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Sweden, forests & wind storms

Developing a model to predict storm damage to forests in Kronoberg county

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Sweden, forests & wind storms: Developing a model to predict storm damage to forests in Kronoberg county

Sverige, skogar & stormar: Utvecklingen av en modell för att förutsäga stormskador på skog i Kronobergs län

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Sweden, forests and wind storms:
Developing a model to predict storm damage to forests in Kronoberg county

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Abstract

In Sweden forests cover 56% of the total land cover, within which 95% of these forests are used for forestry. This makes forests a fundamental part of the national and rural economy. Each year however, forest stands across Europe are damaged by wind, which has prompted several analyses on wind interactions with forests, and what alternatives there are to mitigate storm damage. Predicting wind climate and changes in storminess is difficult, and past storms have varied in both strengths and intensities. Along with this, varying levels of storminess will be felt at local levels compared to regional, and at regional compared to global, further complicating the prediction process. With this in mind, the aim of this thesis is to create a model that can predict storm damage to forests. The model was developed using Multi-Criteria Decision Making (MCDA) techniques, with data from Kronoberg county, Sweden. This county was chosen as the study area as it is the county which has experienced the most storm damage to forests in Sweden. This model was implemented on forest cover from two time periods, 2000 and 2013. The runs on the first time period were carried out in order to predict the storm damage for the storm that hit in 2005, Gudrun. Validation of model effectiveness was done by comparing its predictions to the observed damage from that storm. The model was run 17 times on the forest cover from 2000, with each run having slight alterations and different factors. The final predictions suggested that most damage was to be felt in the central and eastern regions of the county. The damage predictions for the central regions matched the observed damage fairly well, but there were disagreements between the predicted and observed damage in the eastern regions. Model runs 5 and 17 were chosen to be implemented on the forest cover from the second time period, 2013. Model run 5 predicted again that most damage is to be observed in the central and eastern regions, whilst model run 17 predicts severe damage across the county. The main conclusions drawn were that the model runs do not reliably predict future storm damage. More research into this topic must be conducted in order to produce accurate predictions, which could include more in-depth studies into the factors as well as the inclusion of more factors.

Sammanfattning

Skog täcker 56% av all markyta i Sverige, och 95% av denna skogsmark används inom skogsbruk. Detta gör att skog är en grundläggande del av national- och landsbygdsekonomin. Varje år så blir Europas skogar utsatta för stormskador, vilket har lett till analyser av vindinteraktioner med skog, och forskning inom de alternativ som finns för att minska stormskador. Att förutspå vindklimat och dess förändringar är svårt, och tidigare stormar har varierat i både vindstyrka och intensitet. Dessutom så finns det olika nivåer av stormstyrkor som upplevs på lokal nivå jämfört med regional, och på regional nivå jämfört med global, vilket yttligare komplicerar försöken att skatta stormstyrkor. Syftet med denna avhandling är då att skapa en modell som kan förutsäga stormskador på skog i Sverige. Modellen är utvecklad genom Multi-Criteria Decision Analysis (MCDA) tekniker, med data hämtad från Kronobergs län, Sverige. Detta län var valt som studieplats eftersom det är länet som har upplevt värst stormskador på skog i Sverige. Modellen genomfördes på skog från två tidsperioder, 2000 och 2013. Modellkörningarna på första tidsperioden genomfördes i syfte att försöka förutse skadorna inför stormen som drabbade Sverige i 2005, Gudrun. Validering av modelleffektivitet gjordes genom att jämföra förutsägelserna från modellen med observerade skador från stormen. Modellen kördes totalt 17 gånger på skogsdatan från 2000, med små förändringar och olika faktorer i varje körning. De slutliga förutsägelserna pekade på att de flesta skador kommer drabba de centrala och östa delarna av Kronobergs län. Skadorna som förutspåddes i de centrala delarna matchade de observerade skadorna bra, men inte i det östra delarna. Modellkörningarna 5 och 17 valdes att genomföras på skogsdatan från den andra tidsperioden, 2013. Modell nummer 5 fortsatte att förutse flest skador i de centrala och östra delarna av länet, medans modell nummer 17 förutser allvarliga skador over hela länet. De viktigaste slutsatserna är att modellerna redovisade här kan inte förutse framtida stormskador tillförlitligt. Mer forskning inom detta ämnet behöver genomföras för att få fram korrekta prognoser, vilket kan omfatta mer ingående undersökningar av faktorerna liksom införandet av fler faktorer.

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1. Introduction

Each year, windstorms cause disturbances to the environment, the economy and society in general. However, it is difficult to predict wind climate and potential changes in storminess. Past storms have varied in strengths and intensities, and extreme winds are often felt at a local level rather than a global one. This makes it more difficult to simulate potential storminess at a global level, or even a regional level (Lindner et al. 2013).

Managing forest damage and analysing the impact of severe windstorms has become of increasing importance, since they are a major disturbance factor. It is important to understand the mechanisms of wind damage, as they are a part of forest dynamics (Schuck and Schelhaas 2013). In Europe, it has been estimated that about 0.12% of all forest stands are damaged each year (around 38 million m^3/year) with 51% of all this damage being caused by wind. For this reason, several analyses have been conducted on wind interactions with forests, and how to mitigate forest damage (Gardiner 2013).

Swedish forests cover 56% of total land area and are dominated by conifers, mainly Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*). In 2002 – 2006, 42% of all conifers in Sweden were Norway spruce and 39% were Scots pine. In terms of deciduous trees, birch is the most common (Nilsson 2008). Roughly 95% of Swedish forests are used for forestry, making them a fundamental part of the national and rural economy since they create a large range of forestry related jobs. As they are an important part of the economy, they are managed intensively (Schylter et al. 2006). The forests are mainly grown as monocultures, and are managed by clear felling. After felling, the land is allowed to regenerate, either by planting seedlings or by allowing natural regeneration (Subramanian 2016). As many of these forests are even-aged monocultures, they are more vulnerable to

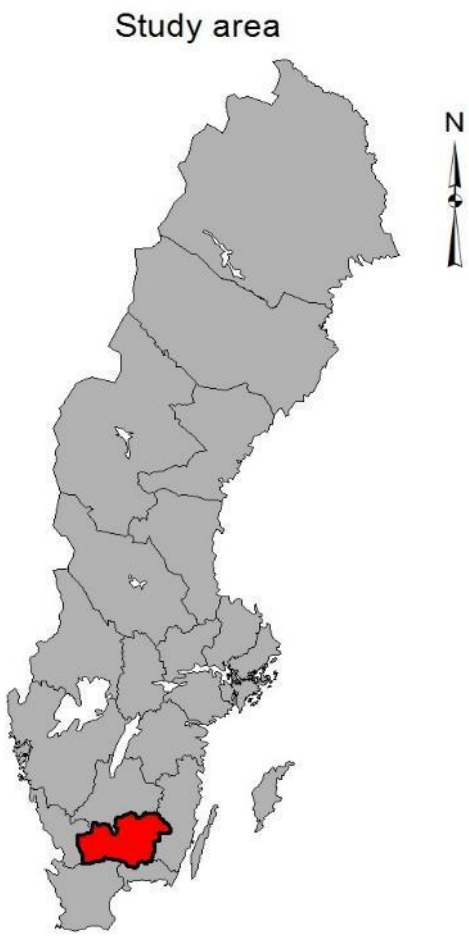

Figure 1. Location of study area, Kronoberg county (ESRI 2015)

damage from wind storms because of their uniform structure with less preconditioning to wind than in natural forests (Lindner et al. 2013; Everham and Brokaw 1996).

This study looks at wind storms in southern Sweden, focusing on Kronoberg county (figure 1, marked in red) and investigating what effects these storms have on forests. The damage to forests from high wind speeds will be analysed in ArcMap and presented as a series of maps. The highest frequency of strong winds develop in Sweden during autumn and winter, with the regional wind speed variations dependent on changes in the landscape, such as large-scale topography and the positioning of landmasses and lakes (Nilsson 2008). Wind speeds that are above 25 m/s are classed as storm wind speeds, a recurring phenomenon that can be felt across Sweden (Fridman et al. 2006).

1.1 Aim

The aim of this project is to create a model based on multi-criteria decision analysis (MCDA) that will predict storm damage to forests. The development of this model will be split into several phases:

- Create the model based on forest cover data from 2000, and assess its validity in predicting damage by comparing it to observed damage data from 2005.
- Testing how different resolutions would affect the model. The resolutions to be compared are 50x50m and 100x100m.
- Testing the sensitivity of the model.
- Implement the final version of the model on more recent forest cover data (2013) to suggest areas that are more at risk than others to damage from storms.

1.2 Background

1.2.1 Damage caused by European wind storms

Europe often experiences mid-latitude cyclones, and they have been the cause of enormous amounts of damage. The cyclones develop as the warm tropical air masses (circulating from the south) meet the colder air from the polar front. The combination of temperature difference, pressure differences and the Coriolis force (which is higher closer to the poles) leads to the development of frontal low-pressure systems (cyclones) that sweep across Europe. Such events most commonly happen during the autumn and winter months, as this is when the temperature and pressure differences are greater (Nilsson 2008).

These events are defined by their magnitude and strength, which can be measured as a class using the Beaufort-Simpson scale of wind. This scale, originally invented in 1805 by Admiral Sir Francis Beaufort to scale wind conditions at sea, was developed and expanded in 1926 by G.C. Simpson to also measure winds on land (Nilsson 2008). This scale has 12 classes, with 0 representing calm wind speeds of 0 – 0.2 m/s, and 12 representing severe wind speeds of 32.7 m/s and higher (SMHI 2015b). Storms that reach class 10 on this scale are strong enough to uproot and cause structural damage to trees (Nilsson 2008).

In 1999 the storms "Anatol", "Lothar" and "Martin" swept across Europe with devastating effects. Anatol caused 20 deaths as well as €2.9 billion in economic loss (see table 1) (Dailey 2004). This was classed as the storm of the century for Denmark, where gusts reached 43m/s (Ulbrich et al. 2001).

Later, in the same month, Lothar developed. On December 26th, this storm crossed France in only 9 hours, with wind gusts recorded at around 50 m/s. Injuries occurred in Paris from falling walls and collapsing roofs. After passing France, Lothar moved through Switzerland. The total death count from this storm reached 110 (Dailey 2004).

Just one day after Lothar had left Western Europe, the next storm, Martin struck on December 27th. This storm, although less intense than Lothar, was still responsible for 30 deaths as well as €4 billion in economic losses (Dailey 2004). The peak gusts for Martin were recorded at slightly over 40 m/s (Ulbrich et al. 2001).

The death count and overall costs for several major storms to hit Europe are shown in table 1.

Table 1. The overall cost and death count of recent storms in Europe

Storms				
English name	**Swedish name**	**Date**	**Deaths**	**Economic loss**
Anatol	Carola	3rd of December, 1999	20+	€2.9 billion
Lothar		25th of December 1999	110	€11.5 billion
Martin		27th of December 1999	30	€4 billion
Erwin	Gudrun	8th of January 2005	20	€2.8 billion
Hanno	Per	14th of January 2007	6	
	Gorm	29th of November 2015		

Several other storms have had devastating effects across Europe; however this report will focus on the storm Gudrun in 2005 that had a devastating impact on Swedish forests.

1.2.2 Gudrun

A storm began to develop northwest of the British Isles on the 7th of January 2005. On the 8th of January, this storm struck southern Sweden. This storm was given the name "Gudrun". The maximum wind speeds varied between 35 to 42 m/s along the coastlines. According to the Beaufort-Simpson scale, this storm reached class 12, the same class achieved by the three storms in 1999: Anatol, Lothar and Martin. The distribution of maximum wind speeds during the storm can be seen in figure 2. Further inland, Växjö, located in Kronoberg county (figure 1) experienced gust speeds of 32 m/s (Nilsson 2008). Two stations recorded wind speeds in Kronoberg, one in Ljungby and one in Växjö. Unfortunately, the Ljungby station sensor broke during the storm, and only the Växjö station recorded the wind speeds throughout the storm (SMHI 2015a). The wind directions for this storm altered slightly between the directions S, SW, SSW and WSW (Nilsson 2008).

The morning after the storm the landscape was barely recognisable in many regions. Blocked roads and railroads hindered movement and around 415,000 houses were without electricity (SMHI 2015a).

It is estimated that Gudrun caused around 70 million m^3 of damage to Swedish forests. Of this, an estimated 80% of all damage was to spruce trees (Fridman et al. 2006). Gudrun was thus categorised as one of the most severe storms in Swedish history (Nilsson 2008). The overall economic toll of this storm was €2.8 billion, which can be seen in table 1.

In order to better prepare for future storms like Gudrun, "Projekt Storm Analys" was set up. This was a co-operation between several authorities to work together and share prevention and mitigation ideas. The agencies involved in this project included The Swedish Forest Agency, The Swedish University of Agricultural Sciences, and The Swedish Environmental Protection Agency (Skogsstyrelsen 2006).

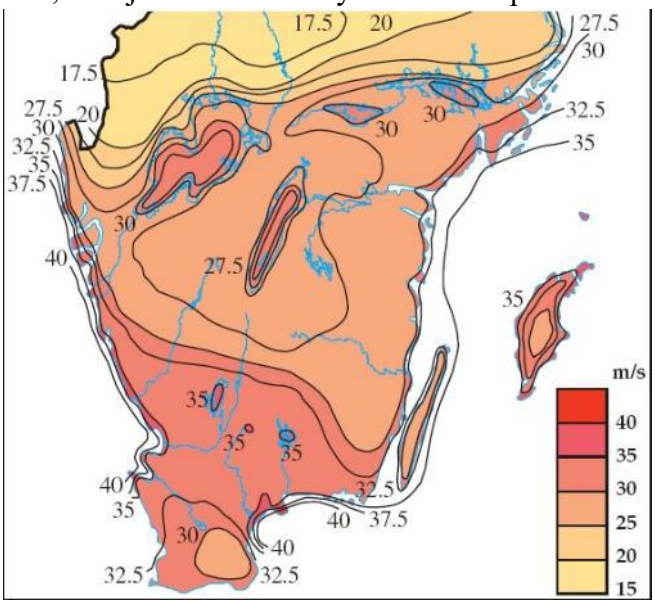

Figure 2. The distribution of maximum wind speeds during the storm Gudrun, 2005 (reproduced with permission from SMHI 2015)

1.2.3 Susceptibility to wind damage

How susceptible a tree is to wind damage is determined by the properties of wind climate, with factors such as wind speed, forest structure and the soil type or topography of the area in interest

(Brunet et al. 2013). It is also important to consider the season at which high wind speeds hit, since whether or not the ground is frozen can impact the amount of damage (Nilsson 2008).

In terms of forest structure, aspects that affect the susceptibility of a tree are forest edges, fragmentation and the ages of the trees (if they are even-aged or uneven-aged). Forest edges will cause the nature of airflow to change, making the edge trees and the trees close to the edge more vulnerable to wind damage compared to trees found deeper in the forest (Brunet et al. 2013).

One consequence of storm damage is the creation of gaps and the fragmentation of forests, which are important factors to consider for the regeneration of forests. A previous study done in Draved Forest, a mixed deciduous forest in Denmark showed that more than half of the trees with a breast diameter over 10 cm were damaged over the last 50 years (Wolf et al. 2004).

Tree characteristics such as species and tree height also play a part in how susceptible trees are to wind damage. Previous statistical analyses of storm damage to tree species have suggested that conifers are more susceptible to storm damage than broadleaved trees. One reason for this could be because evergreen coniferous forests will experience higher drag during winter storms as they still have needles then, whereas the broadleaved tree species will be leafless. When considering the difference in vulnerability of specific tree species in Europe, spruce and poplar trees are among the most vulnerable (Brunet et al. 2013).

The general prediction of how tree height affects vulnerability is that with an increasing tree height, the trees will experience an increasing damage probability. This particular factor has become more commonly documented than other factors such as diameter in recent times as advances in LiDAR (Light Detection and Ranging) have now enabled us to measure tree heights in a forest at relatively low cost (Brunet et al. 2013).

When considering site conditions, both the topography and soil conditions can affect susceptibility. The investigations that have been made have suggested that at the top of an upwind slope, the movement of wind through the canopy may be more pronounced. The following downwind slope could potentially experience damaging wind speeds/conditions (Brunet et al. 2013). The angle of the slope should also be considered here. In a study done on the storm Anatol, that hit southern Sweden in 1999, results showed that almost twice as much forest damage was caused on gently sloping, wind-exposed hills and there was less damage seen on the steeper slopes, suggesting a reduction in susceptibility. This was also

suggested by (Nilsson 2008) where it was shown that slopes between the angles 0 – 5/6 received significantly more damage than steeper slopes. As the slope direction plays an important part in determining if a slope is exposed to the wind or not, aspect and slope should be analysed together (Schütz et al. 2006). It is usually assumed that most damage would occur on the windward side of a slope (Nilsson et al. 2007).

Different tree species may grow on a variety of different soil types, but they will thrive on the most suitable sites, and these sites vary between the species. Sandy soils are known to be poor in fertility and loose in texture. This means that water can be absorbed fast, but is also drained fast. Tree species that do not require a lot of water or nutrients will grow well in such regions. Loam soils are medium textured with overall more nutrients than sandy soils. Loamy soils are porous and have good ability to retain water, nutrients and air, making them desirable to many tree species (Osman 2013).

One of the main factors that determine how susceptible a tree is to wind damage is the anchorage capacity, which is determined by the root development of the tree. This property is affected by many of the already mentioned factors, such as tree characteristics and soil properties, as well as the general management of the forest. Studies show that the more vulnerable trees are the taller, older ones compared to the younger and shorter trees (Nilsson 2008).

If wind storms hit when the ground is frozen, the trees may have better anchorage of roots, but there would be an increase in stem breakage. The amount of damage depends on soil type and its characteristics (Nilsson 2008). Information regarding the seasonal depth of frozen ground is critical when determining aspects such as root injuries and plant hardiness (Vermette and Kanack 2012).

1.3 Study area – Kronoberg county

The study area in this report is Kronoberg county, located in southern Sweden (figure 1). It is a gently sloping region covered mostly with coniferous trees. Figure 3 visualizes the land cover for the study area in the year 2000. The data is from that year as it shows what the forest cover looked like before the storm Gudrun hit in 2005.

The county is 9,426 km^2 and was the county to receive most damage from the storm Gudrun in 2005. As can be seen in figure 3, most of the county is covered in forests, which led to forest damage and losses being extremely high after the storm, which is why Kronoberg was chosen as the study area.

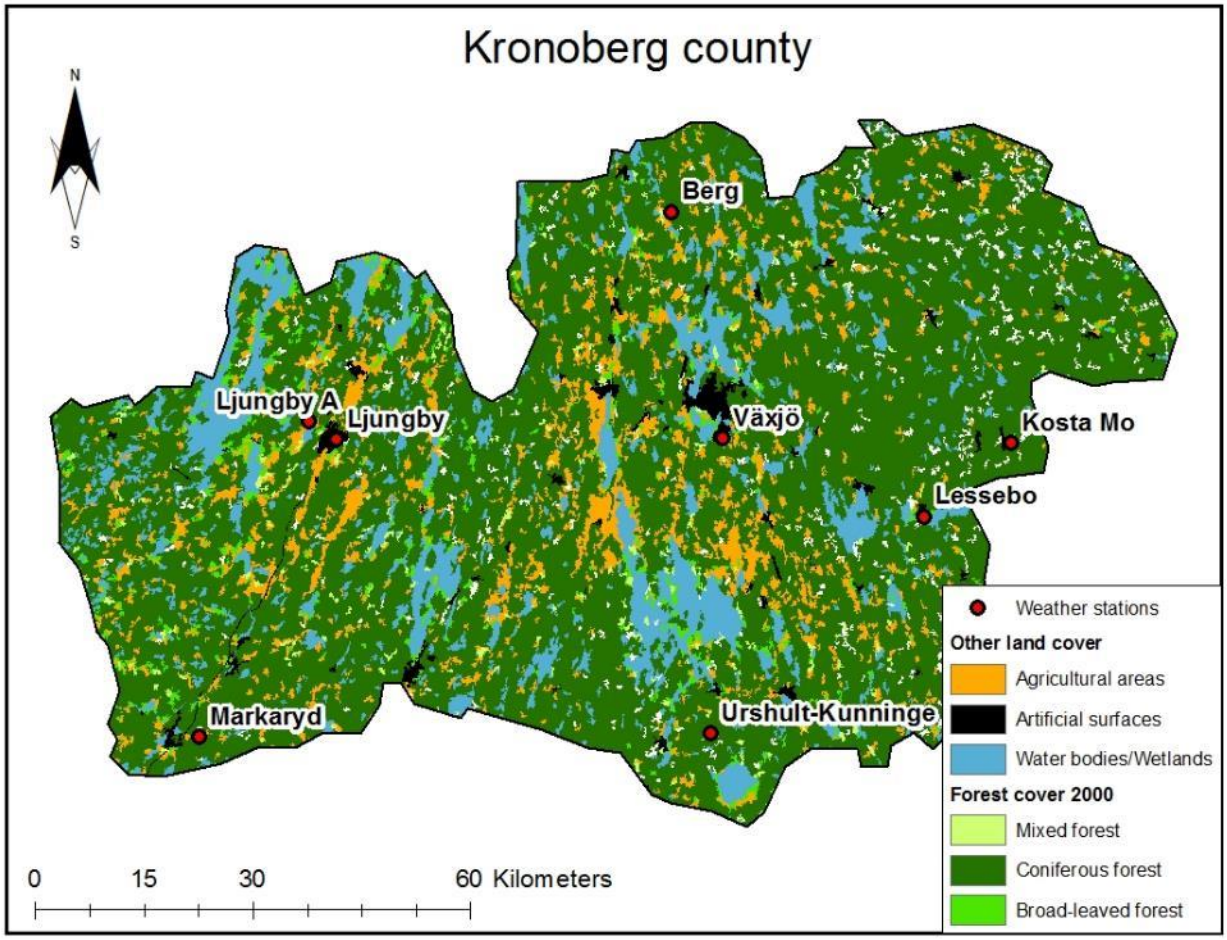

Figure 3. The land cover of the study area, Kronoberg county, from the year 2000 - before the storm Gudrun in 2005

1.4 Previous studies

A similar study was conducted out in 2015 by Frida Ulfves, as a Bachelors project at Lund University. She also made a model to predict the spread of damage, the results of which can be seen in figure 4, presented here with her permission. The factors included in this model were; aspect, topographic exposure, slenderness ratio, soil depth, spruce and pine forest cover and deciduous forest cover. This result showed that the least vulnerable regions were in the far eastern sections of the county. The high damage areas are concentrated to the central regions, and around Växjö (north-east) and as Tingsryd (south-east).

The main idea of this thesis is to create and further develop a model that predicts storm damage like the one presented in the 2015 study by performing sensitivity tests on the datasets. The model will be created using a Multi-Criteria Decision Making (MCDA) technique and will incorporate several datasets that are linked to the vulnerability of forests and their susceptibility to wind damage.

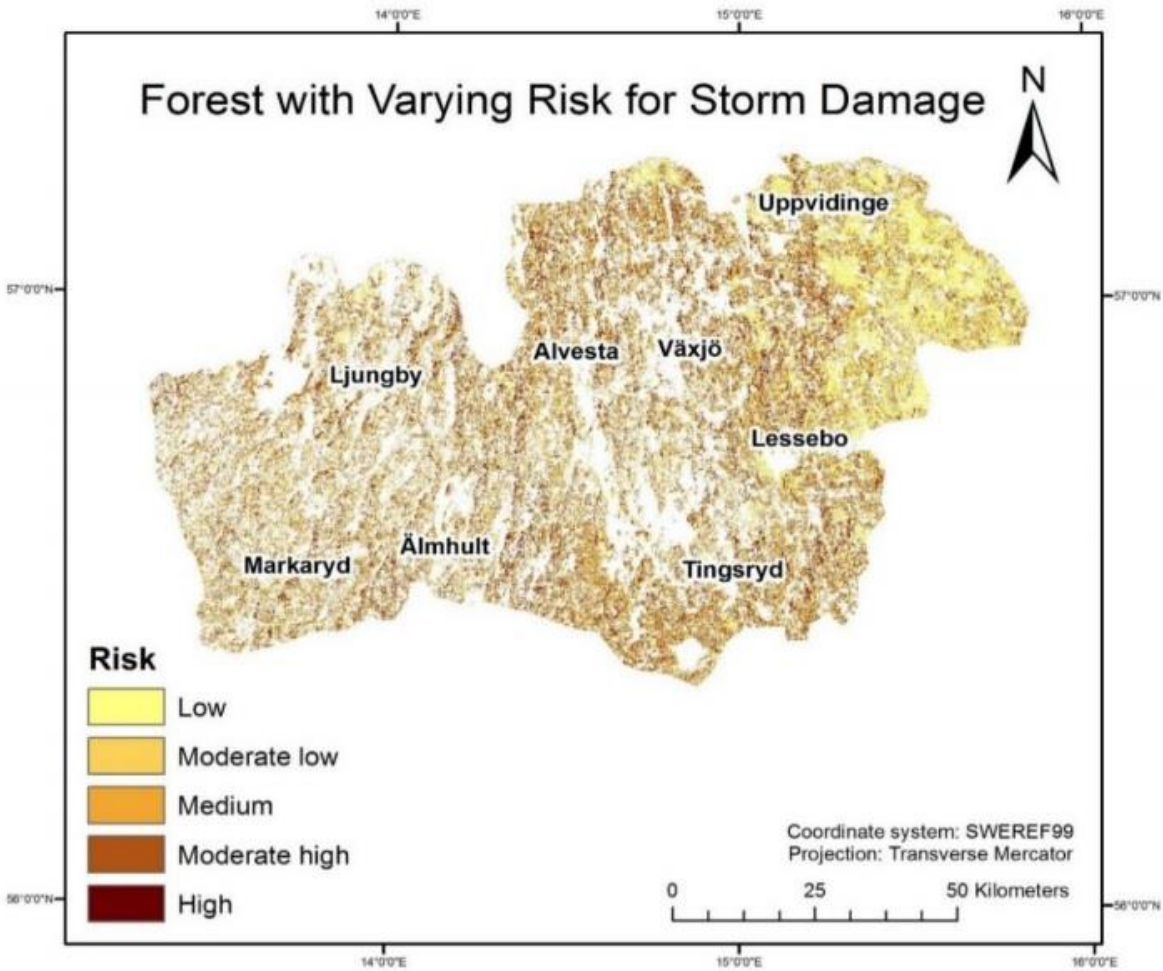

Figure 4. The predicted spread of damage according to Frida Ulfves model. Reproduced with permission from Ulfves 2015, with permission from publisher.

From the results presented in figure 4, I would expect that my model should also show that the central regions of the county are amongst the more vulnerable to storm damage, with a decreasing amount of damage seen in the north-eastern extremities.

1.5 Research questions/hypotheses

Three main phases build up this thesis, so each section will be split up into these phases. The phases are;

- Build the model
- Develop the model
    - Test the sensitivity of the model
    - Compare the model to a 'null model'
- Apply the model to more recent data (forest cover from 2013)

2. Methods

The programmes used to manipulate and visualize the datasets and results were ArcMap 10.4.1, provided by ESRI, and Microsoft Excel.

The sources for all the data used in this report can be seen in table S1 of the appendix, along with their original resolutions and data type.

Almost all the data used in this report are remotely sensed, the only exception being the wind speed data, which were collected from weather stations. Remotely sensed data are data such as the state and condition of an object or landscape that have been collected from a distance. There are several different platforms that can be used to collect such data, such as unmanned aerial vehicles (UAVs), aircraft and satellites. Depending on what platform is used, the resolution of the data can vary as the distance between the platform and the remotely sensed object will be different. Generally, the further the distance between the sensing platform and the object of interest, the lower the resolution of the data (Chuvieco 2016).

2.1 Data

This section provides a short description of each dataset considered for the model. All the figures depicting the datasets can be seen in section 7.2 in the appendix.

The geographic extent of most of the data collected exceeded the size of the county, so a shapefile outlining the county was created and used as a mask to extract the data required for this project.

Two main resolutions have been used for all the data, 50x50m and 100x100m. All data that did not match these resolutions were resampled. This function changes the cell size of a raster without changing the extent of the dataset. There are four techniques of how the raster can be resampled, and in this work, the technique 'Nearest' was used as this one did not change the values of the cells, only the resolution of the whole layer. This technique implements a nearest neighbour assignment, which means that the value of every cell in the output raster is calculated by using the values of the nearest cells in the input raster, without changing the values in the input raster. This technique was favoured over the others as it was important to keep the original values from the input rasters, as these were the specific weights assigned to each dataset used to determine if a location was vulnerable or not (ESRI 2016h).

2.1.1 Landscape data

Digital elevation model (DEM) data were downloaded through SLU's (Sveriges Lantbruks Universitet) GET portal (table S1, appendix). These data are based on laser scans taken across Sweden with a standard error of around 1m. As this portal only allows the user to download data of selected sizes across the country, a total of 8 DEMs with the resolution 50x50m were downloaded and mosaicked together to encompass the whole study area of this report. Mosaic works by merging several raster datasets together, and is possible to perform when the rasters all contain the same number of bands and bit depth (ESRI 2016f). After this, the extent of the new DEM was clipped to the study area using a polygon of the county extents as a mask. From this new DEM, slope and aspect maps were created. Figure S1 (appendix) depicts the DEM within the selected, smaller study area.

The slope algorithm calculates the maximum rate of change in the value of a cell (the elevation in this case) in comparison to its eight neighbouring cells. The cells with the greatest rate of change between them represent the steepest downhill slope (ESRI 2016d). After the slope map was derived from the DEM, it was reclassified to highlight the slopes of interest. As the gentler slopes (between the angles of 0 – 6) have been suggested as more susceptible to storm damage (Nilsson 2008), figure S2 (appendix) was made to give an idea of the general slope angles in the study area. The green and yellow locations shown are the most susceptible whilst the orange/red locations are the least susceptible.

Aspect is derived from slope by using the values calculated by the slope algorithm, which indicate the compass direction depending on the value. The values will range from 0 (north) to 360 (north again) and encompass all slope directions. Flat areas are assigned a value of -1 (ESRI 2016b). Similarly to the slope map, the aspect map was also reclassified in order to extract the slope directions of interest, which were southwest (SW), west (W) and northwest (NW). These were the slope directions of interest as it is from these directions that the wind most commonly moves across Sweden (Nilsson 2008). The aspects of interest can be seen in figure S3 (appendix).

2.1.2 Forest cover (2000)

Land cover data from 2000 were downloaded from the European Environment Agency homepage. The data were part of the CORINE land cover set, which stands for 'CoORdination of INformation on the Environment', a prototype project set up by the European Union in 1985 to share land cover data (EEA 1995). These data were collected by

three satellites and the land cover is divided up into 5 classes; artificial areas, agricultural areas, forest and semi-natural areas, wetlands and water bodies. Image quality can vary due to factors such as atmospheric conditions and relief. Each class also has several subclasses (Bossard et al. 2000). The forest subclasses, mixed, coniferous and broad-leaved were extracted from the forest and semi-natural areas class. The original resolution of these data was 100x100m. The forest cover data from the smaller study area can be seen in figure S4 (appendix).

2.1.3 Forest cover (2013)

The forest cover data for 2013 were received by ESRI via their ArcGIS online services. The dataset was developed by MDA (MDA 2017) and consists of around 9,200 Landsat 8 images, with a high spatial resolution at 30x30m, all captured between 2013 and 2014. The dataset is divided into fourteen land cover classes, four of which relate to forest cover. However, only an excerpt of the dataset which contained the forest cover data was downloaded. The forest cover classes are deciduous, evergreen, mixed and woody wetlands. The classes mixed forest and woody wetlands were only available within the continental U.S. so were not included in this report (ESRI 2015). Forest data for Kronoberg county were extracted, which included data on deciduous and evergreen forest types. This forest cover is depicted in figure S5 (appendix). In both figures S4 and S5 (appendix), the white areas represent areas with no forest cover.

2.1.4 Forest volume, height and diameter

The average forest volume can be seen in figure S6 (appendix). The units m3sk/ha stand for the volume of the tree trunk, including the bark, per hectare (SkogsSverige 2017). Most of the coverage is between 1 – 250 m3sk/ha with a few 250 – 500 m3ska/ha regions. Forest volumes of 500 – 2,292 m3sk/ha are sparsely spread across the study area. The original resolution of the forest volume, height and diameter are all 12.5x12.5m, and are all from the same laser scan.

The average tree diameter and height data were collected by the Swedish National Land Survey, when they performed a laser scan of Sweden in 2014. These data are available free of charge from the Swedish Forest Agency's homepage. The data are divided up by county, so only the data from Kronoberg county were downloaded. These data were then used to calculate the tree slenderness coefficient (TSC). Figures S7 and S8 (appendix) depict the diameter and height data before they were merged in the TSC calculation.

2.1.5 Tree slenderness coefficient

The TSC is a calculation that can indicate the susceptibility of a tree being wind-thrown, based on tree height and diameter. Large values suggest tall and narrow trees which are more susceptible to damage. Generally, tree slenderness ratios of above 80 are in risk of being wind-thrown or experiencing damage. The equation used to calculate the slenderness coefficient, taken from (Adeyemi and Adesoye 2016) is shown in equation 1 in the appendix.

2.1.6 Soil type data

Topsoil data were downloaded from the European Soil Data Centre (ESDAC). These data contained clay and sand content and were collected at 250,000 sample sites spread across Europe (ESDAC 2015). The resolution of the rasters was 500x500m. Since the only soil data required were for the study area, that extent was extracted using the county borders as a mask. The sand and clay content are depicted in figures S9 and S10 (appendix).

In comparison to the other data, the soil type resolution is very coarse at 500x500m. Due to this, the data were downscaled to a resolution of 100x100m and 50x50m by resampling it using the 'nearest' technique in ArcMap.

Soil depth data were available as vector data in point format from the Swedish University of Agricultural Sciences (table S1, appendix). This dataset was interpolated across the study area using Inverse Distance Weighting (IDW) which is a function that determines cell values across a raster surface from sample points. The default exponent of distance (a power of 2), which controls the significance of values from surrounding points on the overall interpolated value, was implemented. The assumption made in the interpolation is that the variable's influence decreases with distance from the sampled points (ESRI 2016c). The values interpolated will never be higher or lower than the maximum and minimum values from the sample points as IDW is a weighted distance average (ESRI 2016e). The deepest soil depth recorded within the study area is 48 cm. The soil depth was divided up into two classes for the study, 0 – 25cm depth and 25 – 48 cm (the max depth for the study area). As most of the study area was within the class 0 – 25cm depth, no figure is provided.

Soil moisture content data were supplied by (Patrik Olsson, Skogsstyrelsen. pers. Comm) the format of 25 rasters with resolutions of 2x2m. These rasters were first resampled to a coarser resolution of 10x10m, and then mosaicked together. The resolutions had to the changed before the merging as the study area is too large for the ArcGIS programme to properly compute and render them all simultaneously as one cohesive layer. Whereas the resolution of

the raster was high, the actual resolution of the soil moisture data was coarse. The original scale of values went from 0 – 255, but the data provider pointed out that rather than showing a scale of how moist the area was, it was more a suggestion of wet and dry regions, scaling from 0 – 100, with 1 representing water bodies. Due to this, all values above 100 were not included in the analysis, and 4 classes were created for the values 0 – 100 (figure S11, appendix).

2.1.7 Observed forest cover change 2004 – 2005

A raster layer depicting the damage to forests observed from the storm Gudrun was supplied by Skogsstyrelsen. This raster is the result of a difference analysis created from satellite imagery from 2004 and 2005. The data are a greyscale image depicting the forest changes in the MIR/SWIR band (mid-infrared and short-wave infrared, respectively). Images from before and after the storm were used, and what the layer shows are changes in forested areas. To ensure that only changes in the forest cover were detected, a forest mask was used (Patrik Olsson, Skogsstyrelsen. pers. Comm).

This layer came with a couple of different classes which showed what regions were not affected by the storm, where clouds covered the imagery and the regions which were affected by the storm. The values 0 – 171 represented where there was no recorded change in forest cover, or where there was cloud cover, and the values 172 – 255 represented where there was a visible change in forest cover. To simplify this, the values were re-classed to show what areas were affected (assigned a value of 1 = damage) and what areas were not affected (assigned a value of 0 = no damage). This meant that the values 172 – 255 were re-assigned a value of 1, whereas all values below this (the regions were either no change in forest cover was detected or there was cloud cover) were re-assigned a value of 0. This logic was also implemented in a thesis from 2015, where the same data were used (Ulfves 2015).

The resolution of these data was 2x2m initially. This was scaled up to a 50x50m resolution using the function resample with the ‘nearest technique’ in ArcMap, so that it would match the resolution of the DEM data, making it possible to make a comparison between the predicted damage and the observed damage. The resampled version of the observed forest cover change can be seen in figure 5.

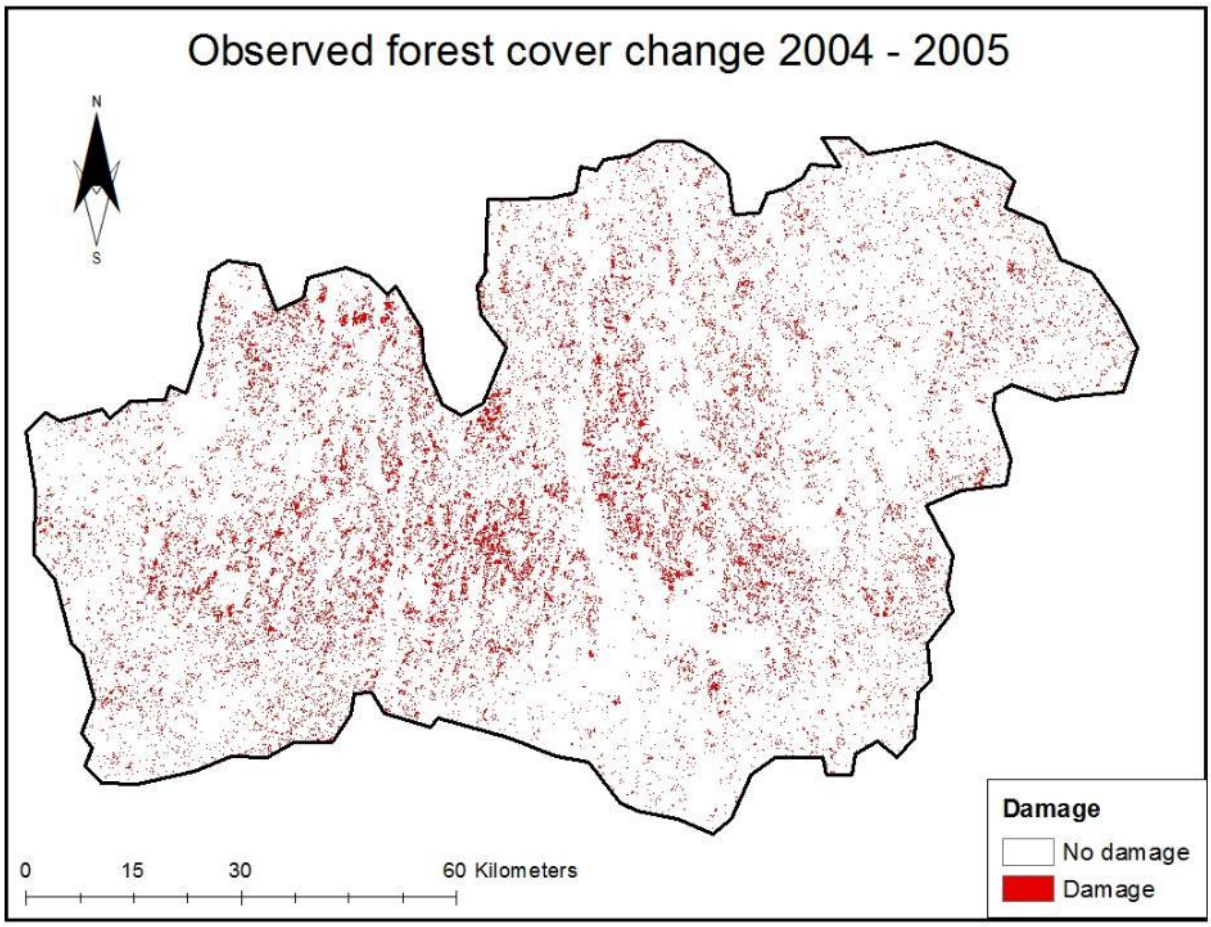

Figure 5. The observed forest cover change 2004 – 2005 created from the dataset received from Skogsstyrelsen

2.2 Building the model

The next few sections will outline the steps taken to build the model.

2.2.1 Multi-criteria decision analysis (MCDA)

In order to create a map showing the forest zones more at risk, a Multi-criteria decision analysis (MCDA) was executed. To summarize shortly, an MCDA analysis involves a set of alternatives (the datasets linked to the vulnerability of forests in this case) that are examined to identify potential conflicting information, according to the preferences set by the decision maker. So, an MCDA analysis analyses decision problems that contain several objects (Malczewski and Rinner 2015). In this report, the objects are the datasets that have been chosen to represent unstable forests that will more likely be damaged in an extreme weather event, such as Gudrun in 2005.

MCDA is one of the methods used to solve forest resource management problems over the last 3 decades. There are several types of MCDA analyses, and the method implemented in this study is the weighted overlay.

2.2.2 Weighted Overlay

An MCDA function that is available in ArcMap is the 'Weighted Overlay' tool. This tool was chosen for this study as it is one of the more commonly used tools when dealing with site selection and suitability modelling. The weighted overlay overlays several rasters by a common measurement scale and weights according to their relative importance (ESRI 2016g). The rasters are combined by first multiplying the cell values by the percentage influence assigned to each dataset, then combining the values of all the cells located in the same place from each dataset. This combination of values from each dataset makes up the weight of that cell. This process is completed for all the cells within the extent selected (ESRI 2016i).

Each raster entered has two main input values. The first is expressed as a percentage of influence in comparison to the other datasets. Once all the datasets have been entered into the weighted overlay, their combined percentage influence must add up to 100%. The percentage influences assigned to each dataset are displayed in table 2. The first percentage influences were determined by the literature study, but throughout the development phase, these percentage influences were altered for testing purposes to try and see how much each factor influenced the model. The alterations in the percentage weights made were prompted by the results from the model runs, which are outlined in the results. As model run 5 later became the accepted 'final' model, the five factors that made up this model run (forest cover, aspect, slope, sand and clay content) all received equal weights of 20% as these were the conditions used when testing the accuracy of model run 5.

Table 2. The percentage weights of the factors in the weighted overlay. The six bold factors are the ones used in model run 5 (forest cover 2000 for the first run, and forest cover 2013 for the future run), each with a percentage weight of 20%

The percentage weights for each dataset	
Dataset	***Percentage influence (%)***
Forest cover 2000	**20**
Forest cover 2013	**20**
Aspect	**20**
Slope	**20**

Average tree height	10
Average tree diameter	10
TSC	10
Volume forest	5
Sand content	**20**
Clay content	**20**
Soil moisture content	10
Soil depth	10

The second input is a set of weights within each dataset, corresponding to each dataset's specific classes. The common measurement scale for these weights will be a range of values (1 - 9) determined by the number of classes in the rasters (ESRI 2016i). For example, in the dataset forest cover from the year 2000, three forest classes were available: coniferous, deciduous and mixed forests. The class that is most vulnerable to damage from wind is coniferous forests, so this class was assigned a higher weight than the other two classes. If possible, it would have been interesting to look at specific coniferous tree species and incorporate them as separate factors to see how the vulnerability may differ between species. Unfortunately, this data was not available. The fundamental scale of how to weight each class in the factors can be seen in table S2, appendix.

An altered version of the scale was derived from the fundamental one, relating to the level of predicted damage to forests. All rasters will receive the same range in order to ensure that they will overlay cohesively in the weighted overlay. This range will relate directly to the susceptibility of damage to the forests from each factor. The range of values as well as how they relate to degree of forest damage is presented in table 3 below. In this case, the value 1 will represent very little damage, the value 9 will represent extreme damage, and all values in between will be a scale of little to more damage. As most of the factors do not have the same number of classes, the factors with fewer classes may not receive the whole range. The 1 – 9 range will still be valid, but could be at a reduced level of detail depending on the factors. For example, the factor slope, only contains two classes, 1 and 9 (table S3, appendix), whereas the factor sand content has the classes 1, 5, 7 and 9. Sand content will thus influence a wider range of weights across the study area in comparison to slope.

Table 3. The adapted range of weights for the datasets. Modified from (Malczewski 1999).

Weighting of datasets - storm damage version	
Intensity of importance	**Description**
1	Very little damage
2 - 4	Little/some damage
5	Moderate damage
6 - 8	A lot/severe damage
9	Extreme damage

Wind speed, although a major factor in this work, will not be included in the function as data from only one station were recovered. This was because the other weather stations all broke during the storm, so did not record wind speed data. Due to this, the wind speed values were assumed to be the same across the study area and so, would not have overlaid properly with the other rasters as the weighted overlay will create a raster showing suitable and non-suitable locations in accordance to the range of values each factor receives. Since wind speed is assumed to be the same, it is not possible to give it the same range as the other factors.

2.2.3 Assigning weights within the factors

Before the factors could be entered into the weighted overlay, each one had to be re-classed. This is because each piece of data in the datasets needed a weight of importance. The division of all factors and their weights can be seen in table S3, appendix. All the weights were determined from literature studies conducted for each factor.

In the layers depicting forest cover, both from 2000 and 2013, coniferous forests required a higher weight then deciduous or mixed forests, as they are more vulnerable to damage from strong winds. So coniferous forests were assigned a weight of 9, deciduous forests were assigned 5 and mixed were assigned 1. In the 2013 layer, the classes were labelled evergreen and deciduous, with evergreen being assigned a weight of 9, and deciduous being assigned a weight of 5.

In terms of aspect, the slope directions that were most prone to wind damage received the highest weight, these directions being west, southwest and northwest (Brunet et al. 2013).

The factors tree height and diameter were both run as separate factors in the model, and as a merged factor in the form of the TSC. This was done to see how the results might change. For the factor, average tree height, the tallest trees received the highest weight, 9, as they would be more exposed, and could catch the wind more easily. For the average tree diameter, it was

assumed that the smaller the diameter, the less stable the tree would be (Coder 2010). This meant that smaller diameters received a higher weight, corresponding to being more vulnerable to damage, and larger diameters received a lower weight. When the two factors were merged in the TSC, the higher values represent more slender trees, which are more susceptible to wind damage. It is generally accepted that all slenderness values below 80 represent stable trees, and all values above 80 represent more unstable trees due to their slenderness (Adeyemi and Adesoye 2016).

Forest volume was divided up into 4 classes, each class increasing by 250 m3ska/ha. As it has been identified that decreasing forest volume has negative effects on the overall stability and protection of forest stands against strong winds (Brunet et al. 2013) the lowest volume class received the highest weight of 9, and the highest volume class received the lowest weight of 1.

For soil content, spruce (*Picea abies*) binds well to sandy soils, which means that areas with a higher percentage of sand content received a lower weight, and areas with a lower sand content received a higher weight (Osman 2013). The soil depth of the study area varies from 0 to 48cm depth. Soil depth is classed as 'very shallow' when it reaches 25cm depth or less, and considered 'shallow' when it reaches 50cm depth or less (The University of Arizona 1998). Due to this, the soil depth factor was scaled into two classes, with the soil depth of 25cm or less receiving the highest weight, 9.

Soil moisture content plays an important role in the growth of roots, which affects the anchorage of a tree, and in turn, the susceptibility to being wind thrown. Soils with high moisture content often cause shallow, but widespread, growth of roots (Crow 2005). As deeper root systems aid in the anchorage of a tree, the regions with high soil moisture content received the highest weight, as these areas could have trees with shallow root systems. Along with this, waterlogging of soils can lead to a lack of oxygen in soils, which results in root death, also making a tree more susceptible to being wind-thrown (Stofko and Kodrik 2008; Crow 2005). This was another reason as to why regions with higher soil moisture content received the highest weights for this factor.

2.3 Developing the model

These next sections will go through how the completed model was tested and developed for improvements.

2.3.1 Model runs

It was necessary to carry out several model runs to see how slight alterations in inclusion or exclusion of factors, percentage weights of factors, or weights within each factor could change the damage predictions from the model runs. Seventeen model runs were completed when developing the model. Each model run prompted a change for the next one. Not all factors were changed in each run, for example, in one run the percentage weights of the factors included would change and the results analysed, and the next model run could instead add another factor to the model, or change the weights within one of the factors. One change was done at a time to judge how much that change altered the model run damage predictions.

Once these seventeen model runs had been finished, the best model run (criteria specified below) was selected and implemented on the forest cover data from 2013 in order to produce tentative predictions of forests vulnerable to storm damage.

2.3.2 Combine

In order to see how well the predicted damage matched the observed damage, the function "combine" was used, which combines multiple rasters and gives them a unique output value for each input. The tool works specifically with integer values within the attribute tables of the rasters (ESRI 2016a). In this study, it calculated how well the predicted damage and the observed damage overlapped. To do this, both rasters also had to have the same scale, and since the observed damage raster only had two values (0 = no damage, 1 = damage) the output from the weighted overlay had to be reclassified to match this. As the scale in the weighted overlay output was 1 – 9, it was decided that everything with a value of 7 or higher would be classed as 'damage', and everything with a 6 or lower would be classed as 'no damage'. The values 7 and above were chosen to represent damage, as these values are the upper scale of the damage predictions and the aim for the model was to correctly predict areas in risk of being damaged.

2.3.3 The Confusion Matrix

The 0 and 1 values produced from the combine function described above were used in a confusion matrix. A confusion matrix is a table that can be used to validate the performance of a model. It compares how well sets of data match (Data School 2014). In this case, it compares how well the number of cells containing damage (1) and no damage (0) classes overlap from the observed damage output to the predicted damage output.

Table 4. The confusion matrix

		OBSERVED	
		NO	**YES**
PREDICTED	**NO**	TN	FP
	YES	FN	TP

How this comparison is done can be seen in table 4 where TN = True Negative, TP = True Positive, FP = False Positive and FN = False Negative.

TN is when the model has predicted no damage, and there actually is no damage according to the observed layer. TP is when the model has predicted damage, and there actually is damage according to the observed layer. FP is a false positive, so when the model has predicted damage, but according to the observed layer, there was no damage, and FN is the opposite, false negative, where the model has predicted no damage, but there was damage according to the observed layer (Data School 2014). An example of the confusion matrix using the number of cells from model run 1 of this report can be seen in table 5. Displayed like this, the overall accuracy can be calculated.

Table 5. Confusion matrix for model run 1. The values are the number of cells found in each class

Model run 1			
		Observed	
		0	**1**
Predicted	**0**	1357097	155774
	1	1160074	144168

The overall accuracy is calculated by taking the sum of the TN and TP, and dividing it by the total sum of cells.

As well as the overall accuracy, the confusion matrix is used to calculate the producer's and the user's accuracy. The user's accuracy is how well the model created matches the reality of the spread of damage (Data School 2014). This accuracy is an evaluation of how well the model works, so in this sense, how well the model accurately predicts the spread of damage caused by wind storms. It is split up into two accuracy values; in this case, the first value being how well the model predicts damage and the second value being how well the model predicts no damage. For example, the number of cells classed as 1 (damage) in areas where there was observed damage according to the observed damage dataset (figure 5).

The producer's accuracy is the fraction of correctly classified cells compared to the ground truth layer, which in this case is the dataset showing the observed damage (figure 5). This accuracy rating gauges the performance of the model (Data School 2014).

The equations for overall, user's and producer's accuracy using the values presented in table 7 are outlined in appendix 7.3, equations 2 to 7. These calculations were performed for every model run and the accuracies compared.

2.3.4 The resolution test

A test to see how much resolution affected the model results was conducted. As explained, all datasets were resampled to the base resolution of 50x50m, which was implemented in all the model runs. The datasets were also resampled to the resolution 100x100m for one additional model run. The factors and weights of this 100x100m resolution run mirrored those of the final developed model run (model run 5). The accuracy of the 100x100m resolution model run was then compared to a 50x50m resolution run, both runs containing the same factors and weights, to see if there were any differences in the accuracies.

2.3.5 The sensitivity test

A sensitivity test was carried out on the developed model (model run 5) to see how much weight each factor carried in the model. Different factors were removed each run (and placed back in for the next run) and the accuracies calculated. This test was carried out only on the factors that were incorporated into the final developed model, which were; forest cover (2000), aspect, slope, clay content and sand content. A total of 4 tests were performed, and the list below informs which factor was removed in each test.

- Test 1 – clay content removed
- Test 2 – sand content removed
- Test 3 – slope removed
- Test 4 – aspect removed

After each test, the accuracy (overall, user's and producer's accuracy) was calculated and examined.

2.3.6 The NULL model

The last test performed to check the usefulness of the model was to compare the combine output from the model (dataset predicting damage in the format 0 = no damage and 1 = damage) to a dataset with randomized 0's and 1s assigned to cells. This randomized dataset

had the same extent as the model output. The accuracy of the randomized dataset was calculated through a confusion matrix, the same way in which the model runs accuracies were calculated.

The idea behind creating this null model is to see if the null model could perform as well as the weighted overlay for predicting damage. If the null model accuracies approach the accuracies of the weighted overlay, then it can be concluded that the weighted overlay does not add appreciably new information. If the null model has a lower accuracy rating, then the model created through the weighted overlay can be accepted as predicting damage, as the accuracy will be higher than that of a randomized dataset.

2.4 Applying the model

As mentioned earlier, after the seventeen model runs had been carried out, the model determined to predict storm damage most correctly was implemented on more recent forest cover data. These forest cover data were from 2013. This was done to produce predictions on how future storm damage to forests in Kronoberg county may be spread. Unlike the forest cover data from 2000, there was no way to validate how accurate these predictions are.

3. Results

The results are split into three sections. The first section shows the first model built with few factors. The second section then moves on to how the model was developed, including the resolution and sensitivity tests. The third section presents the final version of the model implemented on forest cover data from 2013, showing the future predictions for forest cover damage.

3.1 Building the model

3.1.1 First model run

The first run of the model can be seen in figure 6. The resolution of this model run was at 50x50m. The extensive red regions in the map depict locations that are in danger of experiencing severe forest damage, and the orange – green locations that will experience moderate to little damage. The factors incorporated into this run were: forest cover 2000, aspect, slope and soil type (sand and clay). Table 4 (presented in the methods section) corresponds to the damage values seen in figure 6.

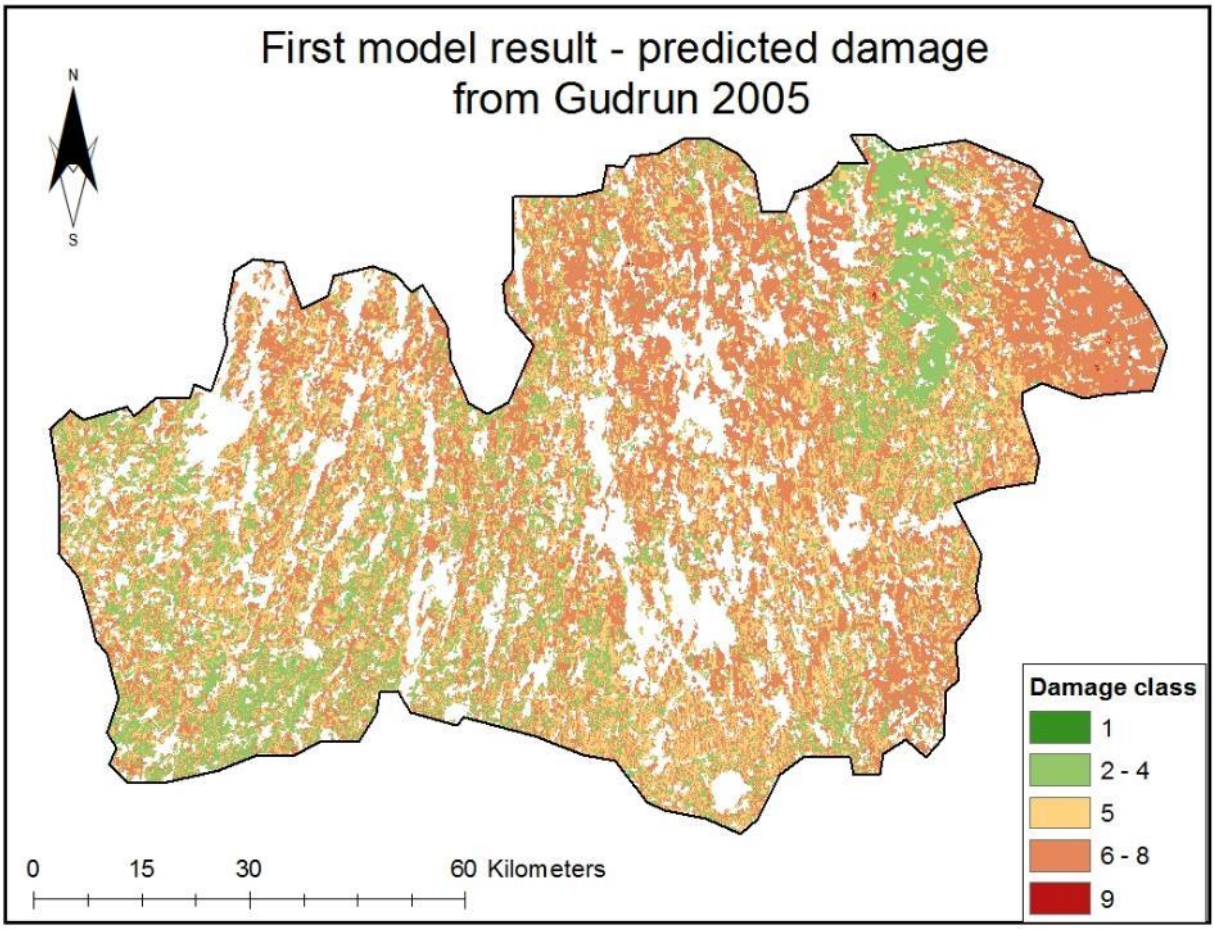

Figure 6. The first model run. See table 4 for explanation of damage classes. The white areas represent regions with NoData, for example urban areas and/or water

The north of Kronoberg is predicted to experience the most damage, with damage especially concentrated on the north-east tip, and central northern regions. The south-west regions have relatively low damage predictions. However, there is also one region in the north-east that stands out with small damage predictions.

The number of cells from the raster that are in each damage class (1 – 9) can be seen in table 6. The majority of the cells (32.65%) are found within weight class 5, representing moderate damage.

Table 6. The division of damage predictions into the weight classes

Model run 1		
Weight	**No. of cells**	**%**
1	23	0.001
2	5006	0.18
3	31858	1.13
4	557324	19.73
5	922219	32.65
6	840175	29.74
7	420854	14.90
8	46434	1.64
9	787	0.03

In order to evaluate how well the model worked, the numbers seen in figure 6 were re-classed into 0 (range 1 – 6, representing less/no damage) and 1 (range 7 – 9, representing damage/severe damage). They were re-classed into only two damage classes as the raster used to validate the results only had those two classes. The overall accuracy of this first model run was 53%. This percentage corresponds to where both the observed damage layer and predicted damage layer reported the same information in terms of damage and no damage.

The producer's and user's accuracy percentages can be seen in table 7. As the user's accuracy for '0' is 90%, it tells us that the model is predicting no damage correctly 90% of the time. The user's accuracy for 1 (damage) is 11%, which means that this model run only predicted damage correctly 11% of the time when compared to the observed damage dataset.

The producer's accuracy tells us that 54% of the no damage areas have been correctly classified, and that 48% of the damage areas have been correctly classified.

Table 7. Accuracy for model run 1

Overall accuracy	Producer's accuracy		User's accuracy	
53%	0	1	0	1
	54%	48%	90%	11%

3.2 Developing the model

As the first model run had an overall accuracy of 53%, and a user's damage accuracy of 11% (table 7) it was decided that it had to be developed as this first model run was only predicting the spread of damage correctly 11% of the time, even with an overall accuracy of 53%. The accuracy results for the first model run is what prompted that the model had room to improve. Figure 7 depicts a graph that contains the results of the overall accuracy, user's accuracy and producer's accuracy for the 17 model runs. Table S4 in the appendix provides a brief description of how each run was altered in order to try and improve the results.

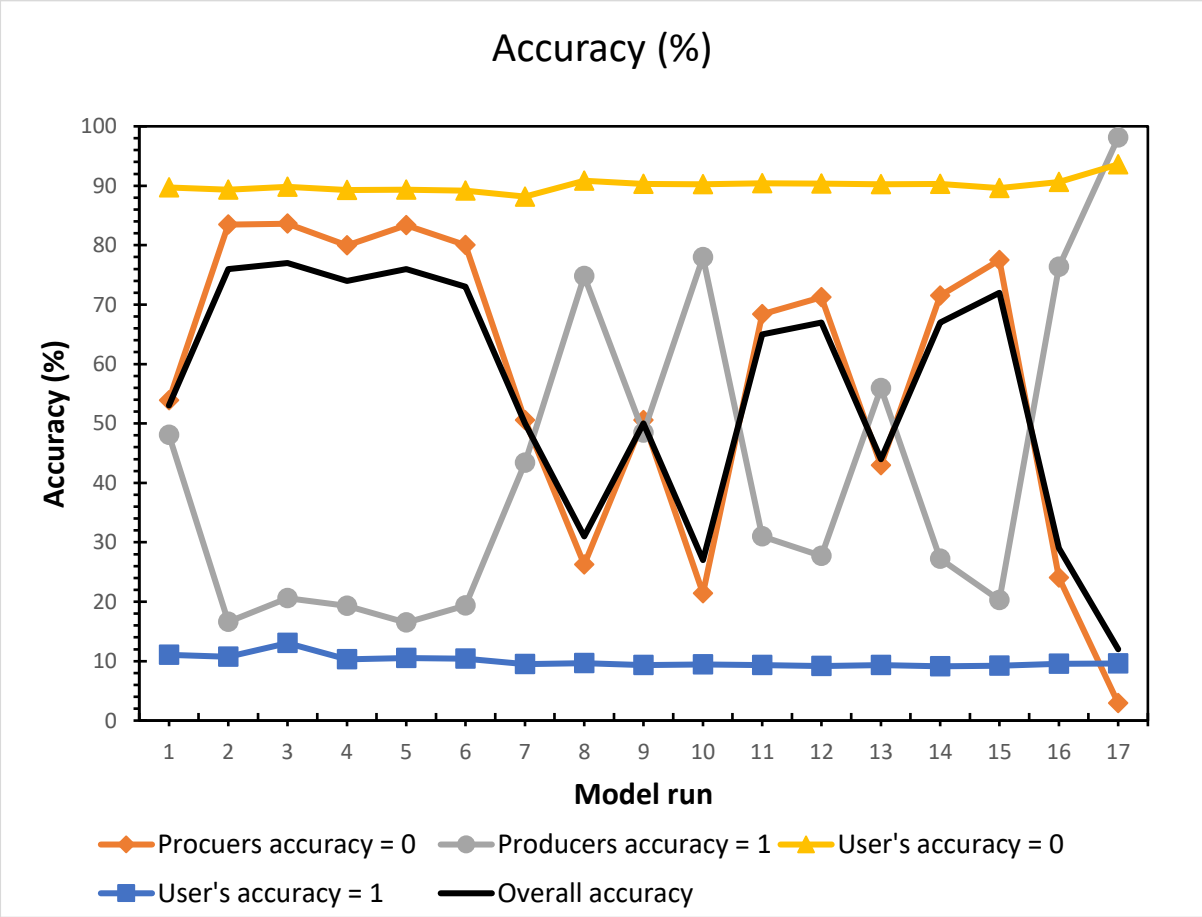

Figure 7. The calculated accuracies for all the model runs according to the confusion matrix

The black line shows the calculated overall accuracy for the 17 model runs which was calculated using a confusion matrix. The highest overall accuracies at 76 – 77% were

recorded for model runs 2, 3 and 5. The lowest overall accuracy was recorded for model run 17 with a 12% accuracy. The blue and yellow lines represent the accuracies calculated for the user's accuracy. The blue line, which is the user's accuracy for damage, is relatively low for all model runs, with the highest value at 13% in model run 3. The yellow line is the opposite of this, and represents the user's accuracy for predicting no damage. All these values are around 90% apart from in model run 17 when it increases to 94%. The grey and orange lines represent the producer's accuracies for predicting damage and no damage, respectively.

New datasets were introduced from model run 7 and onwards. These new datasets immediately influenced accuracy percentages (figure 7).

The total number of cells in each raster for each model run was also compared. Table 8 shows the total number of damaged and undamaged cells from three model runs compared to the number of damaged and undamaged cells in the observed forest cover change raster. The total number of cells in each model run is lower than the number of cells present in the observed forest cover change raster as the model will have removed all NoData regions, which may have included regions which contained forest damage.

Whereas model runs 1 and 5 had fewer datasets incorporated into their runs (table 8), they have a larger sum of cells in the final output in comparison to model run 17, which had more large scale factors.

Table 8. The percentage of cells in the classes "damaged" and "undamaged" in the observed forest cover change raster compared to the model run 1, 5 and 17

	Observed change (figure 5)	**Run 1**	**Run 5**	**Run 17**
Damaged	9%	46%	17%	97%
Undamaged	91%	54%	83%	3%
Total no. of cells	94404611	2824680	7845862	887580

As the fifth model run was one of the most accurate (76% overall accuracy) it was implemented on the more recent forest cover to predict vulnerable forest zones. This model run was used rather than model run 3, which had an overall accuracy of 77% because in model run 3 the aspect was reclassified so that all the exposed slopes were classed as non-exposed, to see how greatly it would affect the final result.

By contrast, the last model run (run 17) was chosen as a point of comparison, as it was one of the least accurate (12% overall accuracy), but incorporated all datasets.

3.2.1 The resolution test

As the model run number 17 produced the damage prediction with lowest accuracy, the factors and weights from that run were implemented at the resolutions 50x50m and 100x100m to see if a resolution change would alter the results. This model run, although with the worst overall accuracy at 12%, (table 9), was selected to see whether it would improve at a different resolution. The result from the 50x50m resolution run can be seen below in figure 8. Compared to the first model run, run 17 has predicted a lower overall damage spread, as there are a lot more regions presented that will experience no damage (white areas). However, the damage that is predicted is on a more severe scale. So, there are fewer regions with green/light green colouring which represent slight to moderate damage, and more regions with light red to red colouring which represent a lot to severe damage predictions.

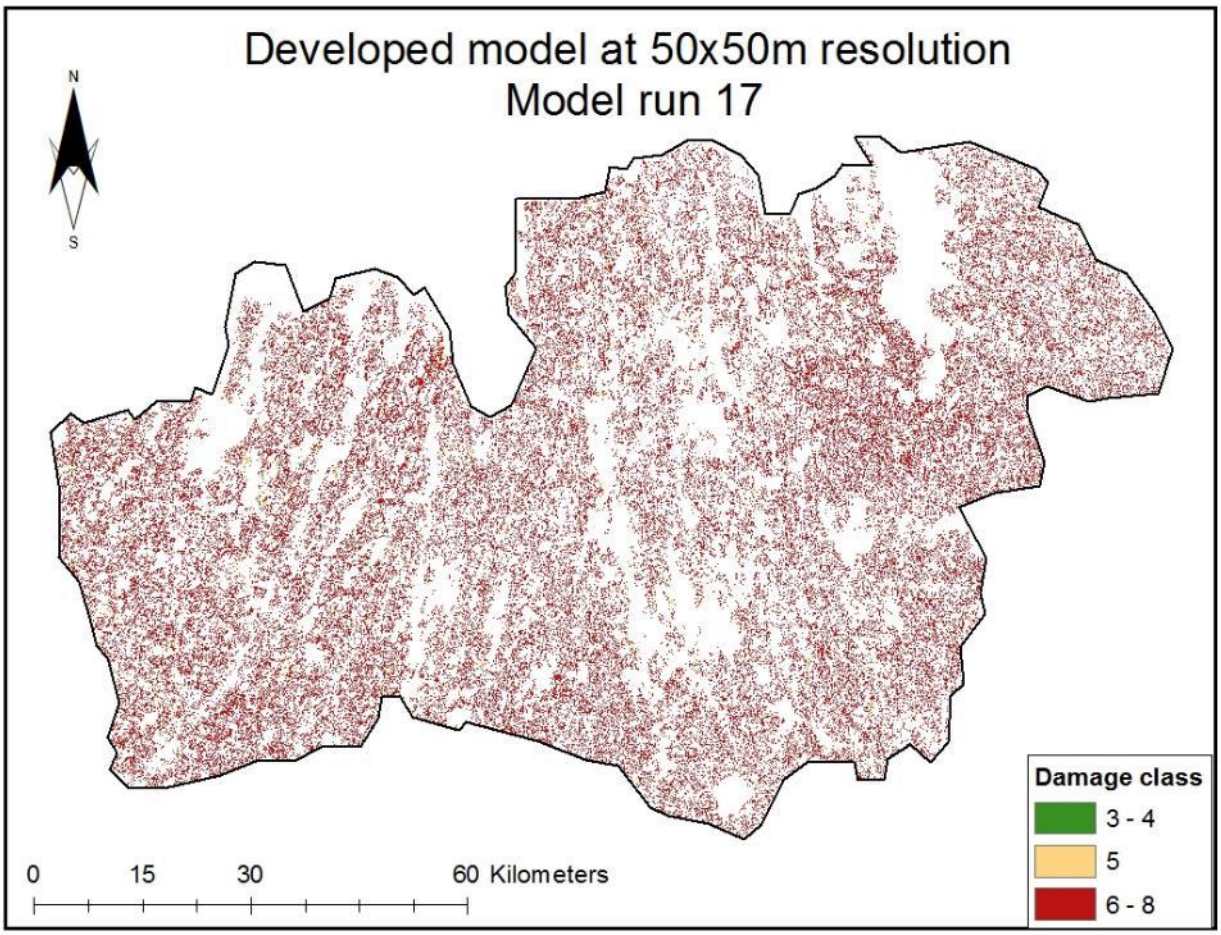

Figure 8. The damage predictions according to model run number 17 at a resolution of 50x50m. Although this model run predicted a lower overall damage spread, the damage that is predicted is on a more severe scale than other model runs.

Table 9. Accuracy for model run 17 at 50x50m resolution

Overall accuracy	Producer's accuracy		User's accuracy	
12%	0	1	0	1
	3%	98%	94%	10%

The model result from the 100x100m resolution is not included as the overall percentages of damage prediction barely altered from changing the resolution. This can be seen in table 10, which displays the unchanging user's and producer's accuracy values.

Table 10. Accuracy for model run 17 at 100x100m resolution

Overall accuracy	Producer's accuracy		User's accuracy	
12%	0	1	0	1
	3%	98%	94%	10%

3.2.2 The developed model

The model run with one of the highest overall accuracy percentages (76%) was determined to be the most valid model run. This was model run number 5. This model run was also appealing due to its equal percentage influence weights, as all the factors received a 20%

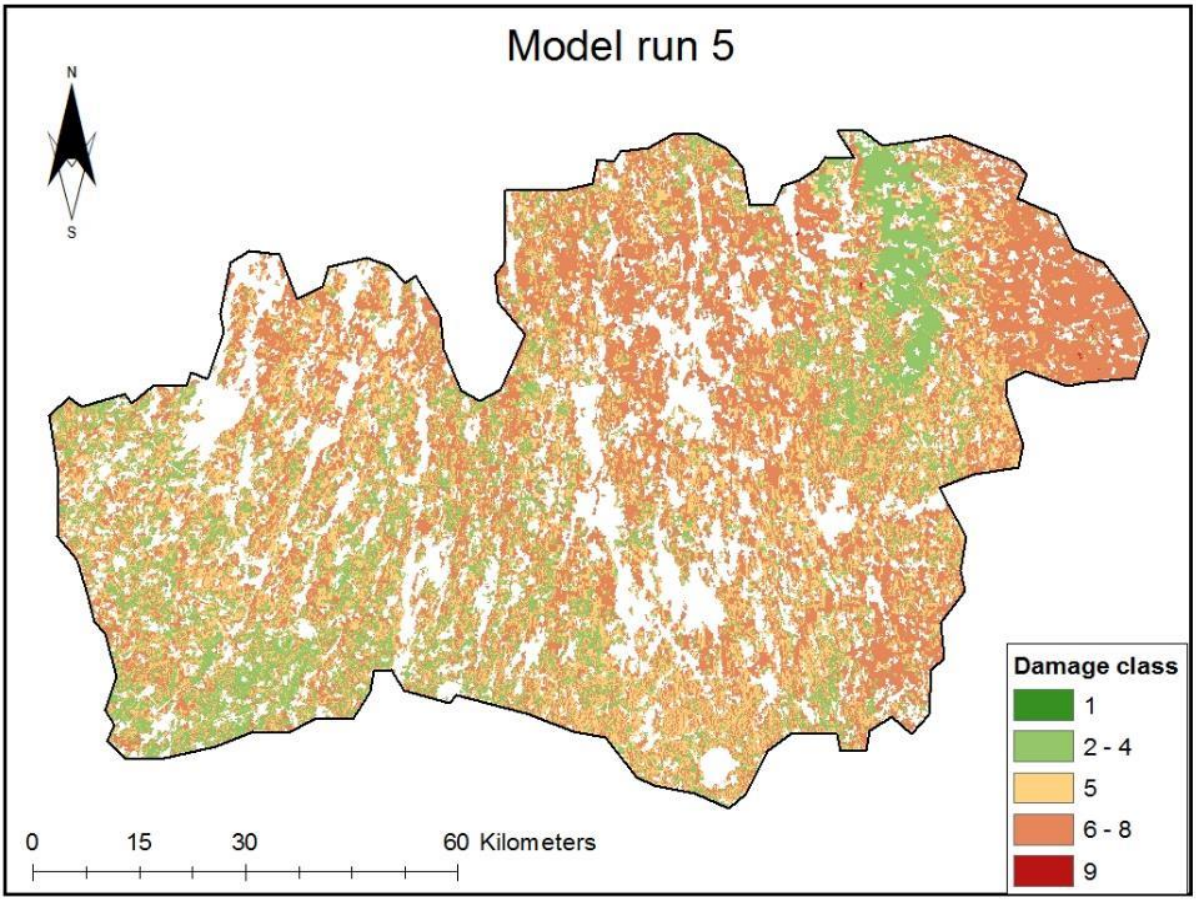

Figure 9. Areas with a high risk of damage at the timing of the storm Gudrun (2005) according to model run 5. The western regions are predicted to receive the least damage, whilst the central and northern regions face damage predictions of increasing severity

weight each, which means that no factor was considered to be 'more' important over another when the model was run. The results from this model run can be seen in figure 9. The damage classes 1 and 9 are barely visible, as the locations within the factors with those weights often did not overlap. The classes most visible in this map are 2 – 4, representing little/some damage and class 6 – 8, representing a lot/severe damage. The western regions are predicted to receive little/some damage (class 2 – 4) with the severity of damage predictions increasing the further east you move across the county. The north-eastern regions are predicted to receive the most damage, with high concentrations of damage classes 6 – 8. However, there is a ribbon of damage classes 2 – 4 also present in the north-eastern region of the county.

The producer's and user's accuracy for model run 5 are presented in table 11. Again, the model is best at predicting where no damage will occur as is seen with the user's accuracy of 89% when predicting no damage, and worse at correctly predicting the spread of damage, as can be seen by the 11% user's accuracy.

Table 11. Accuracy for model run 5

Overall accuracy	Producer's accuracy		User's accuracy	
76%	0	1	0	1
	83%	16%	89%	11%

To assess the validity of the damage predictions presented in table 11, these accuracy results were compared to the accuracy results from the null model, which can be seen in table 12. The null model, (figure S12, appendix) was created for validation purposes. If the user's accuracy from the created model is worse than the user's accuracy of a model that randomly assigns 'damage' and 'no damage' across the same study area, then the created model is invalidated. This is because it would suggest that the created model is less accurate than a random model.

Table 12. Accuracy for the null model run

Overall accuracy	Producer's accuracy		User's accuracy	
76%	0	1	0	1
	50%	50%	91%	9%

3.2.3 Comparing model run 5 to the observed damage dataset

To better visualize how well model run 5's damage predictions matched the observed damage from Gudrun (figure 5), figure 10 was produced. This map outlines where model run 5

correctly predicted damage and no damage, as well as where this model run over-predicted and under-predicted damage. The most wide-spread colour is green, which represents correctly predicted no damage areas. This agrees with the high user's accuracy for predicting no damage, which is at 89% (table 11). The colour which can be seen the least is red, which depicts the areas where damage is correctly predicted. This also corresponds well to the user's accuracy seen in table 11, as the user's accuracy for correctly predicting damage is at 11%. The black and orange colours represent over-predictions and under-predictions of damage, respectively. Overall, there is more over-prediction of damage, with the most concentrated regions being in the north-east and central north of the county.

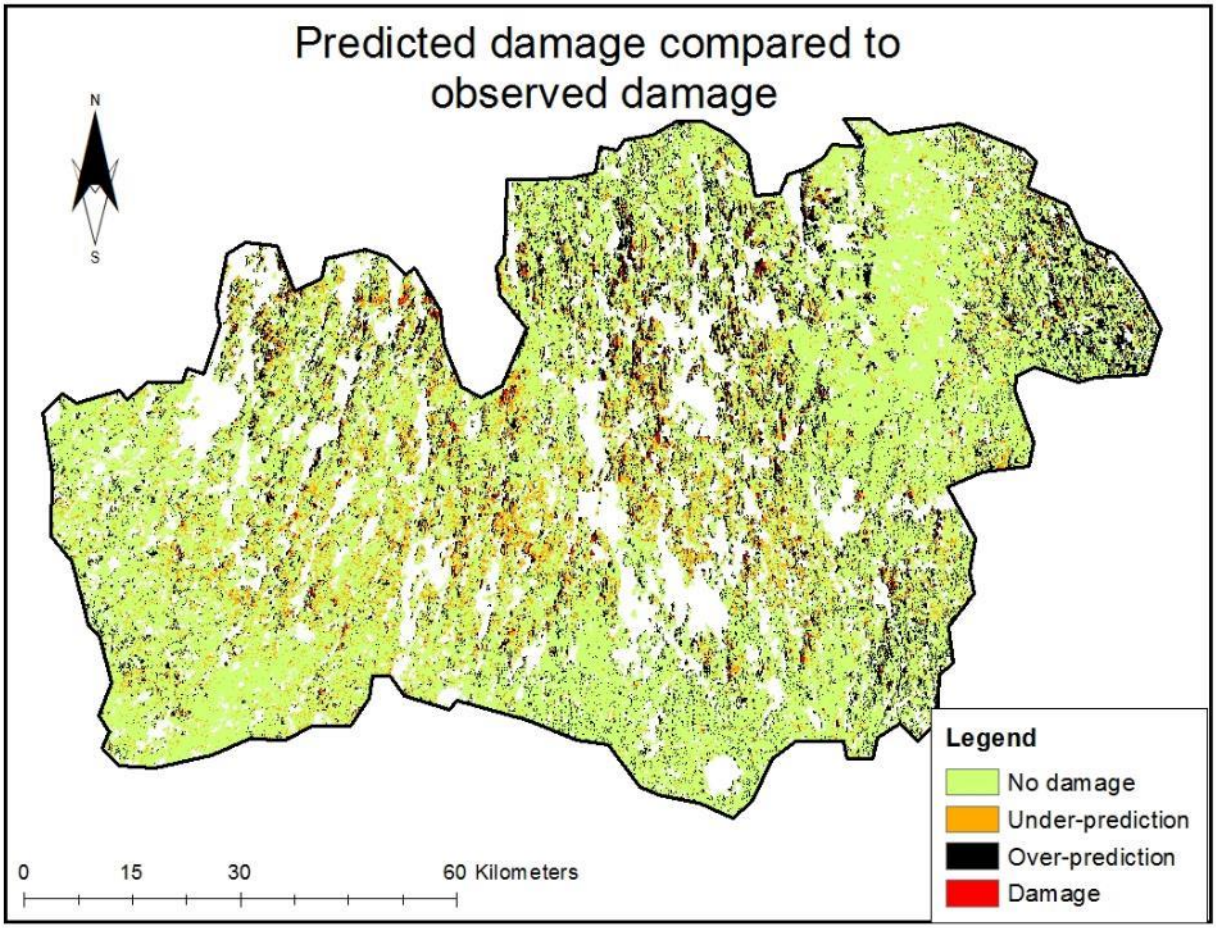

Figure 10. A map to show how well model run 5's damage predictions matched the observed damage from the storm Gudrun

3.2.4 Sensitivity testing of model run 5

A sensitivity test was conducted on model run 5 to see how much the final result altered by removing datasets. The values compared are the overall accuracy, as well as the producer's and user's accuracy from model run 5, which can be seen in table 13. This was divided up into 4 separate tests. In test 1, the dataset clay was removed. In test 2, the dataset sand was removed. In test 3, the dataset slope was removed, and in test 4 the dataset aspect was removed. The overall accuracy results as well as the producer's and user's accuracy can be seen in table 13. The dataset that was removed in each test was replaced for the next test, for example, clay, which was removed in test 1, was placed back into the model for test 2, and this process was repeated for all factors.

In test 1 when clay was removed, the overall accuracy decreased to 59% (original accuracy was 76%) suggesting that clay could be responsible for 17% of the overall accuracy. At the same time, the user's accuracy for damage stayed constant at 11%. The sand dataset on the other hand, seems to be responsible for only 6% as the overall accuracy decreased to 71% when this dataset was removed in test 2. When slope was removed, the overall accuracy increased to 83%, but the user's accuracy for damage decreased to 7%. In test 4 when aspect was removed the overall accuracy decreased to 68%, but all the producer and user accuracy percentages increased compared to the original values (table 11).

Table 13. Sensitivity tests 1 - 4

Test 1 (Clay removed)	**Overall accuracy**	**Producer's accuracy**		**User's accuracy**	
	59%	0	1	0	1
		62%	37%	89%	11%
Test 2 (Sand removed)	**Overall accuracy**	**Producer's accuracy**		**User's accuracy**	
	71%	0	1	0	1
		78%	21%	89%	10%
Test 3 (Slope removed)	**Overall accuracy**	**Producer's accuracy**		**User's accuracy**	
	83%	0	1	0	1
		93%	7%	89%	11%
Test 4 (Aspect removed)	**Overall accuracy**	**Producer's accuracy**		**User's accuracy**	
	68%	0	1	0	1
		73%	30%	90%	12%

3.3 Applying the model

The final model run mimicked the factors and weights from run number 5, but used forest cover data from 2013 rather than 2000, to try and predict what regions are more or less vulnerable to future storm damage. This prediction can be seen in figure 11. There is a larger variation in visible damage classes, the two most widespread classes being class 2 – 4, (dark green) representing little/some damage and class 6 – 8 (light red) representing a lot/severe damage. Some of class 5 (moderate damage, light green) is visible in the central southern regions and in the north-east. Only a few areas received the damage class of 9, so it was difficult to see them in the map; however, there is a small patch present in the north-eastern region.

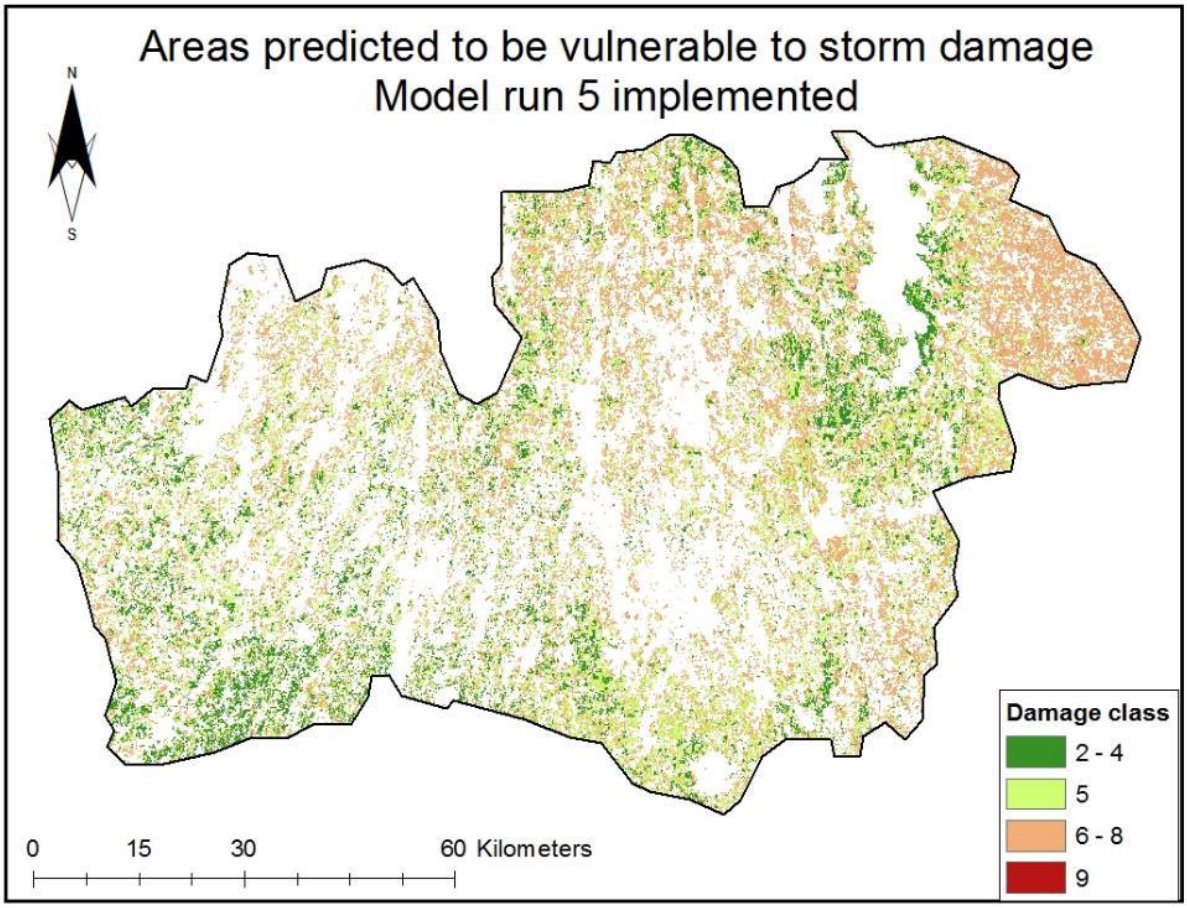

Figure 11. The spread of vulnerability to storm damage according to model run number 5. The north-eastern regions are predicted to experience the most damage, whilst the western regions have a less severe damage prediction.

The number of cells in each damage class for model run 5 can be seen in table 14. The most abundant class is class 5, (moderate damage) at 32.7% and class 6 (a lot/severe damage) is the second most abundant, making up 29.8% of all the cells. Class 9 only made up 0.03% of

the cells, which explains why it is almost impossible to see it in figure 11, and the same goes for class 1.

Table 14. The division of damage predictions into the weight classes from run 5

Future vulnerability to storm damage - run 5		
Weight	**No. of cells**	**%**
1	71	0.001
2	837	0.01
3	98714	1.3
4	1537001	19.6
5	2567209	32.7
6	2334730	29.8
7	1176063	15.0
8	129060	1.6
9	2177	0.03

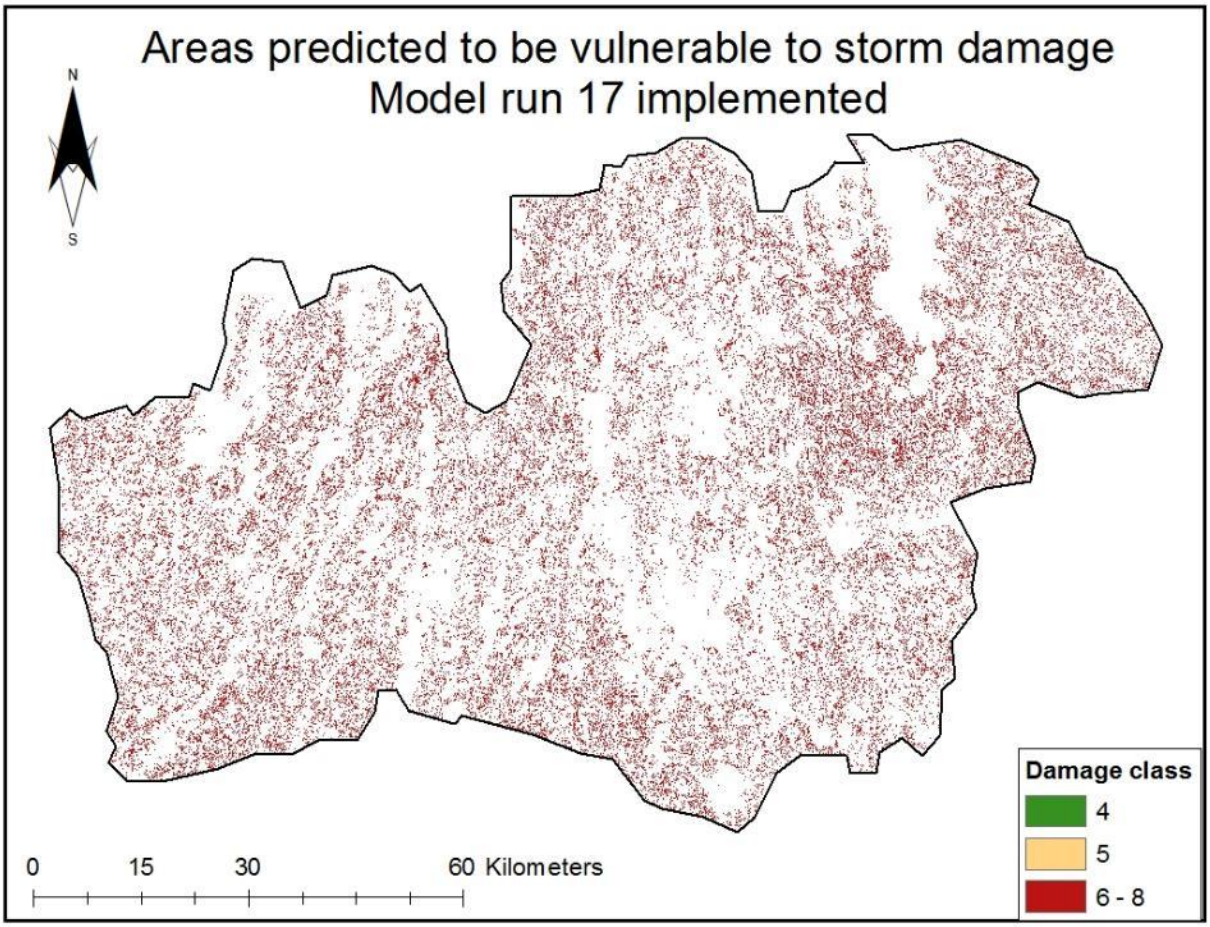

Figure 12. The spread of vulnerability to storm damage according to model run number 17. Similarly to when it was implemented on the 2005 forest cover, this model run predicts a more severe scale of damage across the county

As a comparison to model run 5, model run 17 was also implemented on the 2013 forest cover data. This prediction can be seen in figure 12. The division of cells into each damage class are depicted in table 15, which shows that 96.6% of all the cells landed in the classes 6 and 7, representing the "a lot/severe" damage class. Whereas the lowest predicted damage is in class 4 ("little/some damage"), all the white spaces in the map represent regions that are predicted to experience no damage. The damage classes 1 – 3 and 9 are not present in this result. This is because there would not have been enough datasets where the weights 1 - 3 overlapped. Instead a class that had the weight 9 may have been overlapped with a class that had a lower weight, which would have lowered the overall predicted weight. The same will have happened for the damage classes 1 – 3, but here there would not have been enough classes overlapping with these low weights to produce damage predictions with those weights. Instead a region with a factor weight of 1 would have been overlapped with a factor with a higher weight, most probably 4 or higher, since the lowest damage weight class seen is 4.

Table 15. The division of damage predictions into the weight classes from run 17

Future vulnerability to storm damage – run 17		
Weight	**No. of cells**	**%**
4	4	0.0002
5	10751	0.5
6	971282	49.5
7	923786	47.1
8	54810	2.8

4. Discussion

4.1 Building the model

The first model run (figure 6) is the result of using few factors to try and predict storm damage. These factors were forest cover (2000), aspect, slope and soil type (percentage sand and clay content). The regions predicted to experience least damage are concentrated to the west, with increasing damage predictions eastwards. The north-eastern tip of the county has the widest spread of the damage class 6 – 8, representing a lot/severe damage. There is, however another section in the northeast that does not follow this trend of increasing damage. Instead, it displays a patch of land that predictions show will experience little/some damage. According to the observed forest cover change (figure 5), the regions which experienced the most damage were the central regions. The amount of damage decreased slightly in the extremities of the county. The damage predicted in the central regions of the first model run (figure 6) match the observed damage (figure 5) fairly well, however the predictions for the north-eastern regions do not, although it is important to note that there are differences in how both results are presented. The model result (figure 6) tries to predict what areas are prone to damage, and what scale of damage they may receive, whilst the observed forest cover change (figure 5) simply shows where forest cover change has occurred.

The overall accuracy for this model run was 53% (table 9). This suggests that the model has just over a 50% chance to predict correctly, so half the time, it is possible that it is predicting incorrectly. The user's accuracy, which tells us how well the classified values in the model run fit to the damage classes presented in the observed dataset (figure 5) also suggests that this first model run is far from perfect. According to the percentages seen in table 9, the model has an 11% chance of being correct when predicting damage, and a 90% chance of being correct when predicting no damage. This tells us that the model is very good at correctly predicting no damage, but bad at predicting damage. Hence, this model run was concluded to have too low an accuracy to properly represent future damage predictions.

4.2 Developing the model

Sporadic changes are seen in the damage predictions and overall accuracies (figure 7). Model runs 1 and 7 – 17 display the most variations whilst model runs 2 – 6 generally have the same accuracy trends. Model runs 1 through 6 all incorporated the same datasets; forest cover (2000), sand content, clay content, aspect and slope. Model run 1 stands out as different compared to run 2 – 6 in figure 7. The overall accuracy for model runs 2 – 6 vary between

73% and 77% (black line in figure 7), and these are the highest overall accuracies out of all the 17 model runs presented. The high accuracies could be due to the high chance of correctly predicting no damage. In figure 7, the line representing no damage predictions (yellow triangles) according to user's accuracy varies between around 71% to 75%, which tells us that these model runs predicted areas with no damage most correctly. This is further supported by producer's accuracy results as for every single model run, the producer's accuracy for predicting no damage correctly was above 88%. However, the user's accuracies (blue and yellow lines in figure 7) tell us that the high overall accuracy is related to the high chance of correctly predicting no damage, rather than actual damage. The user's accuracy for predicting no damage (yellow line in figure 7) remains around 89 – 90% for all 17 model runs, whereas the user's accuracy for predicting damage is around 9 – 12% for every model run. As the user's accuracy for predicating no damage is so high, it must be the factor that corresponds to the high overall accuracy since the user's accuracy for predicting damage suggests that the model is very inaccurate when predicting damage.

The total number of cells varied slightly between the model runs, as can be seen in table 8. For example, model runs 1 and 5 had a higher total number of cells in comparison to model run 17. However, model run 17 contained more factors, and this could suggest that adding more factors fine-tuned the model and removed cells assumed to be 'redundant' according to the factors, or simply, removed as they were classed as NoData in one (or more) of the factors. In table 8 the division of cells into the two classes changes greatly between the model runs. Model run 1 had 46% of all its cells classed as damage, whereas model run 5 only had 17% of its cells classed as damage. However, model run 5 had a higher overall accuracy of 76% compared to model run 1's accuracy of 53%. Unfortunately, even though the overall accuracy of model run 5 is higher, the user's accuracy for damage remains at a constant 11% for both model run 1 and 5.

In model run 17 on the other hand, 97% of all cells were placed in the class damage, which suggests that there is some over-prediction of damage occurring in this model.

4.2.1 The resolution test

One issue that arose with the data was all the different resolutions that all the datasets started with. Access to data with the same original resolutions could have improved the final result as resampling of datasets would not have been necessary, but such data were not available. Due to this, many datasets were resampled before being placed into the model. It was deemed

necessary to perform a resolution test to see if altering the resolutions had an impact on the result. The results from this test however, tell us that a resolution change from 50x50m to 100x100m did not greatly alter the damage predictions made by the model as can be seen from the unchanging accuracy values in tables 9 and 10.

The highest resolution dataset was the soil moisture, with a resolution of 2x2m, and the lowest resolution datasets were the soil type (sand and clay) at a resolution of 500x500m. The original geometric resolution of each dataset can be seen in table S1 (appendix). This meant that a new 'base' resolution had to be chosen, and all datasets had to be converted to fit this resolution. In the end, the resolution 50x50m was selected as the base resolution, and the resolution test was implemented to see how much changing resolutions could alter the result. By upscaling a high-resolution raster to that of a lower resolution, some detail is lost. Before the base resolution was chosen, one idea was to try and implement the model using high resolution data at 2x2m resolution. However, not all the factors were available at this resolution. It was possible to resample them to this resolution, but it was decided that this would reduce the detail too much for the factors like soil type, which started at 500x500m resolution. The factors that were available at 2x2m resolution (soil moisture, slope and aspect), were downloaded and an attempt was made to merge the datasets so that they would cover the whole study area. Unfortunately, the study area was too large for that amount of high resolution data, and the ArcMap program could not compute that amount of data.

Assessing the accuracy of the data used in this report is important, as it directly affects the model runs. Most of the data implemented were in the form of rasters. The level of detail that can be seen in raster datasets depends on the cell size, also known as the spatial resolution of the raster. Smaller cell sizes mean higher resolution, but it also means longer processing times (ESRI 2008). As the extent of the datasets for this report span a whole county, the resolution of some rasters was simply too high to process. Also, in order for the weighted overlay to work properly, all rasters inputted had to have the same resolution. Both of these issues were solved by resampling the datasets to the chosen resolutions of 50x50m and 100x100m.

4.2.2 The developed model - run 5 compared to run 17; the 'best' and 'worst' model runs

Model run 5 which had an overall accuracy of 76% was compared to model run 17, which had an overall accuracy of 12%, to try and determine the reasons for the great difference in accuracy. One reason for this difference could be that model run 5 incorporated fewer

datasets. Only the factors forest cover (2000), soil type, slope and aspect were incorporated into run 5, whilst run 17 had all these as well as soil depth, soil moisture content, tree height and width and volume forest. However, as soon as more datasets were included in the model, the percentages of over-prediction and no damage started changing drastically, as can be seen in figure 7. Adding these extra factors could be contributing to more stochastic variation, which appear to have reduced the accuracy of the model performance.

In figure 8, depicting the predicted damage spread of Gudrun according to model run 17, it is very difficult, if not impossible to see damage classes 3 – 4 and 5. The only class visible is 6 – 8, suggesting that most of the forest cover in Kronoberg is in danger of experiencing a lot/severe damage from future wind storms. In comparison, more damage classes are visible in figure 9 which depicts the damage spread according to model run 5. Model run 5 suggests that the western regions of Kronoberg are less vulnerable, and that most damage will be felt in the central and eastern regions.

When comparing these runs to the observed forest damage (figure 5), model run 5 generates the closest match. Most damage was observed in the central regions, with an overall decreasing trend when moving to the extremities of the county. Model run 5 predicted most damage in the central and eastern sections, with less severe or even no damage in the west. There is also a clear green 'ribbon' of space in the north-east of Kronoberg, showing that this whole area is predicted to experience little – some damage. This 'ribbon' of less damage was most probably caused by the aspect factor, as this whole area is flat land according to the aspect dataset, which is classed as 'not exposed' in this study. This better fit is also backed up by the high overall accuracy (76%) of the model. By contrast, model run 17 predicted a high risk of severe damage across the county, but also had the lowest overall accuracy at 12%. However, model run 17 does eliminate more regions (all the white spaces in figure 8) which are all classed as NoData (including the green 'ribbon' in the north-east), also representing regions where no damage was predicted to occur.

Model run 5's user's accuracy for predicting no damage correctly has decreased to 89%, whereas model 1's accuracy was at 90%. However, the accuracy of the model to correctly predict actual damage has remained constant at 11% in model runs 1 and 5. This means that whereas the overall accuracy of the model decreased, the accuracy of correctly predicting damage remained constant. However, the overall accuracy of model run 5 has increased to 76% in comparison to model runs overall accuracy of 53%. This increase is due to the

producer's accuracy. According to the producer's accuracy, model run 5 has 83% accuracy when predicting no damage. This is a large increase compared to model run 1 producer's accuracy of 54% when predicting no damage, and it could be this increase which affected the overall accuracy of model run 5.

The most useful model in this project is run 5, due to a combination of having a high overall accuracy, fewer factors incorporated and equal percentage weighting of each factor. This model run was chosen to be represented as the developed model run even though it had a low user's accuracy when predicting damage, as all model runs contained this fault.

4.2.3 Comparing model run 5 to the observed damage dataset

When comparing the output of model run 5 to that of the observed damage cause by Gudrun (figure 5), over-prediction and under-prediction of damage is clear within the created model. Figure 10 depicts where these over- and under-predictions of damage occur. The most abundant class in this figure is 'No damage', and this agrees with the user's accuracy for predicting no damage in model run 5, which is up at 89%. The user's accuracy also agrees with the amount of correctly predicted damage, which is at 11%. These are the red regions in figure 10, which are mostly found in the central regions. The over-prediction of damage is quite evenly spread across the county, but with a definite higher concentration in the north-eastern tip. As can be seen in figure 11, the north-eastern tip of the county was placed in the damage class 6 – 8 representing a lot/severe damage. When comparing this to figure 10 it is clear that a lot of this damage prediction is a result of the model over-predicting damage. As for under-prediction of damage, this too is evenly spread across the county, but exists in far less amounts compared to the over-prediction of damage.

4.2.4 Sensitivity testing of model run 5

According to the sensitivity testing, the dataset with most significance was clay content, as the overall accuracy decreased from 76% to 59% when this dataset was removed (table 13). This could be related to the root system types of coniferous trees. Spruce trees are generally regarded to have plate-like root systems with some characteristics from heart-like root systems. The plate-like root system limits root growth to around 50cm depth, whereas the heart-like root system allows root growth to depths of 1m. A study looking at the influence of soil types on the stability of trees concluded that heart-like root systems were more resistant to wind damage on clay-rich soils (Dupuy et al. 2005). This supports the idea that clay content is an important factor to include when modelling the stability of trees. However, the

user's accuracy remained the same (11% for damage and 89% for no damage predictions), which means that the removal of the factor clay content did not alter the accuracies of the damage predictions.

One possible reason as to why the soil type data had very little impact on the user's accuracy in model could be the resolution of the original dataset, which was 500x500m. This was the coarsest dataset included in the model, and since each cell covered a large area within the study area, which is 9,426km^2, the data did not show the change in soil type as well as a dataset at a higher resolution would have done. It would have been interesting to repeat this model with higher resolution soil type data in order to properly analyse the impact of soil type on tree stability.

Only one of the sensitivity tests increased the user's accuracy for damage, and this was test 4, when the factor aspect was removed. However, the user's accuracy only increased by 1%, suggesting that even this factor removal did not greatly alter the model output.

Interestingly enough, the overall accuracy increased from 76% to 83% when the slope dataset was removed. However, at the same time, the user's accuracy for damage decreased to 7%. Since the user's accuracy tells us the fraction of correctly classified cells, it suggests that removing the slope dataset decreased the models accuracy of predicting damage. Also in test 3, the user's accuracy for predicting no damage increased. So what this test run tells us is that the slope dataset increases the accuracy of damage predictions, but decreases the accuracy of no damage predictions.

4.2.5 The NULL model

The null model was introduced to check if the created model predicted damage at a higher accuracy than a completely randomized output, to which the result is that the created model predicted at a very slightly higher accuracy. The user's accuracy from the null model for predicting damage was 9% (table 12), whereas the user's accuracy for damage in model run 5 is at 11%. From this, it can be concluded that the user's accuracy of the created model is not that much better than the user's accuracy of the null model.

Since it is only an increase in 2%, the validity of the model created in this project can be questioned. If time had allowed, several more of these randomised outputs would have been created and compared to the model output, as with only a 2% difference between a random output and a model output, there is a high chance that when compared to several random outputs, they would have a higher accuracy than the model output.

4.3 Applying the model

As there is less overall forest cover according to the 2013 forest cover data (figure S5, appendix), there are more NoData regions present in the future predictions of forest damage in both the model run 5 and run 17 implementations. According to model run 5 predictions (figure 11), the western forests of Kronoberg county are relatively safe, as most of this area received the damage class 2 – 4 (little/some damage). Higher damage predictions (class 6 – 8, a lot/severe damage) begin cropping up in the north-west and central regions, the coverage increasing in an eastward direction. The areas with the most concentrated amount of damage are the central regions of the county, and the north-eastern tip, where most areas are classed with the damage class 6 – 8. A ribbon of dark and light green (representing damage classes 2 – 4 and 5) is visible in the north-eastern section of the county. So from left to right, the damage predictions across the county go from little/some damage – a lot/severe damage – little/some damage – A lot/severe damage.

Model run 5 predicts a spread of differing amounts of damage from wind storms. It points out that the central and north-eastern regions are more vulnerable, and so, require more protection than the western and some eastern sections. The only major anomaly is the damage predictions for the north-eastern tip of the county, as according to the storm damage from Gudrun, this region received some damage, but not nearly as much as the central regions, suggesting that this location is slightly less vulnerable. However, the user's accuracy for predicting damage on which this model run is based was only at 11%.

Model run 17, also implemented on the 2013 forest cover data (figure 12) shows a more severe spread of damage predictions. Whereas the legend in figure 12 states that three damage classes are present, only the most severe one (in this case damage class 6 – 8) is visible. The user's accuracy for damage that this model run is based on is 10%, which is only 1% worse than model run 5. This is interesting as the overall accuracies between these two model runs vary greatly, but their accuracies in predicting damage correctly are similar.

When comparing the prediction model run 5 to the model presented in figure 4 (Ulfves 2015), similarities can be seen. Model run 5 has concentrated amounts of damage predicted in the central regions of Kronoberg around Växjö and Tingsryd (locations can be seen in figure 4). However, the damage predictions for the north-eastern tip of the county are the opposite. The results presented in this study claim that the north-eastern tip will experience damage, whereas the 2015 study claims that this same region is a low-risk zone (Ulfves 2015). One

reason for this could be that the first model run in this report did not include the same factors as the model run from the 2015 study. The factors included in the 2015 study were forest cover, TSC, topographic exposure, aspect and soil depth, whereas model run 1 in this project had the factors forest cover, slope, aspect, sand and clay content.

One aspect that can greatly affect the vulnerability of forests is how they are managed. Most of the productive forest in Sweden is already heavily managed to increase timber production, with a focus on conifer monocultures (Subramanian 2016). Access to information about the management of the forests could improve the accuracy of models such as this one. There are several ideas on how to prepare for future events that may be damaging to forests. An adaptive strategy that can be used in preparation is to promote the resilience of the forests. This is done in hopes of making forests mode accommodating to changes, such as stronger wind storms or other disturbances. To achieve this, intensive management is required during the first few years since the planting of seedlings. Another way to promote stability of forests is to introduce more species, such as hybrid aspen or hybrid larch, which are less susceptible to storm damage as they lose their leaves during the winter months in Sweden, when strong wind storms are more frequent (Subramanian 2016). Studies have found that the mechanical stability of spruce increases when mixed with other species such as birch or pine. One study found that the susceptibility of wind throw of spruce decreased by 50% when it was grown in forests where 30% was covered by broadleaf trees (Felton et al. 2016). However, as the information about how the forests are (or are not) being adapted or defended for future storms was not readily available, it was not incorporated into the model. The results from model 5 suggest that storm damage could be limited by planting spruce in more clay-rich soils avoiding slopes and probably in mixtures with other tree species

4.4 The datasets

In this section I will go through and briefly discuss how the weights for some datasets could have been developed more. There were some contradictory points found in the literature study for how some of the factors should have been weighted.

A lot more work could have been done in investigating exactly how each factor works with the other factors, and deeper literature studies into what weight may be good for the classes within each factor. Almost an endless amount of model runs could have been done since the classes within each factor had to be assigned a number between 1 and 9, and all manner of

combinations could have been run. However, due to time pressure, this was not possible, so only 17 runs were made when developing the model.

For the aspect factor, the ‘exposed’ slope direction can be discussed. According to (Brunet et al. 2013), the most exposed locations to strong winds are at the top of hills, and at the bottom of the downslope, in this case, the bottom of east sloping hills. This is because winds are most turbulent at the top of a hill, become slightly more gentle going down the other side of the hill (along the ‘less’ exposed slope direction: E and N facing slopes in this report), then become turbulent again at the bottom of the hill (Brunet et al. 2013). This suggests that all east-facing slopes should have received a higher weight than 1, as they may also be more ‘exposed’ to strong winds than originally thought.

As for slope, there seem to be a few contradicting views on how it affects the vulnerability of forests to wind damage. One test, made in 2005 was to see how the vulnerability of Sitka spruce (*Picea sitchensis*) on flat areas compared to the vulnerability to the same trees found on slopes with a ca. 30° angle. The main results were that there was no overall difference in the anchorage of the trees found at both slope angles (Nicoll et al. 2005). However, in this report the slopes between 0 – 6° have been classed as ‘unstable’ and assigned a weight of 9. These slopes were chosen to represent more vulnerable regions, in contrast to the findings of (Nicoll et al. 2005) as two other studies (Schütz et al. 2006; Nilsson et al. 2007) found that most damage to trees from severe wind speeds were recorded in gently sloping regions.

The soil depth classes were adopted from a previous study performed in the same county (Ulfves 2015). However, in other work it is stated that 80 – 90% of major root distributions are commonly located in the top 60cm of soils (Crow 2005). This is what prompted the choice in weight for the second soil depth class in this report. Unfortunately, 99% of the study area had a soil depth of 0 – 25cm, which meant that 99% or the study area received a weight of 9 from this factor. It seems somewhat counter-intuitive that this area would be covered in forest – mostly managed, if the soil depth is insufficient for the trees roots to develop properly.

Soil moisture content is an important factor in how stable a tree or forest stand is during a storm. Firstly, high soil moisture content can directly affect the spread and growth of roots (Crow 2005), and waterlogging of soils leads to less oxygen being readily available, leading to root death (Stofko and Kodrik 2008). Another factor, within soil moisture content, that would have been interesting to study would have been the amount of precipitation that

occurred before the storm Gudrun in 2005. This may have given an idea of how saturated the soil was at the time of the storm, which may have affected the stability of the forest in Kronoberg. This may have been useful when trying to pinpoint what factors affect the stability of forests more than others, but this would be difficult to implement on future storms. This is because to do so, we would need accurate predictions for exactly where and when a storm would hit, and in enough time in advance so that precipitation levels could start being recorded in the regions predicted to receive the most damage to forests. So, it would have been interesting to explore precipitation levels as a factor, but would most probably not be possible.

The root area ratio of a tree increases with the age of the tree and since with more roots comes a higher anchorage capacity, older trees with many roots are less susceptible to being wind-thrown. Of course, root binding also relies heavily on the type of soil, as shallow soils that are poorly drained result in shallow roots, which makes trees in such locations more susceptible (Coder 2010). However, the stand age data were not used in the model. This would have been an interesting factor to add as it would have combined well with soil type and soil moisture content, maybe to give a better prediction of the damage spread as the amount and depth of roots increase with age.

Another factor that may have been very closely linked to the stability of trees, is the temperature of the soil – was the soil frozen or thawed during the storm? As severe storms in Europe usually occur in the winter months, there is a chance that soils are frozen when such storms hit. If the soils are frozen, trees are more likely to snap than uprooted, which would require a higher wind speed for such damage to occur (Peltola et al. 2000).

As mentioned earlier, the slenderness ratio can be used to identify how stable a tree is according to its diameter and height. In this study, it is applied to forested areas, but according to other studies, the threshold for what is considered stable and unstable with this ratio changes depending on whether the trees examined are in a rural or urban location. In urban areas, all trees above the value 50 are considered unstable (Mattheck et al. 2003), a lower value compared to the threshold in rural areas, which is 80 (Moore 2014).

4.5 Limitations

4.5.1 Availability of data

Greater accessibility to data could greatly improve this study. Having the same data at several different resolutions could also improve it as more tests could be run assessing how a

change in resolution could affect the final result. Also, having data from different storms, such as the storms in 2007 and 2015, would have made it possible for more comparisons to be made between predicted storm damage and observed storm damage, rather than only looking at Gudrun, the 2005 storm. This may have helped increase understanding in how the factors affect storm damage to forests.

As mentioned earlier, new factors were entered into the model from run 7 and onwards. Several of these factors (forest volume, average tree height and average tree diameter) were made up of data collected in 2015. As these factors link directly to the amount of forest as well as the shape of the tree, they could be a major source of error for the damage prediction results for Gudrun in 2005 as they are implemented on forest cover from 2000. This is because the scales of these factors will have been altered after all the storms (including Gudrun) that have impacted the county up until 2015. However, these factors will be less of a source of error when implemented on the 2013 forest cover (for the future predictions of damage) as this dataset is a more recent version of the forest cover.

4.5.2 Combine

The thresholds defined in the technique combine, used to try and validate the model could also be the reason as to why the accuracies of predicted damage is low in each test. The dataset used for validation was a raster image that showed damage or no damage across the study area. There were no 'in-between' classes, which means that it was difficult to compare it to a model result that produced a scale of damage. As mentioned earlier, to compare the predicted results to the actual observed damage, the predicted results had to be changed into the damage/no damage classes that the observed results were in. The values 1 – 9 present in the model runs were converted into either a 1 for damage, or a 0 for no damage. It was decided that the upper range of values (7 – 9) would receive a 1 for damage as they represented the areas that were more likely to experience damage. However, there is a varying degree of damage between the classes 7 – 9, but this is not taken into consideration in the validation as the observed damage layer had no such scale. This is where some error may have occurred. Regions where the model predicted 'damage' and 'extreme damage' were merged into one class, which does not help in properly representing the spread of damage. Similarly, all the values below 6 received a 0 for no damage; however, only the value 1 in the model represents no damage, whereas the values 2 – 6 represent little/moderate damage.

5. Conclusion

All the model results presented in this thesis do not reliably predict the risk of storm damage, which suggests that future research needs to be conducted.

How to prepare for storm events will be heavily related to the management of the forests and the adaptive measures that are taken. The models here only give a tentative idea of how the spread of damage may look. Model run 5 predicts that most damage will occur in the central and eastern regions of Kronoberg county. Compared to other models, this model focuses more on the abiotic factors that influence the stability of a tree.

The addition of factors such as soil water saturation content and forest management could improve the damage predictions. Also, considering how other factors incorporated in the model, such as soil type, seem to have little effect on the damage predictions; they could be removed in order to simplify the model.

As for resolution of data, although the tests performed in this thesis (at resolutions 50x50m and 100x100m) yield little difference, it would be interesting to implement the model using coarser resolutions. The resolution 50x50m is high if this model is to be implemented on a larger scale than simply in one county, as is done here.

To conclude, the model created is not particularly useful as it can only predict damage with a 2% higher accuracy than a randomised dataset. However, there is a definite pattern of damage created from this model that is not random.

"All models are wrong, but some are useful"
George E. P. Box

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7. Appendices

7.1 Data sources

Table S1. All the data sources, data types and original resolutions

Data				
File	**Type**	**Description**	**Geometric resolution**	**Source**
stormfg	Raster	Difference analysis using sattelite data from 2004 & 2005	10x10m	Skogsstyrelsen
sksSkogligaGrunddataHgv07	Raster	Average tree height 2015	12.5x12.5m	Skogsstyrelsen
sksSkogligaGrunddataDgv07	Raster	Average tree diameter 2015	12.5x12.5m	Skogsstyrelsen
sksSkogligaGrunddataVol07	Raster	Volume forest 2015	12.5x12.5m	Skogsstyrelsen
Markfuktighet	Raster	Soil moisture content	2x2m	(Patrik Olsson, Skogsstyrelsen. pers. Comm)
hojddataGrid50	Raster	Digital Elevation Model	50x50m	https://atlas.slu.se/get/
g100_00	Raster	CORINE land cover 2000	100x100m	http://www.eea.europa.eu/
g100_06	Raster	CORINE land cover 2006	100x100m	http://www.eea.europa.eu/
Clay_EU23	Raster	Clay content in %	500x500m	European Soil Data Centre (ESDAC)
Sand_EU23	Raster	Sand content in %	500x500m	European Soil Data Centre (ESDAC)
Silt_EU23	Raster	Silt content in %	500x500m	European Soil Data Centre (ESDAC)
Jorddjup_1409_3006	Vector	Soil depth data		https://atlas.slu.se/get/
World Forest 30m BaseVue 2013	Vector	Forest cover 2013		http://www.mdaus.com/

7.2 Factors used in the model

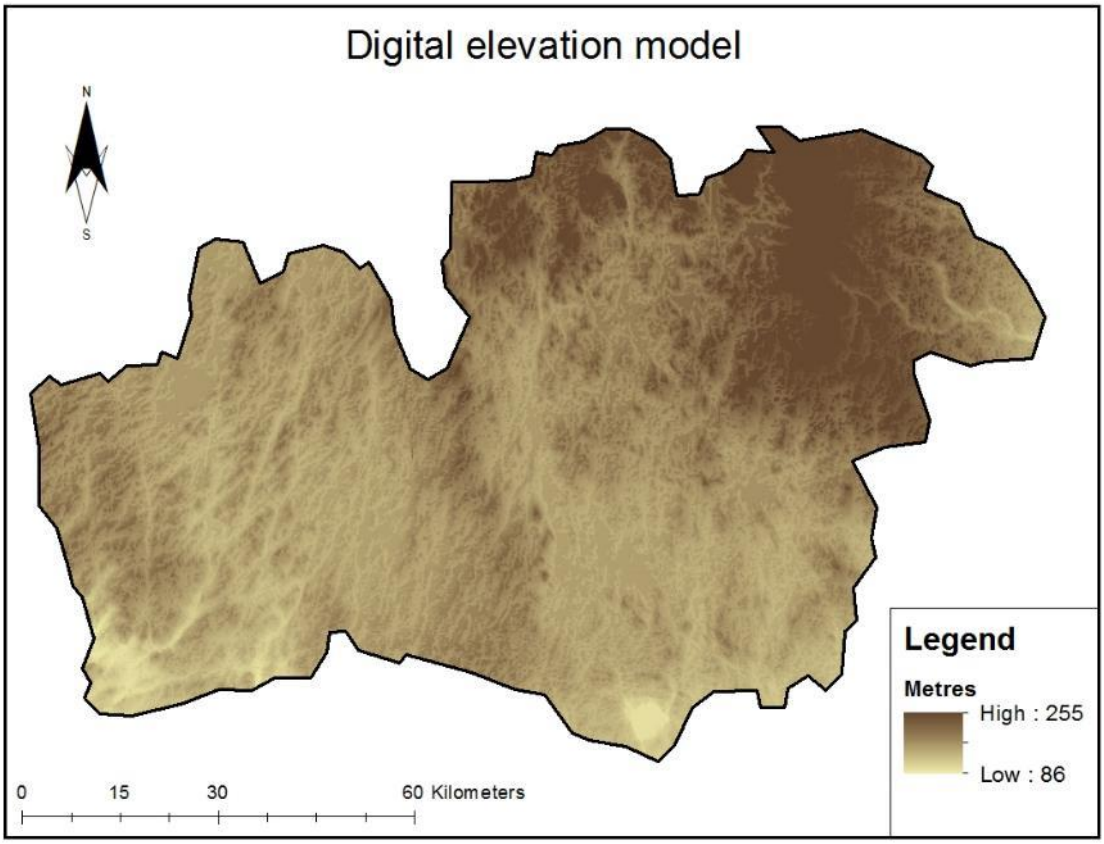

Figure S1. The digital elevation model for Kronoberg county

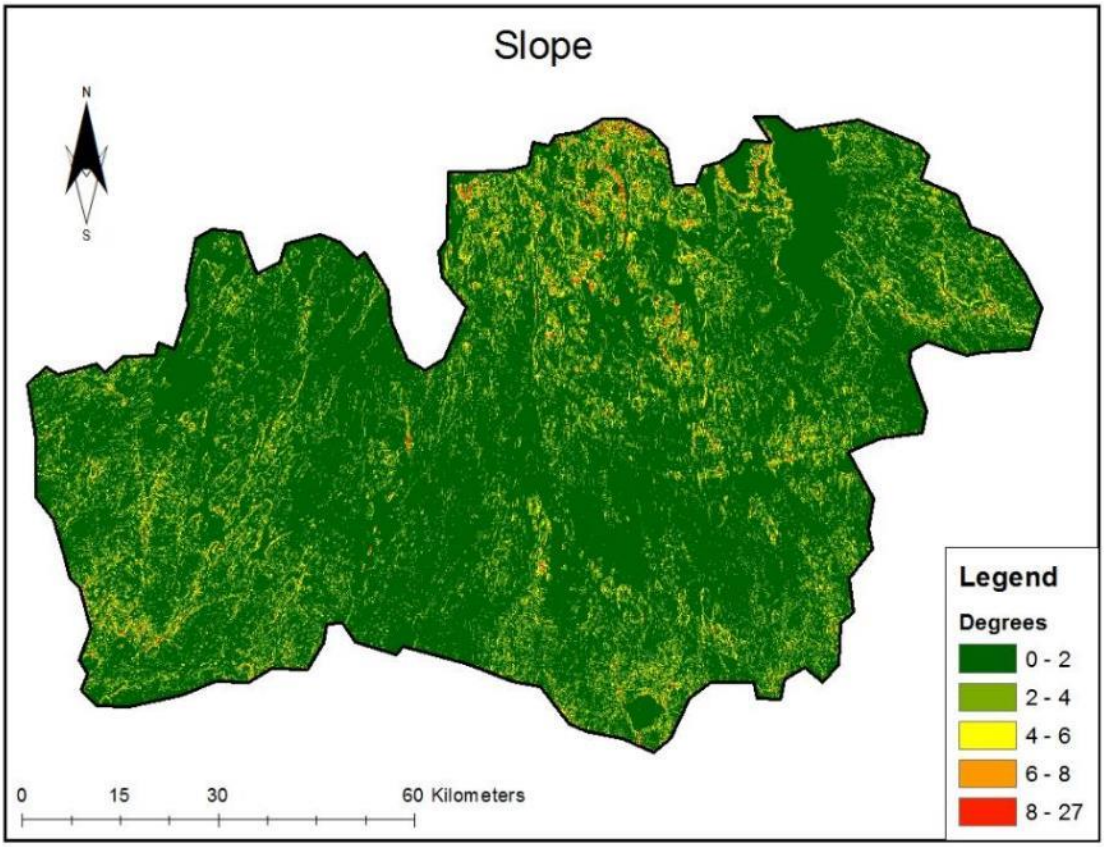

Figure S2. The factor slope expressed in degrees

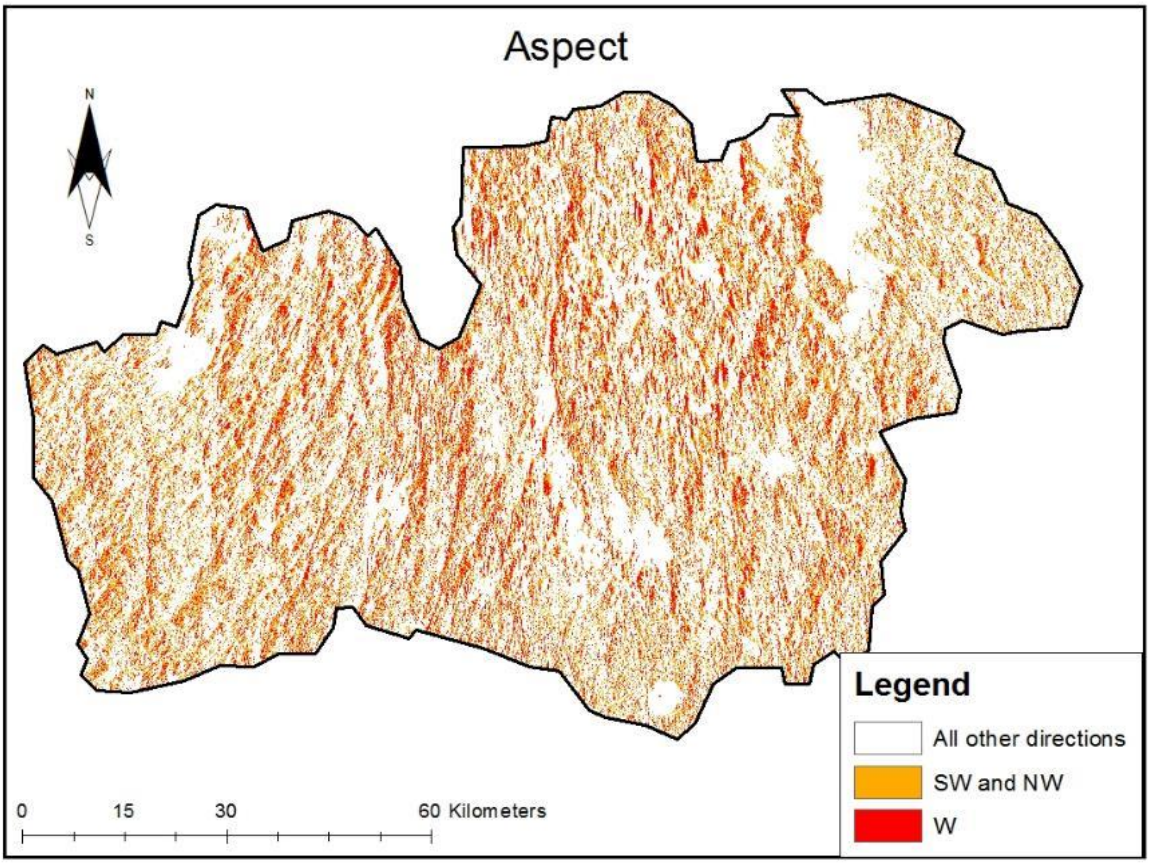

Figure S3. The factor aspect, reclassified to highlight the aspects of interest in this study

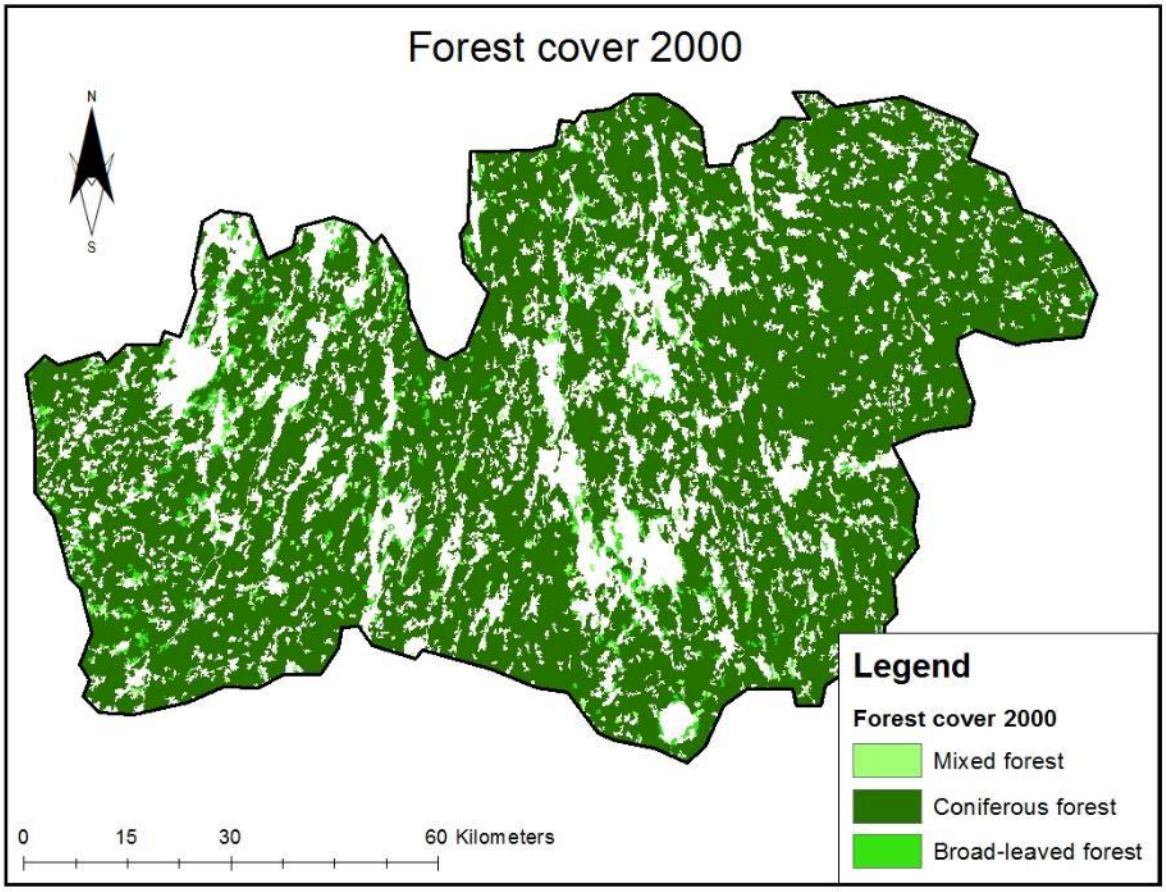

Figure S4. The factor forest cover 2000 divided into three types of forest cover; mixed, coniferous and broad-leaved. The most extensive forest cover is coniferous forest.

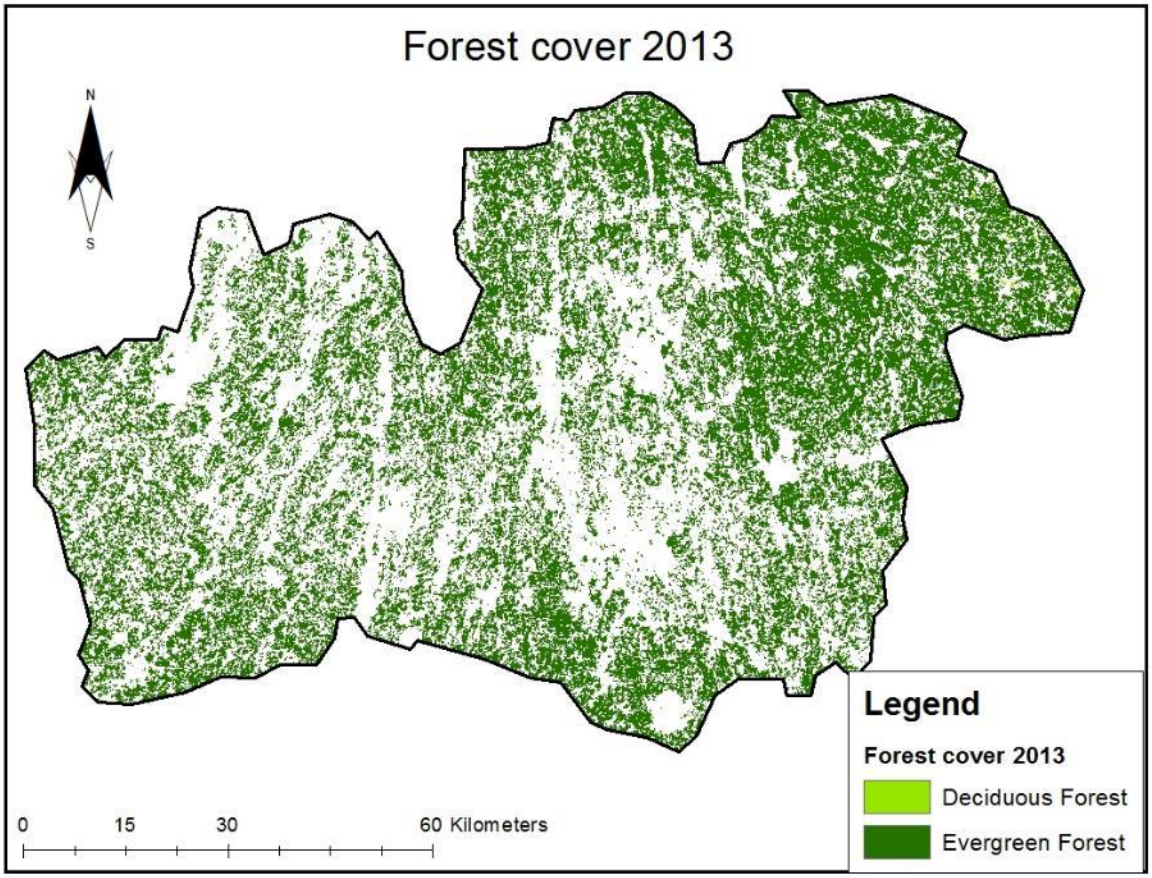

Figure S5. The factor forest cover 2013 divided into two types of forest cover; deciduous and evergreen. The most extensive is evergreen forest.

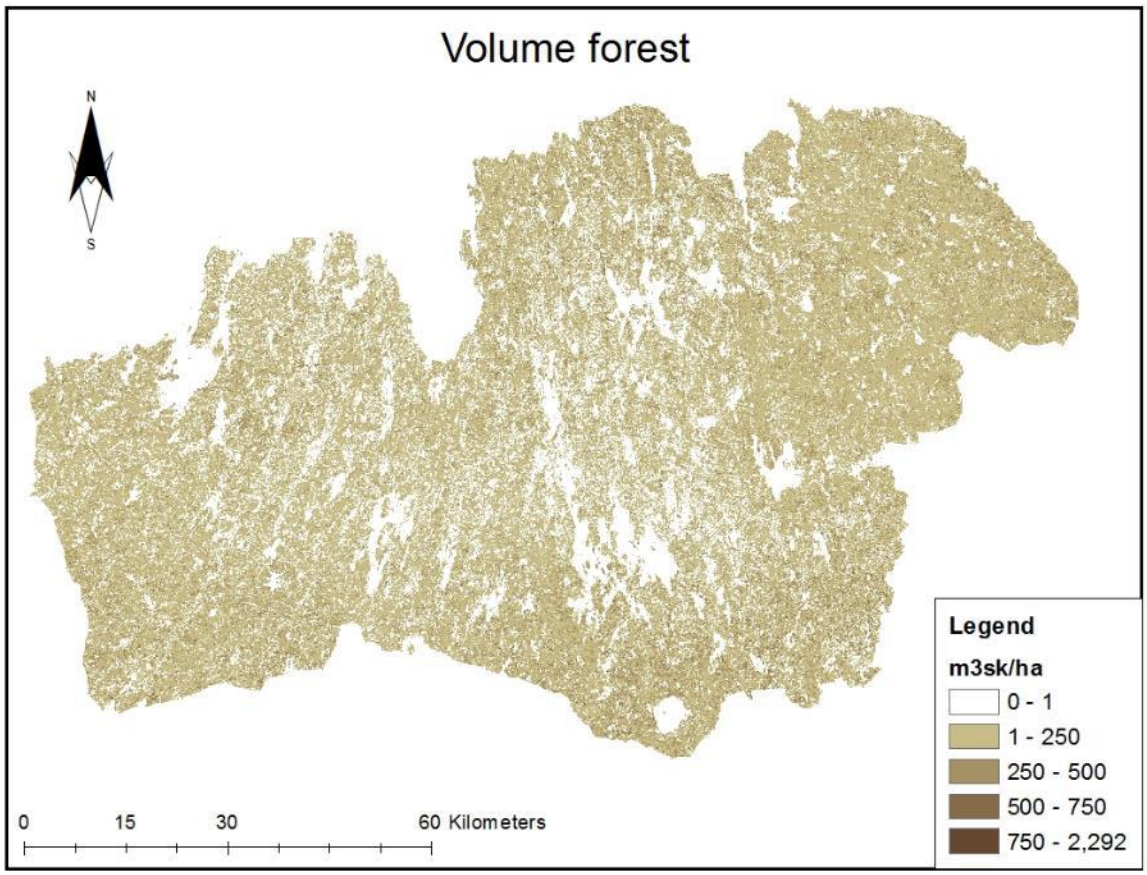

Figure S6. The factor forest volume expressed as m3sk/ha

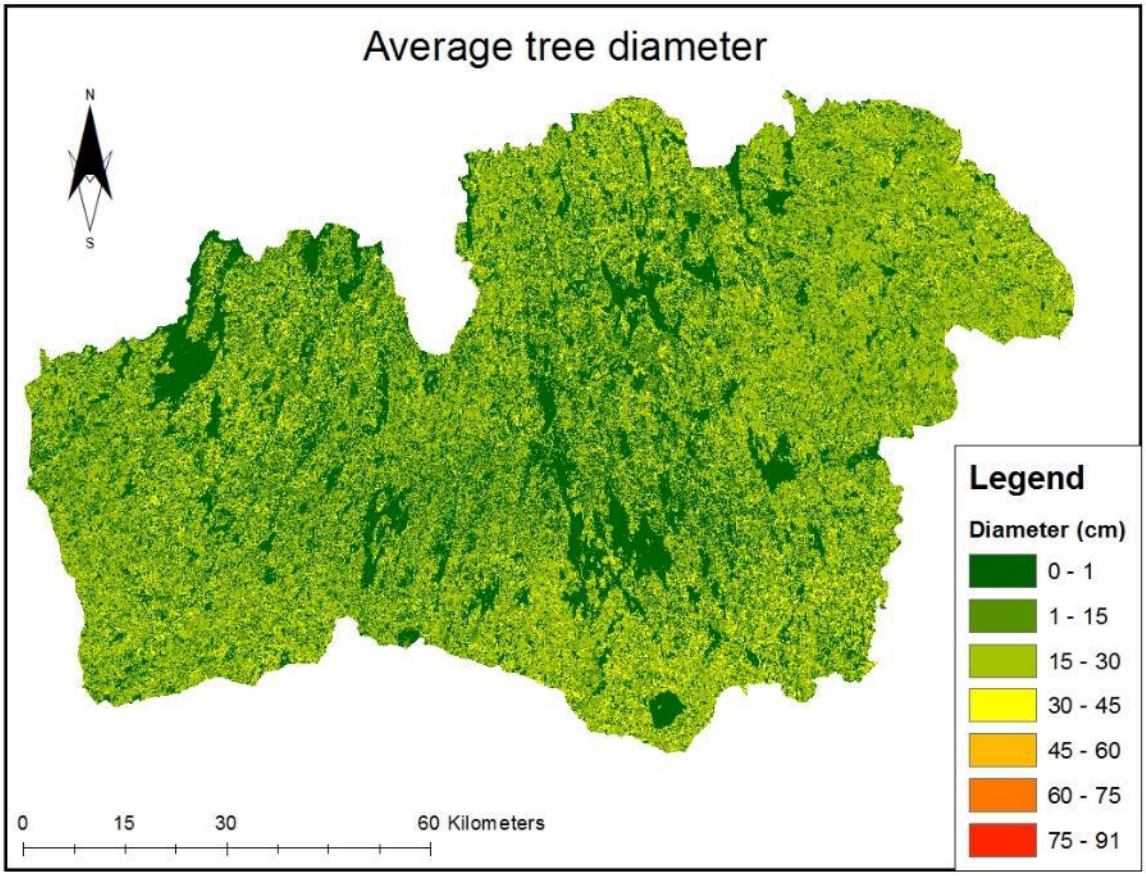

Figure S7. The factor average tree diameter expressed in cm

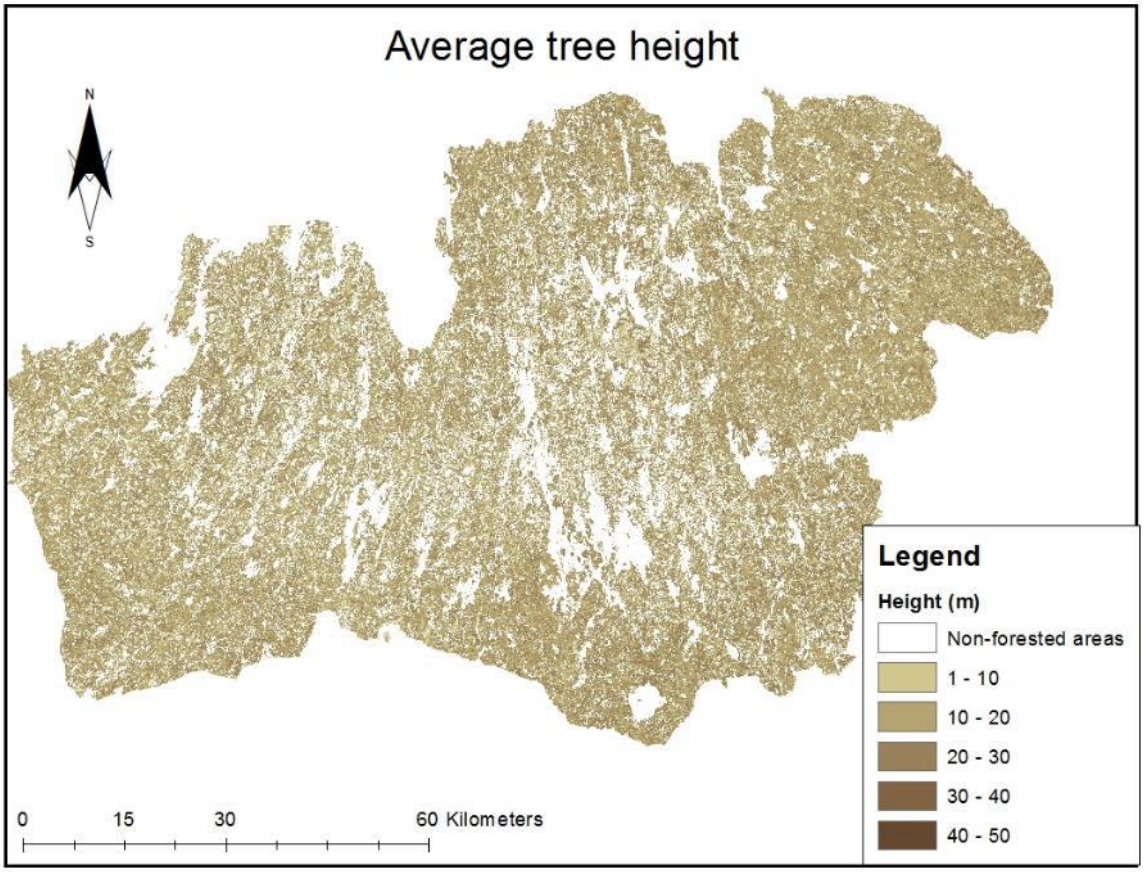

Figure S8. The factor average tree height expressed as height in meters

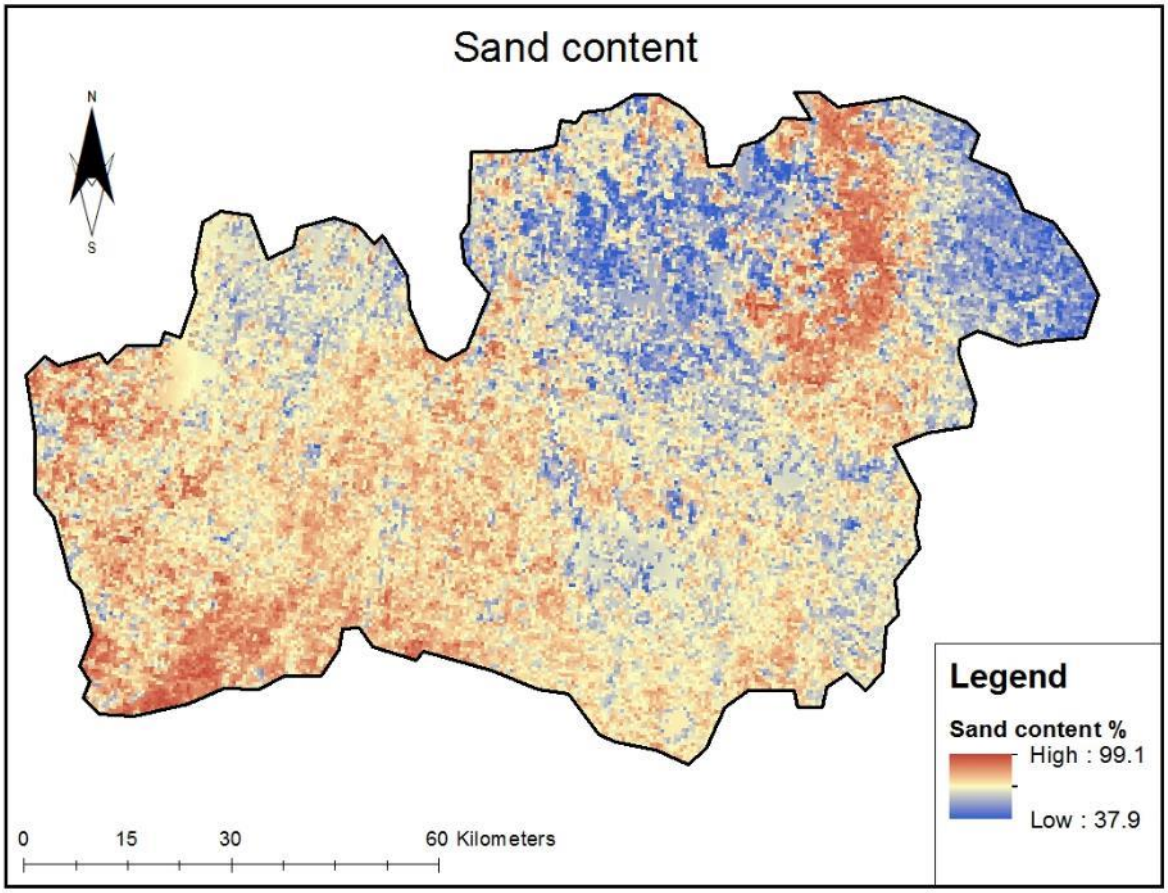

Figure S9. The factor sand content expressed as a percentage

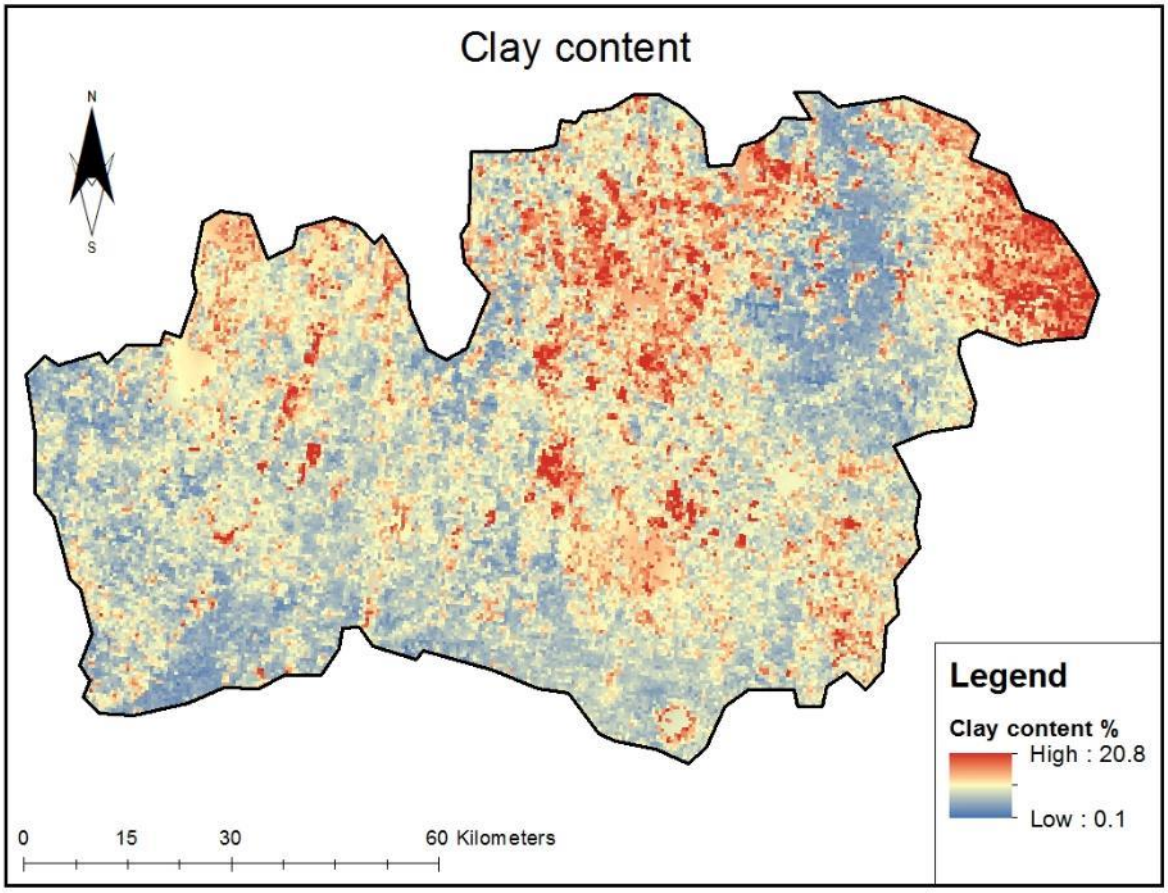

Figure S10. The factor clay content expressed as a percentage

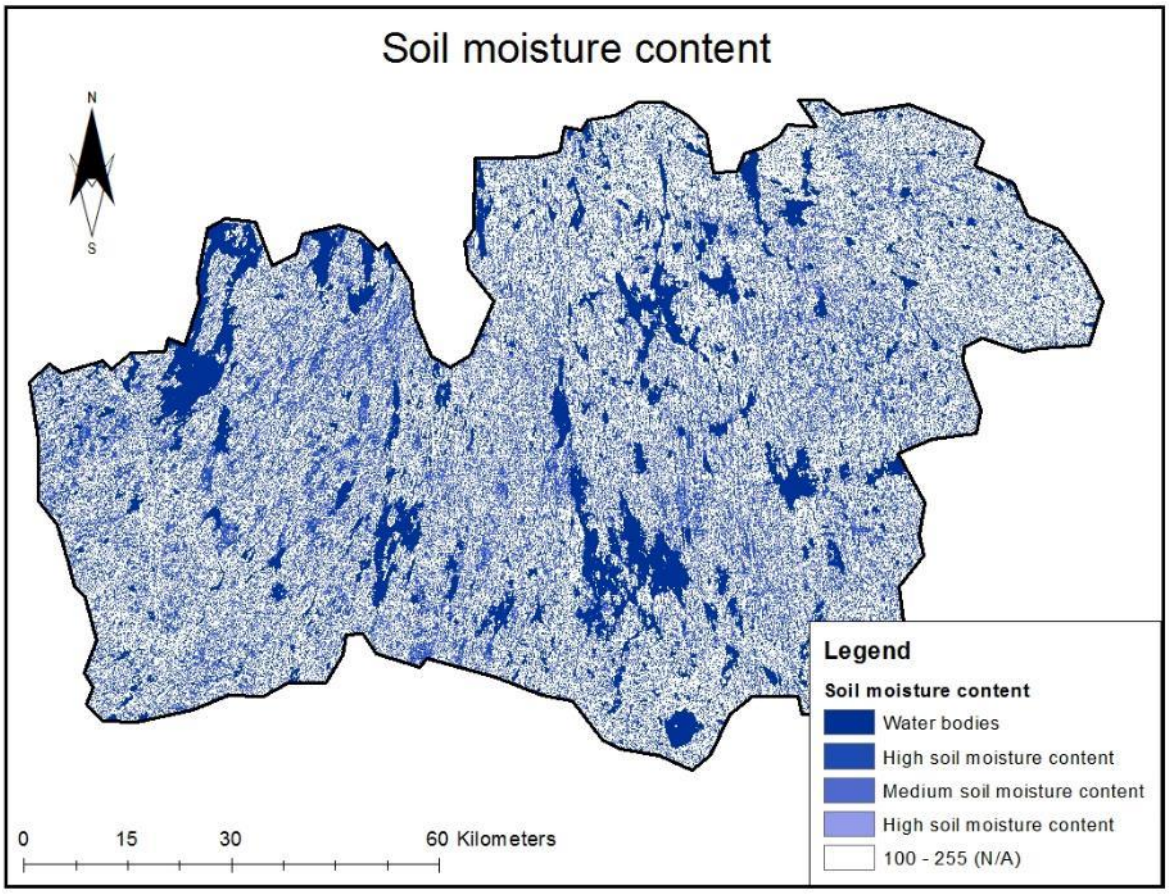

Figure S11. The factor soil moisture content divided into 5 classes where the dark blue represents water bodies. The other classes are divided into high to low soil moisture content, where the darker colours have a higher soil moisture content.

7.3 Assigning weights to the factors

7.3.1 The fundamental scale

Table S2. The range of weights to be assigned to the factors (Malczewski 1999)

The fundamental scale	
Intensity of importance	**Description**
1	Equal importance
3	Moderate importance of one factor over another
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values
Reciprocals	Values for inverse comparison

7.3.2 The weights assigned to the scale within each factor

Table S3. The assigned weight of each scale within the factors

Assigned weights			
Factor	**Range/description**	**Susceptibility**	**Intensity of importance**
Forest cover 2000	Coniferous	Most vulnerable	9
	Deciduous	More stable	5
	Mixed	Least vulnerable	1
Forest cover 2013	Evergreen	Most vulnerable	9
	Deciduous	More stable	5
Aspect	N, NE, E, SE, S	Not exposed	1
	SW, NW	Exposed	5
	W	Very exposed	9
Slope	0 – 6	Unstable	9
	6 – 27	Stable	1
Tree slenderness coefficient	< 80	Stable	1
	80 > < 100	Unstable	7
	> 100	Very unstable	9
Average tree height	1 - 10m		1
	10 – 20m		1
	20 – 30m		5
	30 – 40m		7
	40 – 50m	Unstable	9
Average tree diameter	1 – 15 cm	Unstable	9
	15 – 30 cm		7
	30 – 45 cm		5
	45 – 60 cm		3

	60 – 75 cm		2
	75 – Max	Stable	1
Volume forest	1 – 250	Sparser forest	9
	250 – 500		7
	500 – 750		5
	750 – Max	Dense forest	1
Sand content	37 – 50%	Unstable	9
	50 – 65%		7
	65 – 80%		5
	80 – 99%	Stable	1
Clay content	0 – 5 %	Stable	1
	5 – 10%		5
	10 – 15%		7
	15 – 20%	Unstable	9
Soil moisture content	1 – 30	Wet	9
	30 – 60	Moist	5
	60 - 100	Dry	1
Soil depth	< 25 cm	Very restricted rooting	9
	25 – 50 cm	Somewhat restricted rooting	3

7.4 Calculations

The slenderness ratio:

$$Slenderness\ coefficient = \frac{Tree\ height}{Tree\ diameter\ at\ breast\ height\ (DBH)} \qquad (1)$$

The equation for overall accuracy:

$$Overall\ accuracy = \frac{TN + TP}{Sum\ of\ cells} x\ 100 \qquad (2)$$

Using the values from table 7, the calculation for overall accuracy would be:

$$\frac{1357097 + 1441168}{2817113} x\ 100 = \mathbf{53}\% \qquad (3)$$

Using the values presented in table 7, the equation outlines the calculation for user's accuracy when predicting damage.

$$\frac{144186}{1160074 + 144168} x\ 100 = \mathbf{11}\% \qquad (4)$$

The following equation represents the calculation for user's accuracy when predicting no damage using the values from table 7.

$$\frac{1357097}{1357097 + 155774} x100 = \mathbf{90}\% \qquad (5)$$

The following equation represents the calculation for producer's accuracy when predicting no damage using the values from table 7.

$$\frac{1357097}{1357097 + 1160074} x100 = \mathbf{48}\% \qquad (6)$$

The following equation represents the calculation for producer's accuracy when predicting no damage using the values from table 7.

$$\frac{144168}{155774 + 144168} x100 = \mathbf{54}\% \qquad (7)$$

7.5 How each model run was altered

Table S4. Description of how each model run was altered

Model run	How the run was altered relative to Model Run 1
1	First model run.
2	The resolution of this model run was changed from 50x50m to 30x30m.
3	The exposed aspect directions were swapped with the non-exposed directions to see how much it would alter the result. The east facing slopes were classed as exposed and the west facing slopes were classed as not exposed.
4	The percentage weight for the forest cover 2000 factor (which previously had a weight of 30%) was changed to 20% and the aspect factor weight was changed from 20% to 30%.
5	All the factors received a percentage weight of 20%.
6	The range of values used for the validation was changed. Instead of classing everything with a value of 6 and above as 'damage', everything with a value of 7 and above was used to try and decrease over-prediction of damage.
7	The factors average tree height, average tree diameter and soil moisture content were added.
8	The weights within the aspect factor were re-classed. The NW and SW weights were changed from 7 to 5, in order to try and decrease the over-prediction of damage.
9	The factors slope and forest volume, were removed to see how much they affected the result. They were added again for the next run.
10	The factors sand and clay content were removed to see how much they affected the result. They were added again for the next run.
11	The factors average tree height and diameter were merged in the TSC. The factor forest volume was removed again. Forest volume was not re-added for the next runs.
12	The weights within the TSC factor were re-classed. The class 80 > < 100 was changed from a weight of 5 to a weight of 7 in order to better predict damage.
13	The factor forest volume was added again.
14	The percentage weight for forest cover (which was originally 30%) was reduced to 20% - matching the weights of several other factors rather than being higher than them.
15	The factor aspect received the highest percentage weight of 30%
16	The factor soil depth was added
17	The factors average tree height and diameter were used instead of the TSC

7.6 The null model

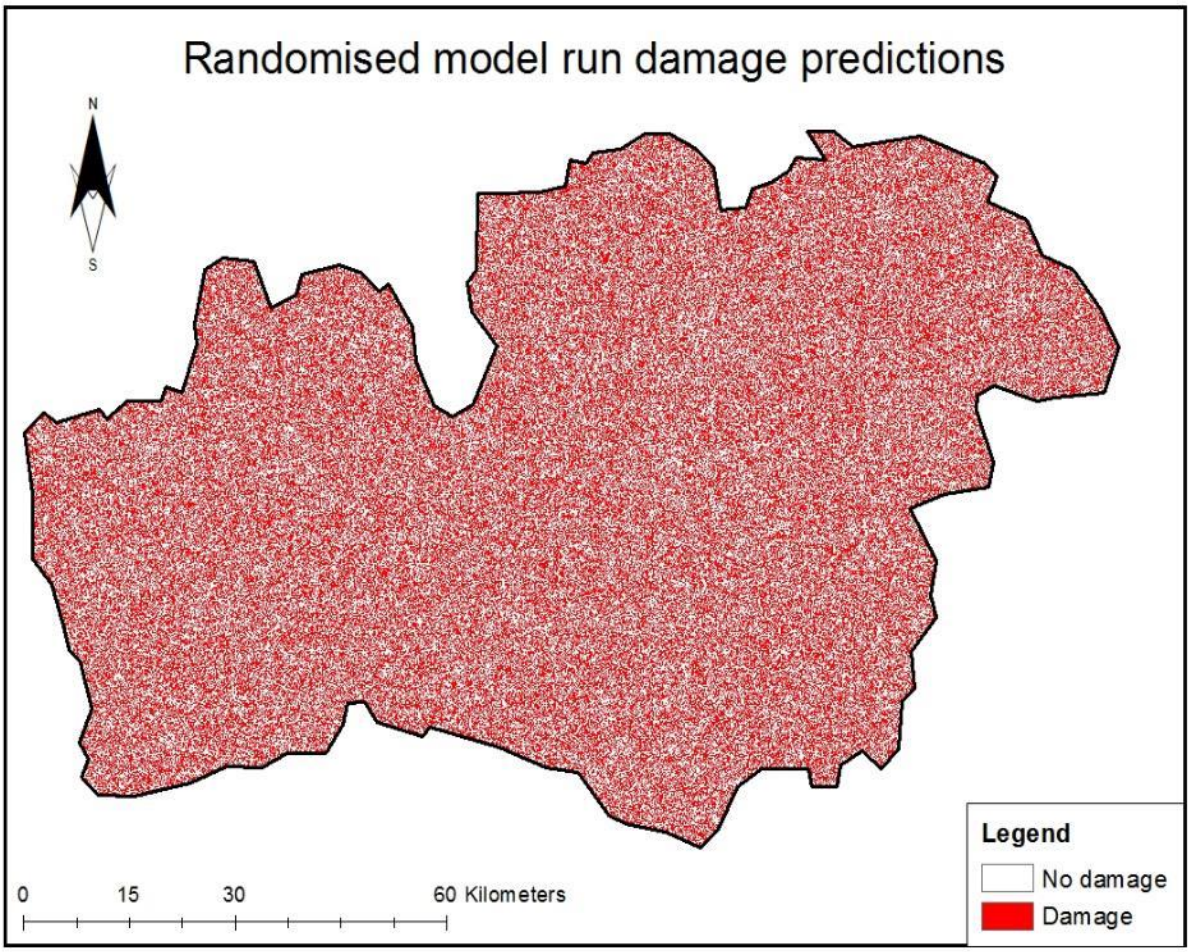

Figure S12. The randomised model run

7.7 The damage reclassifications of model run 1, 5 and 17

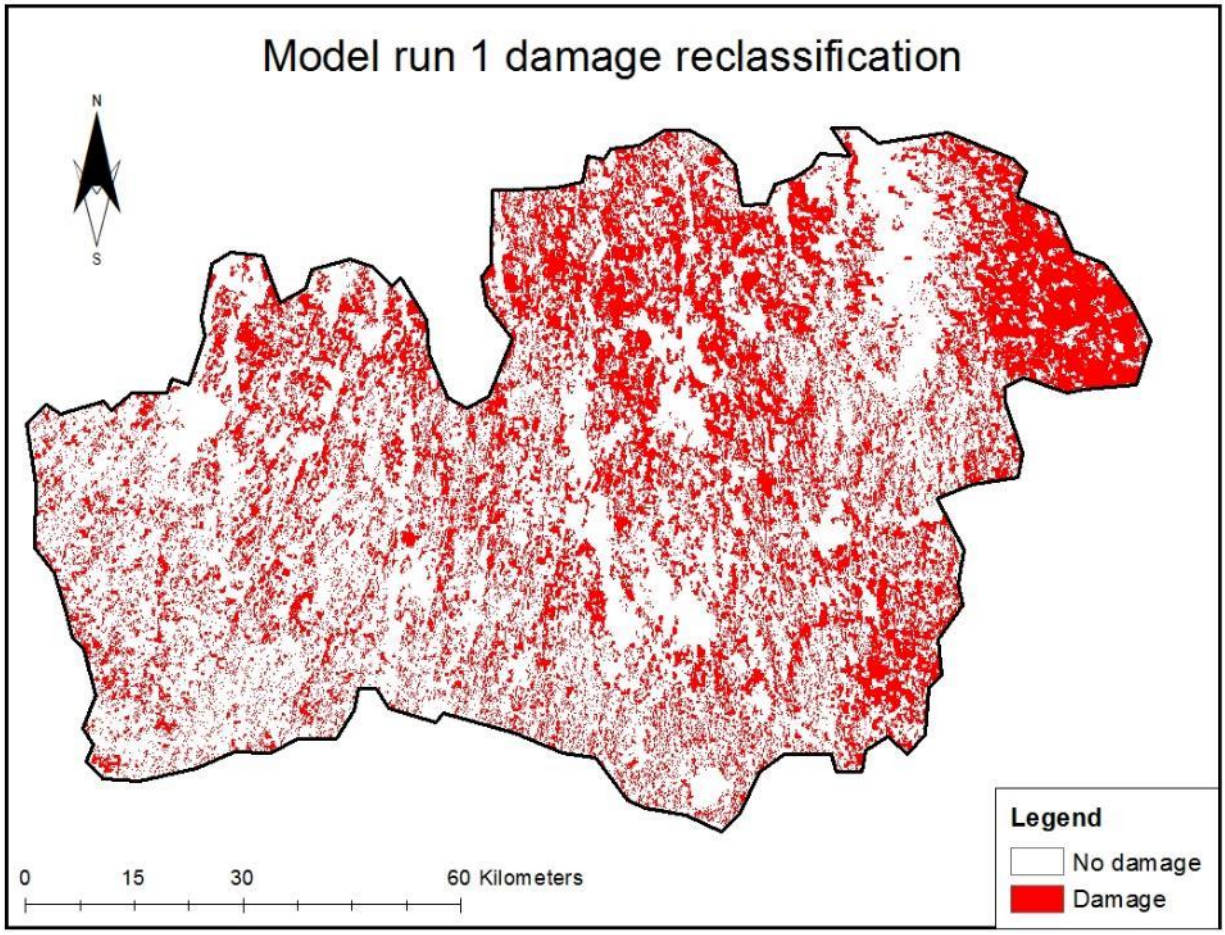

Figure S13. The damage reclassification of model run 1. This is the result when all the values 7 and higher were classed as damage, and the values 6 and lower were classed as no damage

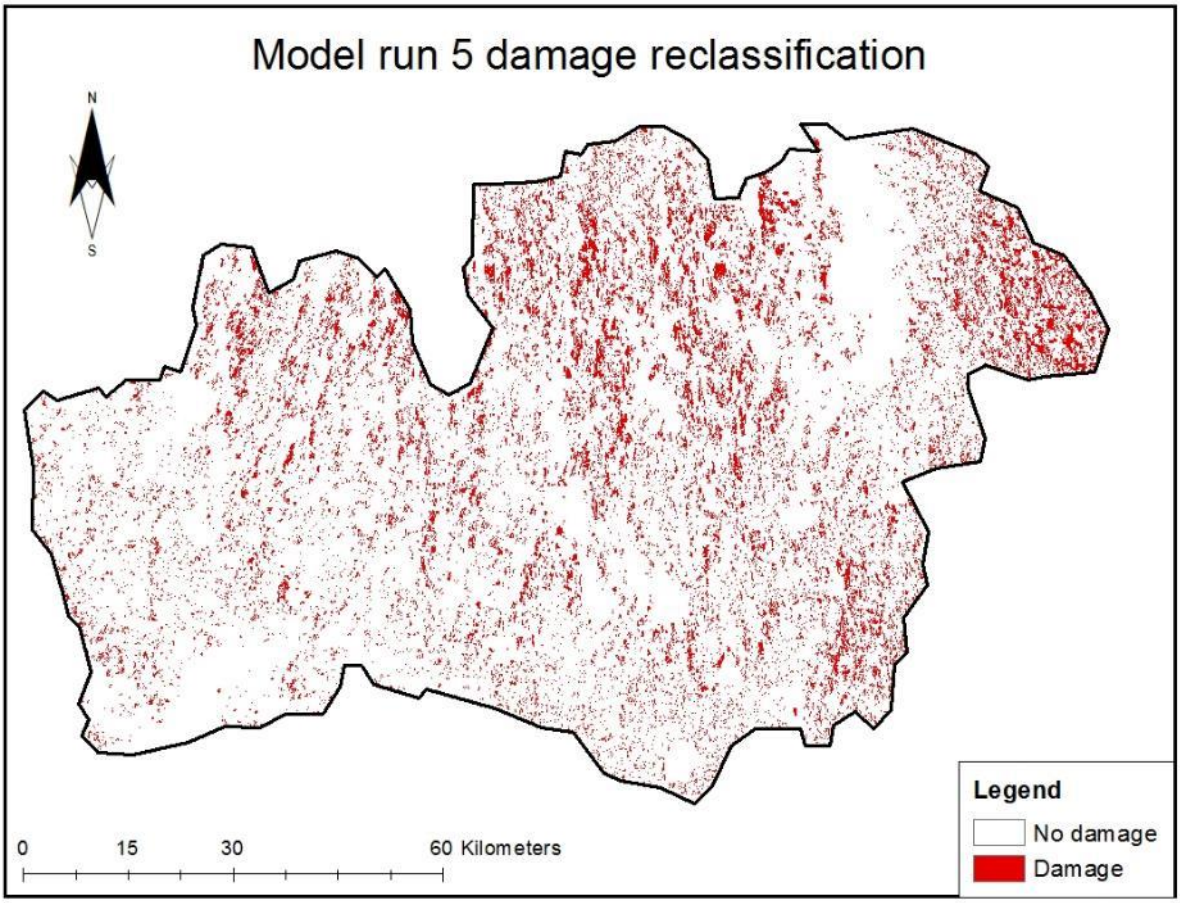

Figure S14. The damage reclassification of model run 5. This is the result when all the values 7 and higher were classed as damage, and the values 6 and lower were classed as no damage

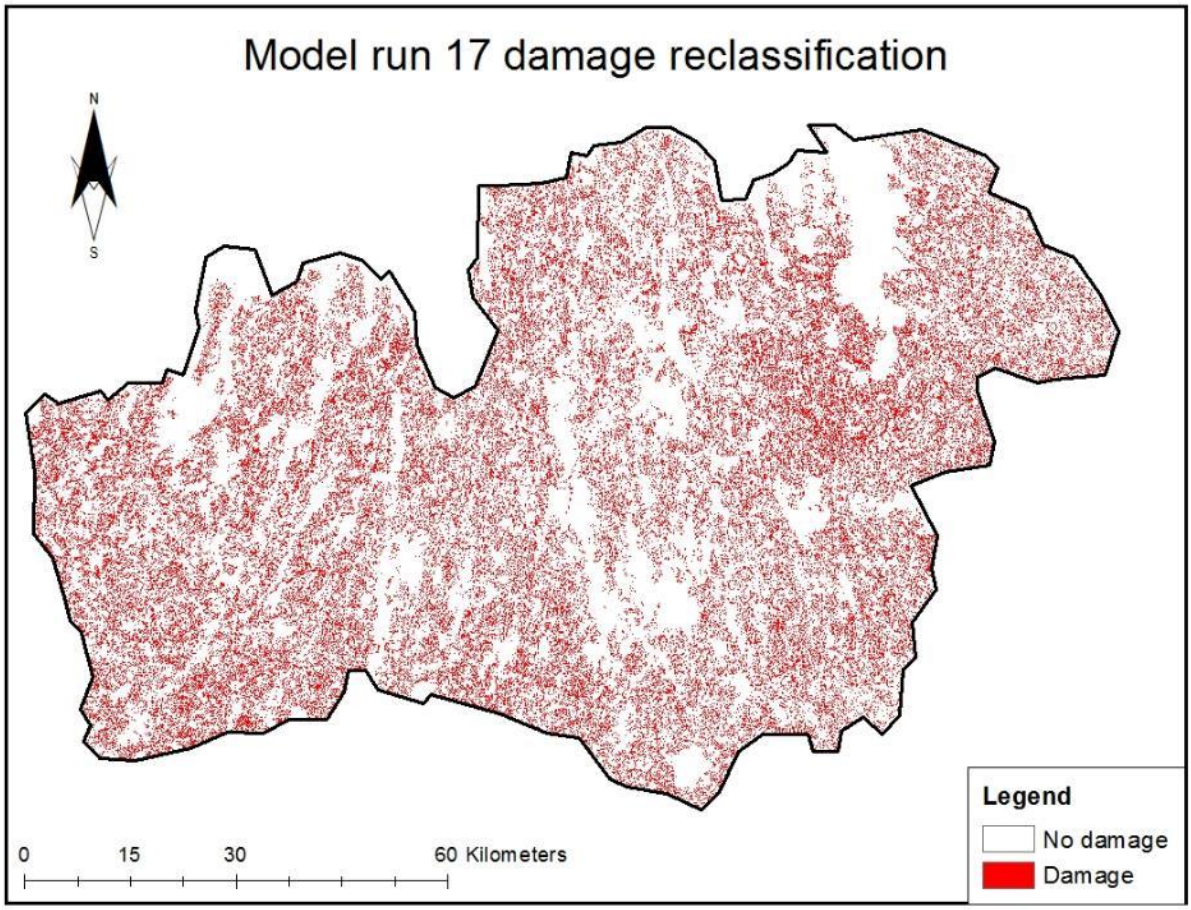

Figure S15. The damage reclassification of model run 17. This is the result when all the values 7 and higher were classed as damage, and the values 6 and lower were classed as no damage

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