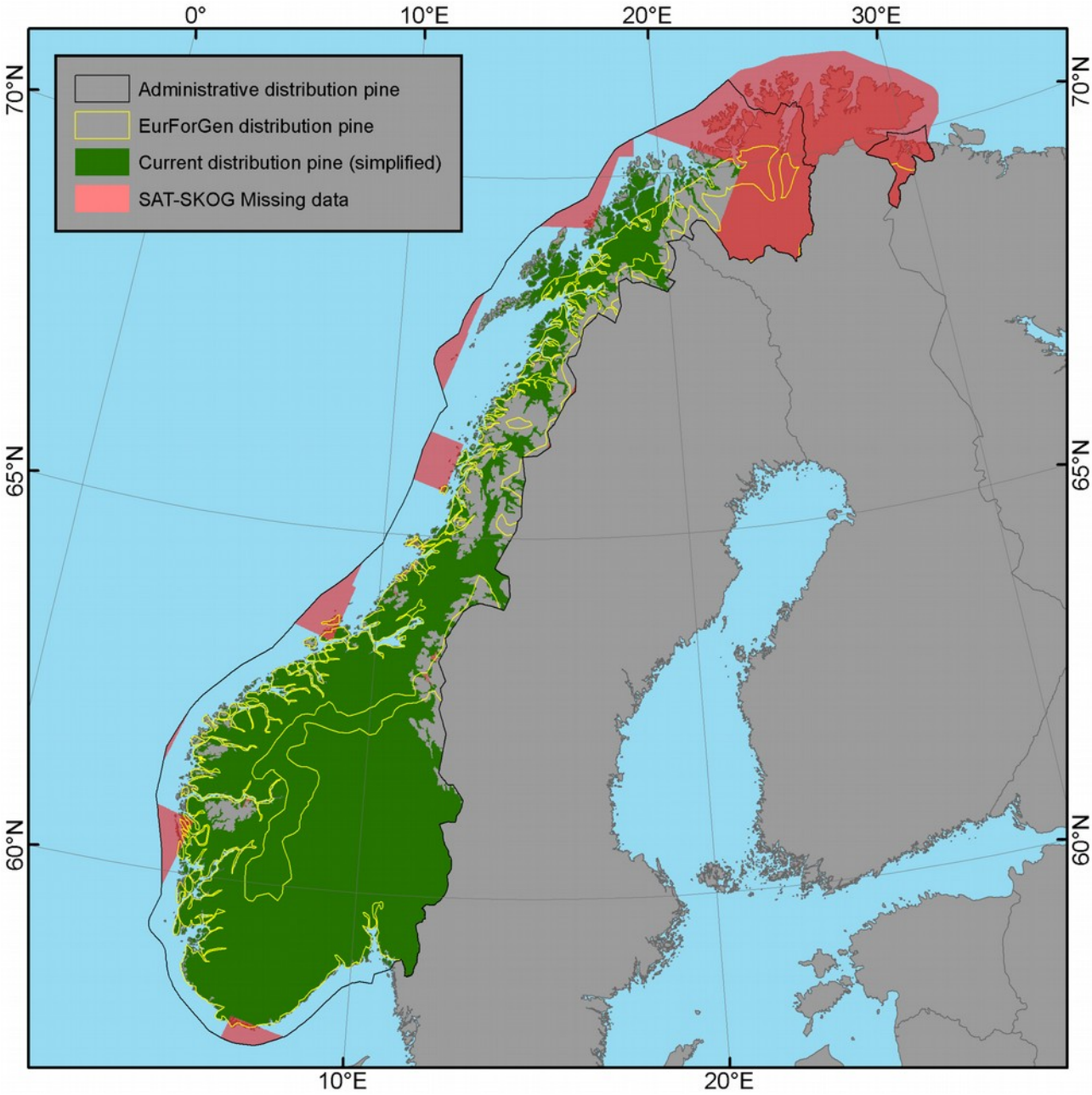


Figure A-1: Natural species distributions map pine (simplified version).The map shows different sources of information on the native distribution of pine in Norway. The current distribution is derived from a combination of a litterature-based administrative distribution, and conifer dominated pixels from the SAT-SKOG map product.

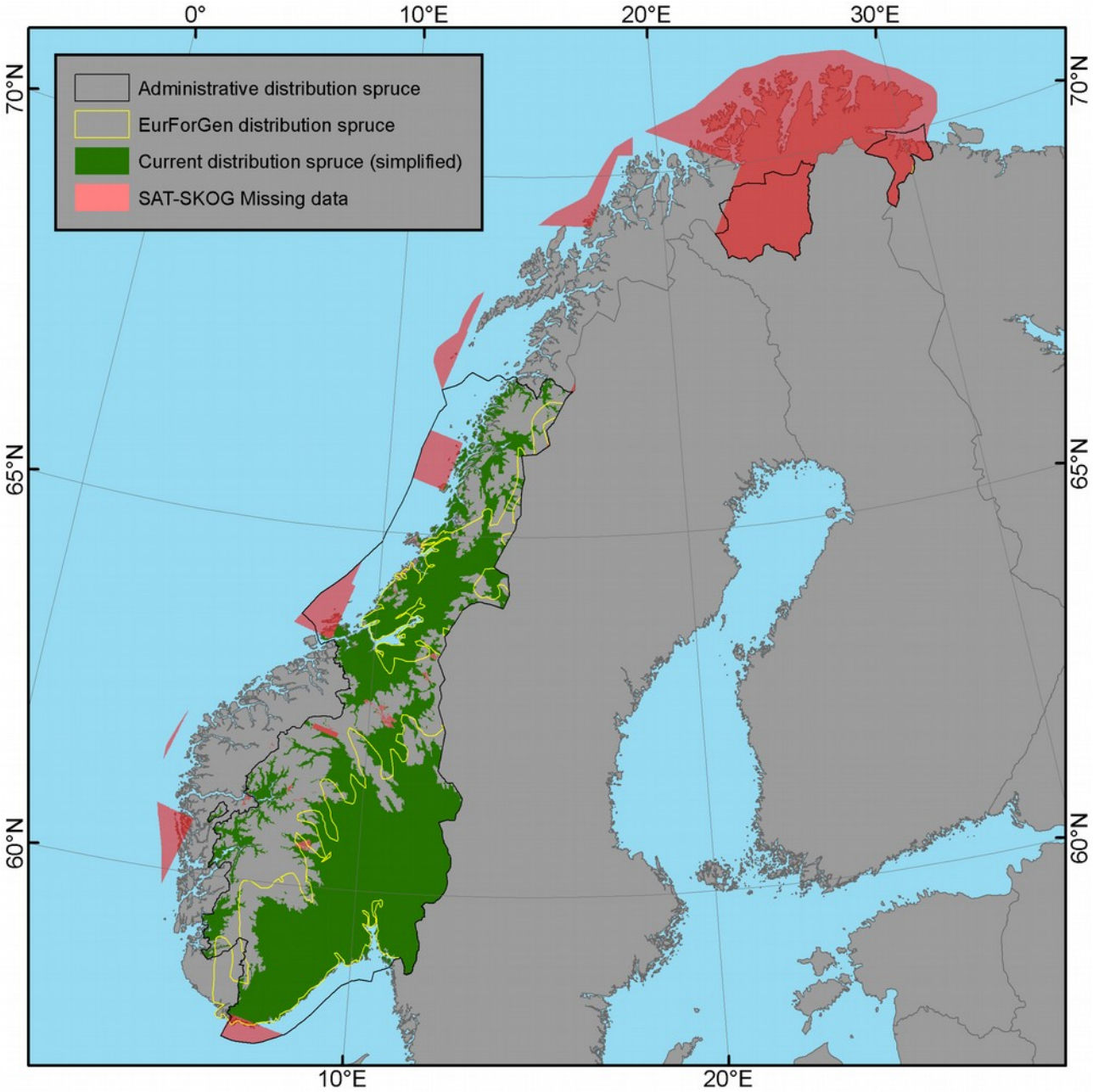


Figure A-2: Natural species distributions map spruce (simplified version). The map shows different sources of information on the native distribution of spruce in Norway. The current distribution is derived from a combination of a litterature-based administrative distribution, and conifer dominated pixels from the SAT-SKOG map product. Some additional adjustments and decisions have been taken to arrive at the depicted current distribution. See text for details.

Detailed non-native spruce species maps for selected areas

These maps show the areas that are mapped as being dominated by non-native spruce species. These are detailed excerpts from the map given in Figure 2-5.

Figure A-3: Stavanger – non-native spruce species distribution map.

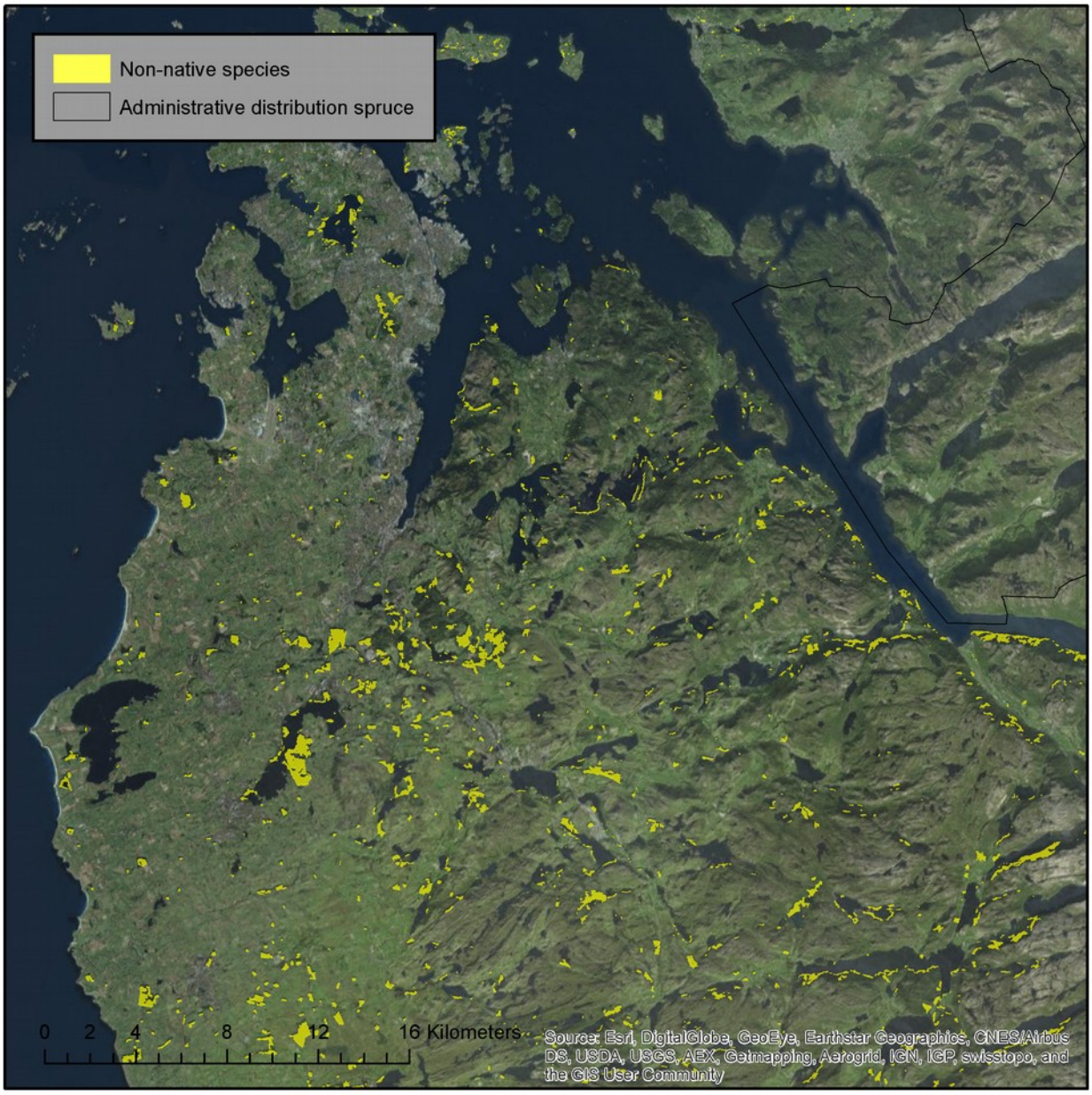


Figure A-4: Stavanger/Jæren area– non-native spruce species distribution map.

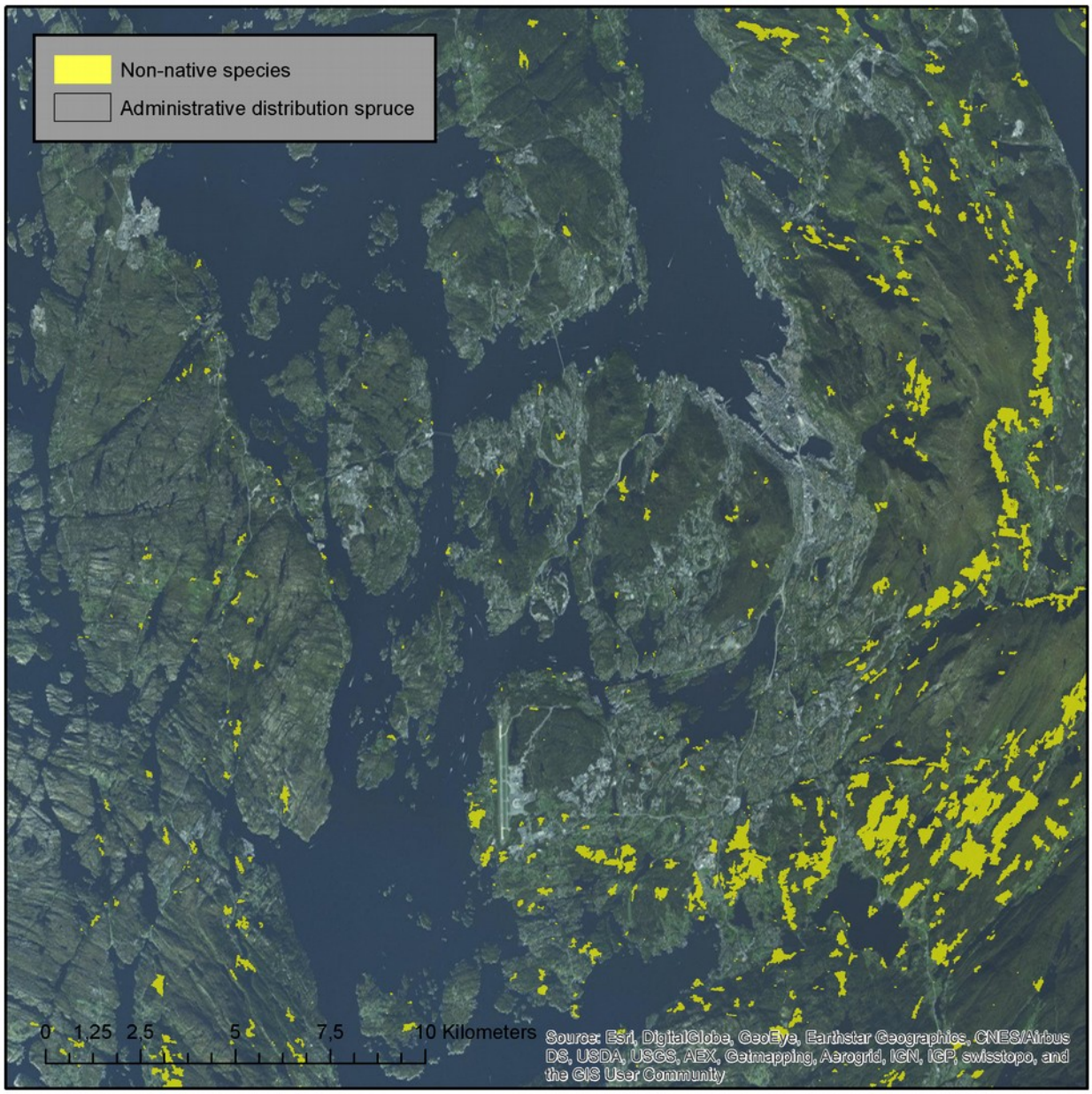


Figure A-5: Bergen – non-native spruce species distribution map .

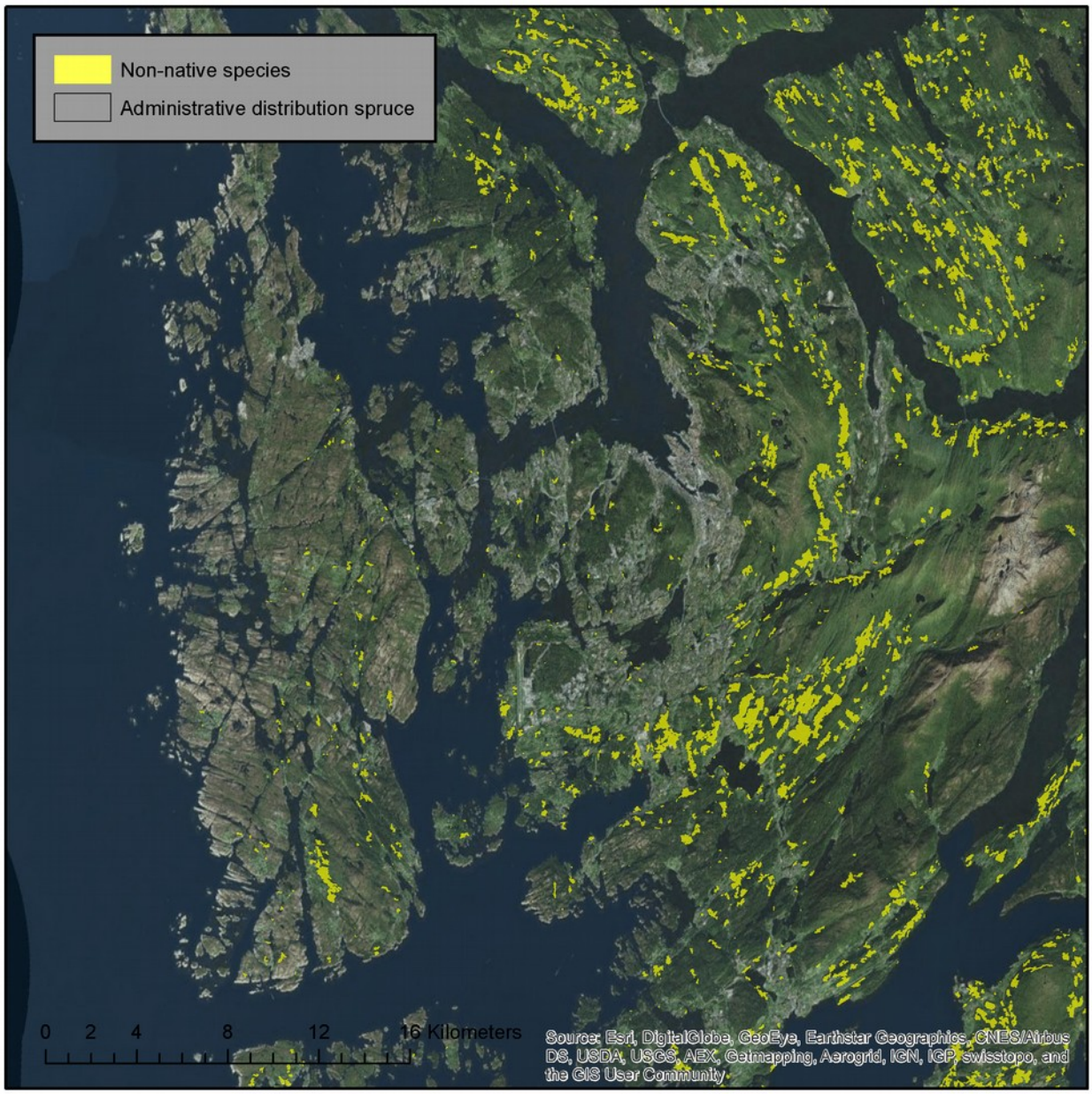


Figure A-6: Bergen area – non-native spruce species distribution map.

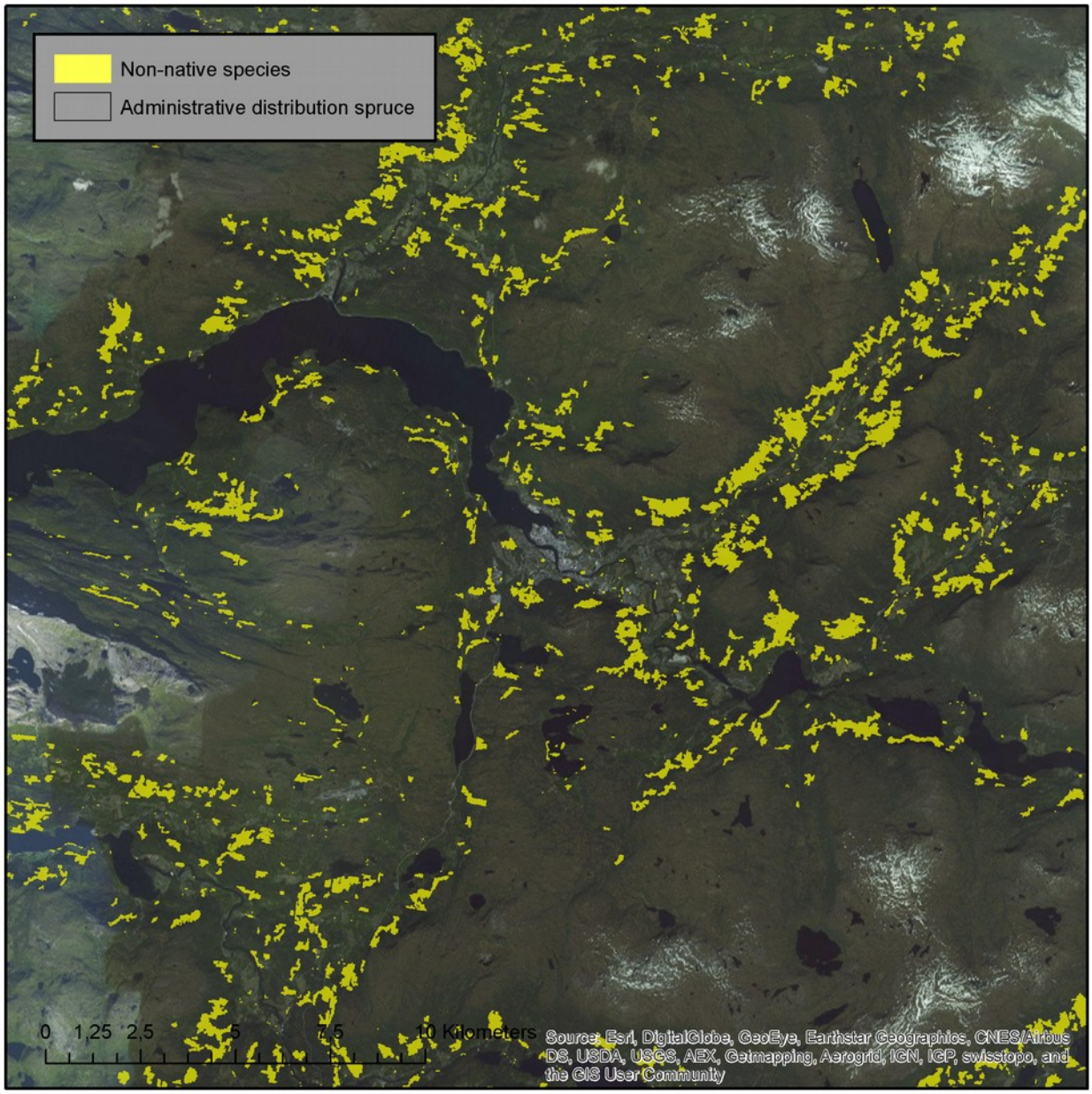


Figure A-7: Førde – non-native spruce species distribution map.

Figure A-8: Molde – non-native spruce species distribution map.

Figure A-9: Molde area – non-native spruce species distribution map.

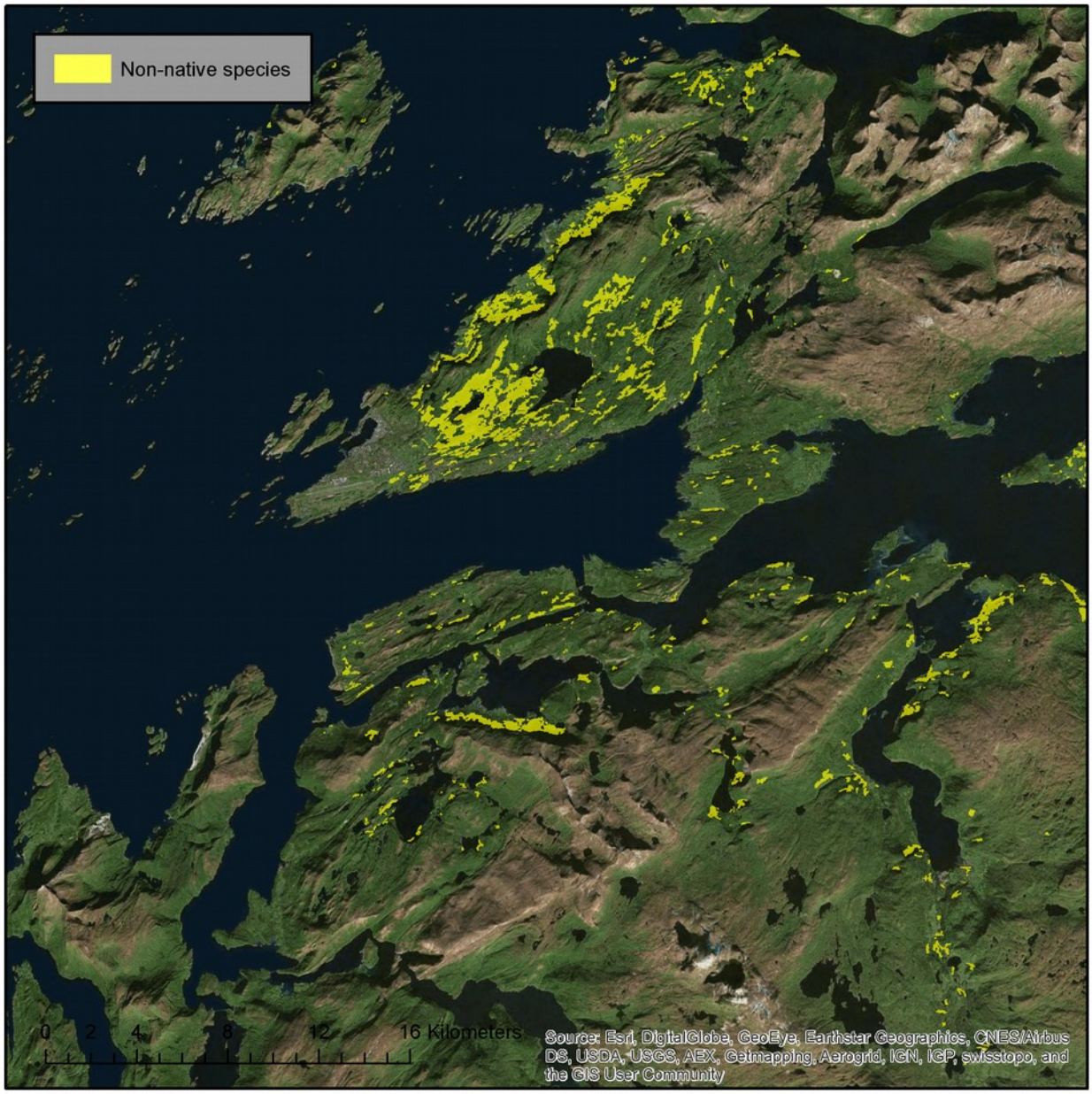


Figure A-10: Bodø area – non-native spruce species distribution map.

Figure A-11: Svolvær area – non-native spruce species distribution map.

Table of selected relevant studies

Platform	Sensor	Spatial Resolution	Spectral resolution	Species	Accuracy	Reference
Satellite	Landsat 5	30 m	Multispectral	*Tamarix spp.*	80.00%	Carter et al. 2009
Satellite	EO-1 Hyperion	30 m	Hyperspectral	*Tamarix spp.*	88.00%	Carter et al. 2009
Satellite	QuickBird	2.5 m	Multispectral	*Tamarix spp.*	91.00%	Carter et al. 2009
Satellite	QuickBird	0.6 m	Panchromatic	*Picea mariana, Pinus Contorta, Picea glauca, Populus tremuloides*	72.50%	Mora, Wulder, and White 2010
Satellite	IKONOS	4 m	Multispectral	*Melaleuca quinquenervia*	85.60%	Fuller 2005
Aircraft	lidar	4 points /m2	-	*Pinus Contorta, Picea sitchensis*	-	Donoghue et al. 2007
Aircraft	Probe 1	5 – 3 m	Hyperspectral	*Euphorbia esula, Centaurea maculosa*	83 – 86 %	Lawrence, Wood, and Sheley 2006
Aircraft	Probe 1	5 m	Hyperspectral	*Centaurea maculosa*	95.00%	Lass et al. 2002
Aircraft	AVIRIS	4 m	Hyperspectral	*Cortaderia jubata, Carpobrotus edulis*	76.20%	Underwood, Ustin, and DiPietro 2003
Aircraft	HyMap	3 m	Hyperspectral	*Egeria densa, Lepidium latifolium, Eichhornia crassipes*	Kappa: 0.49 – 0.87	Hestir et al. 2008
Aircraft	HyMap	3 m	Hyperspectral	*Lepidium latifolium*	88 – 93 %	Andrew and Ustin 2008
Aircraft	AVIRIS, lidar	3 m, 0.4 points /m2	Hyperspectral	*Morella faya*	88.00%	Asner et al. 2008
UAV	-	0.04 m	Multispectral	*Prickly Acacia, Parkinsonia*	88.00%	Reid, Ramos, and Sukkarieh 2011
Satellite	Landsat	30 m	Multispectral	*Lonicera maackii*	-	Resasco et al. 2007
Aircraft	lidar	5 m	-	*Ligustrum sinense*	Kappa: 0.64	Singh et al. 2015

Table A-1. Overview of selected relevant studies.