Estimating peat occurrence by using remotely sensed data at Skrimfjella, Norway

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Master Thesis in Climate Change Management

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Western Norway University of Applied Sciences

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Preface

I would like to offer my special thanks to my main supervisors Knut Rydgren and Inger Auestad, for their help and enthusiasm related to the thesis. The same applies for Mette Kusk Gillespie and Julien Vollering, for their special knowledge in geophysics and statistics.

Additional thanks to Stein Joar Hegland and Mark Gillespie for showing interest in the thesis.

I would also like to thank my fellow students, mainly Karl-Kristian Muggerud for the data collection period and the support in various stages of the thesis. Thanks to the other students of the MCCM class for making me feel welcome and allowing me to tag along for various activities.

This thesis has a sister thesis focusing on peat occurrence in the same study area. It is recommended to read both dissertations to get the full picture of peatlands in Skrimfjella.

Abstract

Peatlands are undeniably an important asset in climate change management. Still, even today many of the natural peatlands in Norway are in danger of being dried in order to build new cabins, highways or wind parks. Traditionally, confirming peat occurrences can require some extensive fieldwork. Traversing the areas by foot has for long been the only method of locating new peat deposits in an accurate way. This study aims to discover and confirm if remotely sensed data could be used to find new peat deposits reliably. Recently, LiDAR and radiometric (gamma-ray spectrometric) data have shown potential, and this is a first time researching peat occurrence in a study area with such a great variation in topography.

The characteristics of the study area in Skrimfjella inspired the predictor selection used in this thesis. 106 peat occurrence points and 123 added positive occurrence points (from peat depth measurements) were visited in the study area and examined in relation to the Digital Elevation Model-derived predictors: elevation, slope, topographic wetness index, heat index and aspect favorability. Additionally, the radiometric predictors uranium, thorium and potassium as well as the combination of these three were used for modeling of the relationships between the predictors and the occurrence points. Slope, topographic wetness index and elevation had the most explanatory value, while uranium was the most predictive radiometric predictor. The final model included these predictors and only had a sensitivity of 0.28, meaning that the model could only identify 28% of the existing peat. The specificity was 0.96, meaning that when the model identified peat, it was typically right. Model accuracy was 50%. The failure of the radiometric predictor performance could be traced back to the various bedrock types affecting the spectrometer measurements in Skrimfjella. The better performance of the topographic predictors not based on aspect, is likely due to the variable characteristics in the study area. With proper spectrometer calibrations and a decent sample size, using remotely sensed data for estimating peat occurrence has a great potential for peatland management and therefore, climate change mitigation.

Samandrag på norsk

Torvmark spiller unektelig en viktig rolle innen planlegging for klimaforandringer. I Norge er fortsatt mange av de naturlige torvmarksområdene utsatt for drenering, dette som følge utbygging av hytter, motorveier og vindparker. Tradisjonelt har ofte omfattende feltarbeid vært nødvendig for å nøyaktig bekrefte forekomst av torv. Herunder har det å nå områdene til fots vært den eneste måten å lokalisere forekomstene på. Denne studien tar sikte på å undersøke om fjernmålte data kan brukes til å avduke forekomst av torv på en pålitelig måte. Nylig har LiDAR- og radiometriske (gammaspektrometri) data vist potensiale, dette vil være den første gangen torvforekomst har blitt forsket på i et studieområde med tilsvarende variasjon i topografi.

Studieområdets karaktertrekk har inspirert utvelgelsen av prediktorene. Innenfor dette området ble 106 punkter for torvforekomst og 123 punkter (fra dybdemålinger) med bekreftet forekomst av torv, besøkt. Punktenes sammenheng med prediktorene (utvunnet fra digitale høydemodeller): høyde over havet, helningsgrad, topografisk våthetsindeks, varmeindeks og gunstig aspekt, ble undersøkt. I tillegg ble de radiometriske prediktorene uran, thorium og kalium – samt en kombinasjon av alle tre, brukt for å modellere sammenhengen mellom prediktorene og forekomst-punktene. Helningsgrad, topografisk våthetsindeks og høyde over havet hadde de mest forklarende verdiene. Uran viste seg å være den sterkeste radiometriske prediktoren. Den endelige modellen bestod av de overnevnte prediktorene og hadde en sensitivitet på 0.28, noe som betyr at modellen kun identifiserte 28% av eksisterende torv. Spesifisiteten var 0.96, som betyr at når modellen identifiserte torv – tok den for det meste rett. Modellens nøyaktighet var 50%. Måten de radiometriske prediktorene feilet på kunne spores tilbake til variasjonen i berggrunnen, noe som har påvirket de tidligere spektrometriske målingene omkring Skrimfjella. Den bedre ytelsen observert hos de topografiske prediktorene (ikke basert på aspekt), er mest sannsynlig et resultat av områdets varierende karakteristikk. Med korrekt kalibrering av spektrometeret og en tilfredsstillende prøvestørrelse, vil denne metoden ha et stort potensial innen forvaltning av myr og torvmark, og derfor også som et avbøtende tiltak mot klimaforandringer.

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Abbreviations

AIC	Akaike's Information Criterion
CO_2	Carbon Dioxide
DEM	Digital Elevation Model
FOP	Frequency of Observed Presence
GIS	Geographic Information System
GLM	Generalized Linear Model
GPR	Ground Penetrating Radar
GPS	Global Positioning System
K	Kalium
R	Statistical program
Th	Thorium
TWI	Topographic Wetness Index
U	Uranium

1. Introduction

There are many types of peatlands in the world, and whether it is the fens of Finland or the mires of Ireland, they all contain peat. Peat is a valuable resource, that has traditionally been exploited, for example as a fuel for heating or a fertilizer for horticulture (Moshynskyi et al. 2021). Additionally, peatlands as environments have not always been recognized for their invaluable ecosystem services or climate change mitigation potential. Rather, countries used to drain them in favor of forestry, agriculture and housing purposes (Holden, Chapman & Labadz, 2004; Joosten & Clarke, 2003). Peat forms in waterlogged conditions when plant material does not receive enough oxygen to decompose properly (Belyea & Baird, 2006). Peat accumulates when the production of organic matter, which in boreal conditions mainly consists of sphagnum mosses, sedges and shrubs, exceeds the decomposition rate (IUCN, 2018). If the groundwater level is lowered due to ditching, the peatland will start to release the carbon it has stored during the past thousands of year in the form of carbon dioxide (CO_2) (Juszczak, 2012). Only approximately 3% of earths land surface is peatlands, yet it makes up to around 30% of carbon held in soil (Xu et al. 2018). The number is rough, as many countries have lacking recording systems for peatland carbon content (Chimner, Ott, Perry & Kolka, 2014). Neverthless, the carbon storing potential of peatlands located in the boreal region alone is second only to the oceans (Alexandrov, Brovkin, Kleinen & Zu, 2019). As written by Alexandrov et al. (2019), for the global carbon cycle to recover from anthropogenic emissions, the importance of northern peatlands is undeniable.

Peatlands are still a somewhat unknown ecosystem to many people and can get easily overlooked in spatial planning, especially the smaller mires not marked on maps. A number of small peat deposits can still hold a considerable amount of carbon in an area where peatlands are abundant. The methods for measuring carbon content are developing fast and getting more accurate as more people are studying peatlands and their potential to mitigate climate change (Chimner, Ott, Perry & Kolka,2014). The aim of this thesis is to increase the knowledge related to modern peatland mapping, by examining the applicability of remote sensing as a peat occurrence detector. Despite being a novel concept, it has already been studied by other researchers (Aitkenhead, 2016; Silvestri et al. 2019). This thesis is inspired by a similar study by Gatis et al. (2018) in Dartmoor, where the focus was on mapping peat depth. The research team was exploring which of the remote sensing-derived predictors would have the strongest relationship with peat depth. They achieved great results with radiometric data, thus it was one of the key aspects of this study too. My eventual goal was to see if the remotely sensed data is an efficient way to estimate peat occurrence and how well it can predict landscape-scale peat area. This can be summarized in the following research question: What kind of characteristics are optimal for peat formation and which of the chosen predictors produce the best predictability for peat occurrence?

Finding an answer to these questions could help future studies on peat occurrence establish the most indicative set of predictors to use. The predictors selected for this study can be divided to topographic and radiometric predictors. Gatis et al. (2019) got a clear relationship between radiometric dose and peat depth, which made the selection of my study area depend on the availability of radiometric data. In my study, I had a set of occurrence points that were selected using the remotely sensed data. This was done by leaving out the already confirmed peat locations and evaluating the landscape structure to get a sample of points where the topographic predictor conditions would apply. By analyzing remotely sensed data and comparing it to field observations of the point locations, I aimed to discover if peat occurrence could be modeled accurately using the selected predictors.

Norway has great potential for interesting study areas, because of the rich and varying nature. However, the rugged terrain, with high elevation variability can make the landscape hard to measure reliably by using remotely sensed data, due to the uncertainty in vegetation mapping (Bryn, Strand, Angeloff & Rekdal, 2018) or the measuring helicopter having to maintain a set altitude from the ground (Baranwal et al. 2013). These are some of the reasons why the research and management of Norwegian peatlands still has room to develop. More accurate measurements and mapping would lead to improved status for such important natural areas. In case of a new wind power or highway construction project, it would be useful to know the extent of the local peatlands beforehand, so that the peatlands can be a factor in a site determining process before the planning phase ends. If even the smaller peat patches could be reliably recorded, the planners would be able to estimate the carbon content of the area in a natural state and make an emission balance comparison of the developed area. (Bartlett et al. 2020) However, the peatlands can often be far away from main roads and measuring every site manually with a peat probe or a ground penetrating radar would take a great amount of time and resources (Parry et al. 2014), which can be limited in modern day spatial planning.

In Norway, the estimate of dried peatlands for various development purpose over the years is only about 20% of the country's total peatland volume, which is considerably lower than the European or Nordic medium (Joosten & Clarke, 2003; Kløve, 1999). Despite that, the mostly protected peatlands of Norway are still threatened by wind power and housing projects. (Jakobsen et al. 2019) These two are the main reasons why natural peatlands can still be drained, as most other purposes have been banned or heavily regulated (Norwegian Ministry of Climate and Environment, 2020). Also, the remaining natural peatlands are not all counted for. The estimates of how much peat there is in the soil to bind carbon are not precise, partly due to the aforementioned issues with remote or inaccessible locations, as well as differences in measuring, archiving or most importantly, the criteria used for defining peat (Chimner, Ott, Perry & Kolka, 2014; Joosten & Clarke, 2003). Success in modeling could lead to remote sensing becoming a more established tool for peatland mapping, that could aid future projects in this field. Mapping peatlands is a step towards better management of these important ecosystems. Moreover, we must keep our focus on peatland restoration and preservation, rather than economically exploiting the natural peatlands that are left. Changing the mindsets of people can take time, but the future looks bright, with peatland conservation gaining international momentum during the last decades (Stoneman et al. 2016; Bartlett et al. 2020).

2. Methods

2.1.Study Area

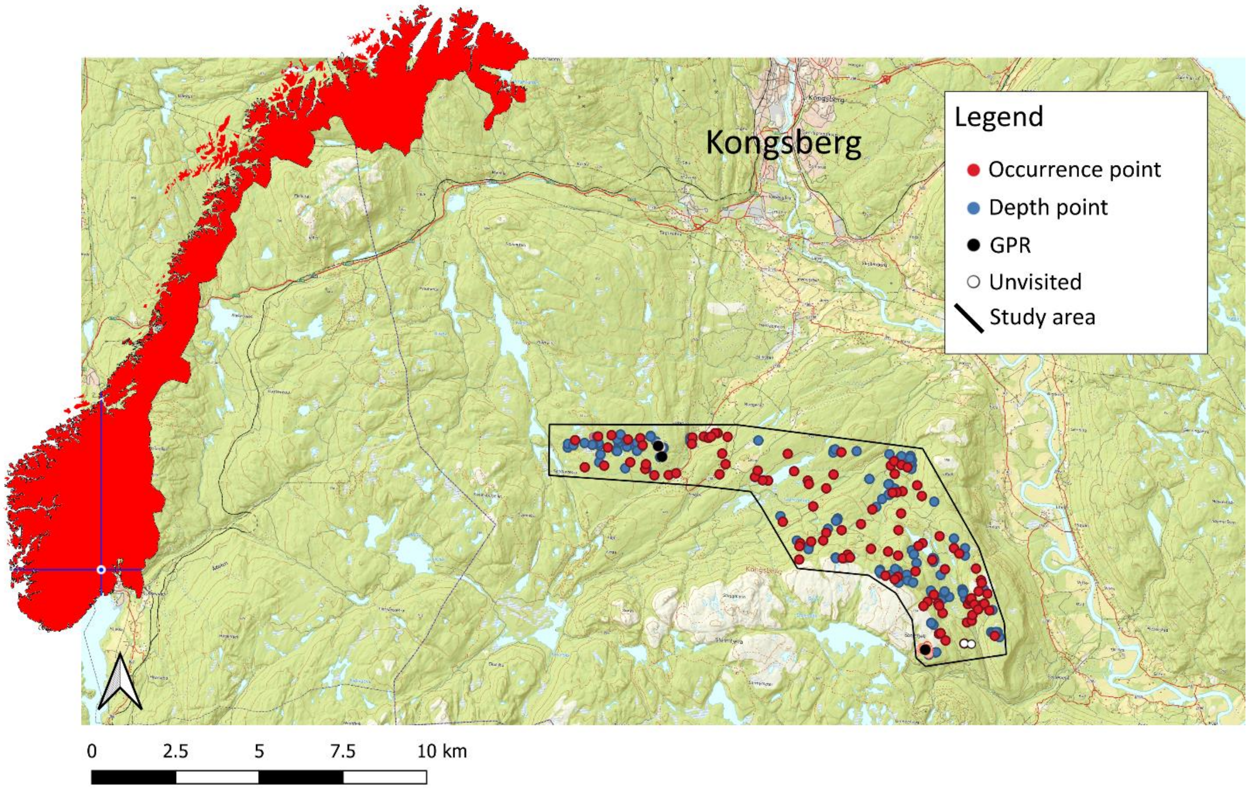


Figure 1. The study area is located south from Kongsberg, highlighted in this map of Norway. The map is presenting occurrence and depth points, as well as the three mires we used the GPR on.

The 40 km^2 study area is located in Skrimfjella, 15 kilometers south of Kongsberg city in the county of Viken (Fig. 1) The elevation within the study area varies from around 200 to 700 m above sea level. Annual precipitation varies from 750-1000 mm of the lower parts in the north to 1000-1500 mm of the higher parts in the south (NVE & MET Norway, 2021). Temperature averages vary from -3°C in January to 18°C in July, with an annual average temperature of 2-6°C (NVE & MET Norway, 2021). Geology in the area varies greatly with granite and limestone being the most common bedrock types (Fig. 2) There are also beds of sandstone and shale in the middle, as well as some monzonite and syenite in the southern edge of the study area, near

Store Stølevann. The area is divided by the Oslo rift and the Kongsberg formation (NGU, 2020). The soil composition in the area includes podzols, lithosols, brown earths, swamp soils, as well as vertic and gleyic cambisols (Norges Geografiske Oppmåling, 1983).

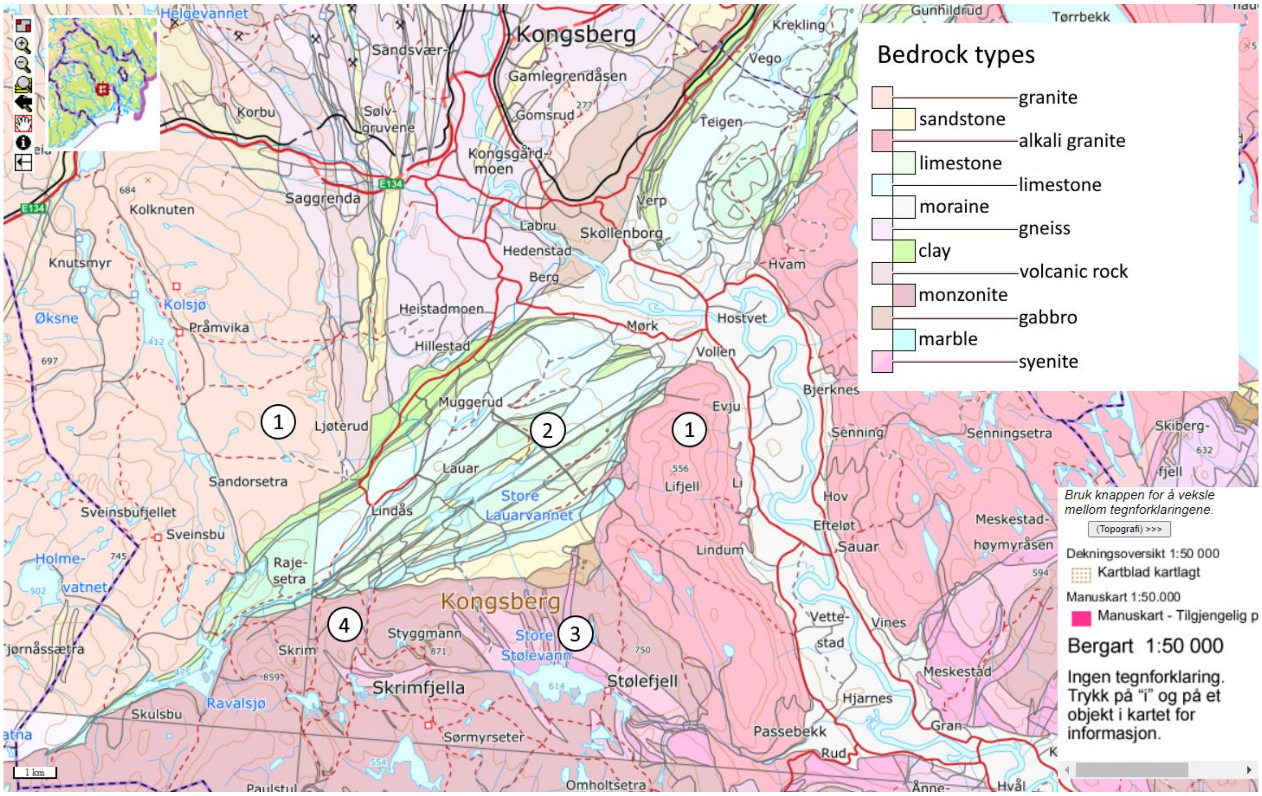


Figure 2. The bedrock variability in and around the study area. The main deposits inside the study area include granite (1) and limestone (2), as well as some syenite (3) and monzonite (4). The limestone is surrounded by small deposits of sandstone and clay. (NGU)

Observations during fieldwork revealed the dominant tree species in the area to be birch (*Betula pubescens*), pine (*Pinus sylvestris*) and spruce (*Picea abies*), with sudden changes in the vegetation along the different parts of the study area. The forests and especially peat deposits in the area are patchy and scattered, which can increase the species diversity, as the peatlands are at different stages of development. Typical field and bottom layer species in these peatlands and their outskirts included sedges, cottongrasses (*Cyperaceae*), starr (*Carex*), heather (*Calluna vulgaris*), blueberry (*Vaccium myrtillus*), lingonberry (Vaccinium vitis-idaea) juniper (*Juniperus communis*), stunted trees etc. Bogs in higher elevations also grew cloudberry (*Rubus chamaemorus*).

2.2.Occurrence Points

The occurrence points in the study area (Fig. 1) were selected by a stratified random method using remotely sensed data. Areas with slopes steeper than 20 degrees were excluded from the sampling because it is very unlikely for peat to occur there (Tallis, 1973). Likewise, areas mapped as mires in national map data (Bjørdal, 2007) were excluded because these areas were proven to contain peat. From the remaining study area, approximately 100 occurrence points were chosen by random using the 'iSDM' R package (version 1.0; Hattab et al. 2017). The chosen points were regularly spaced in predictor space, so-called 'environmentally systematic sampling' (US EPA, 2002). This three-dimensional predictor space was defined by elevation, slope, and potassium dose. The goal for this sampling design was to efficiently cover the range of predictor values in areas that could plausibly contain peat.

Figure 3. A typical occurrence point was in a bottom of the forest, under blueberries (Vaccium myrtillus) or other subshrubs. Most occasions it was hard to determine the occurrence without digging. Pictures taken in August 2020.

The fieldwork for the thesis was done in August, by visiting the 106 occurrence point locations with a handheld GPS-device and a shovel. When arriving within three meters of a point, I examined the soil content for peat by digging 20 cm of the soil, whenever possible (Fig. 3). If the ground was dry and hard to a degree where the shovel would not penetrate the surface, I concluded that it was not possible for peat to occur there. In the case of visible bedrock on the spot, I marked the point as no peat right away. Sometimes there was sphagnum without peat or vice versa. Any case where I was uncertain, I dug 20 cm of the surface and took photographs of the soil and its surroundings for later determination (Fig. 4). Six locations were inaccessible due to them being on private property, fenced area or underwater. These are marked as absences (0) in the dataset. In the end, only one of the points was left unchecked, due to its remote location from the other points. Some locations, especially in steep slopes, caused occasional issues with the GPS accuracy, but this problem was normally fixed by a quick recalibration of the device.

Figure 4. Sometimes the surroundings of an occurrence point location looked suitable, but it was hard to tell if there would be peat without digging. Here an opening in a forest near a confirmed bog grows sphagnum and club moss (part of the Lycopodiopsida) but seems too dry. Picture taken in August 2020.

2.3.Depth Measurements

During the fieldwork, we also measured 109 depth points using peat probe. I eventually used the points in the modeling part as an extra sample to improve the accuracy of the models. To get some perspective on how efficient the most common methods of peat occurrence/depth measuring are compared to the remote sensing, we measured the depth of three individual mires with a ground penetrating radar (GPR), in addition to the probe. (Muggerud, in prep.)

2.4.Preparing the Predictors

First, I fetched a digital elevation model (DEM) of the study area from høydedata.no (Kartverket, n.d.). To be able to compare results with those by Gatis et al. (2018), I used the same predictors with the exception of adding heat index and aspect favorability. I also chose the same 10 m raster cell resolution they used (Gatis et al. 2018). The radiometric data was originally in 50 m resolution, but it was resampled in QGIS (Version 3.10.14; QGIS Development Team, 2021) to fit in with the 10 m rasters. I created the predictor rasters in QGIS using the raster tools “Slope” and “Aspect” on the DEM (Fig. 5). In addition to being individual predictors, these were used for calculating the Topographic Wetness Index (TWI), which is composed of slope and upslope contributing area (Kopecký et al. 2021). In theory, it indicates runoff efficiency, and reveals where water tends to gather, represented by a higher TWI value. High TWI benefits peat formation, but after a certain threshold is crossed, the high wetness will translate as a permanent water body not likely to contain peat. Slope and aspect were also used to calculate the heat index, which is more common in vegetation studies but seemed fitting for the purpose of this thesis (Beers, Dress & Wensel, 1966). It indicates the heat distribution on a topographic emphasis. Aspect was converted into aspect favorability, as the plain aspect was not treating the highest and the lowest degrees (around 0 and 360) as neighbors but opposing high and low values.

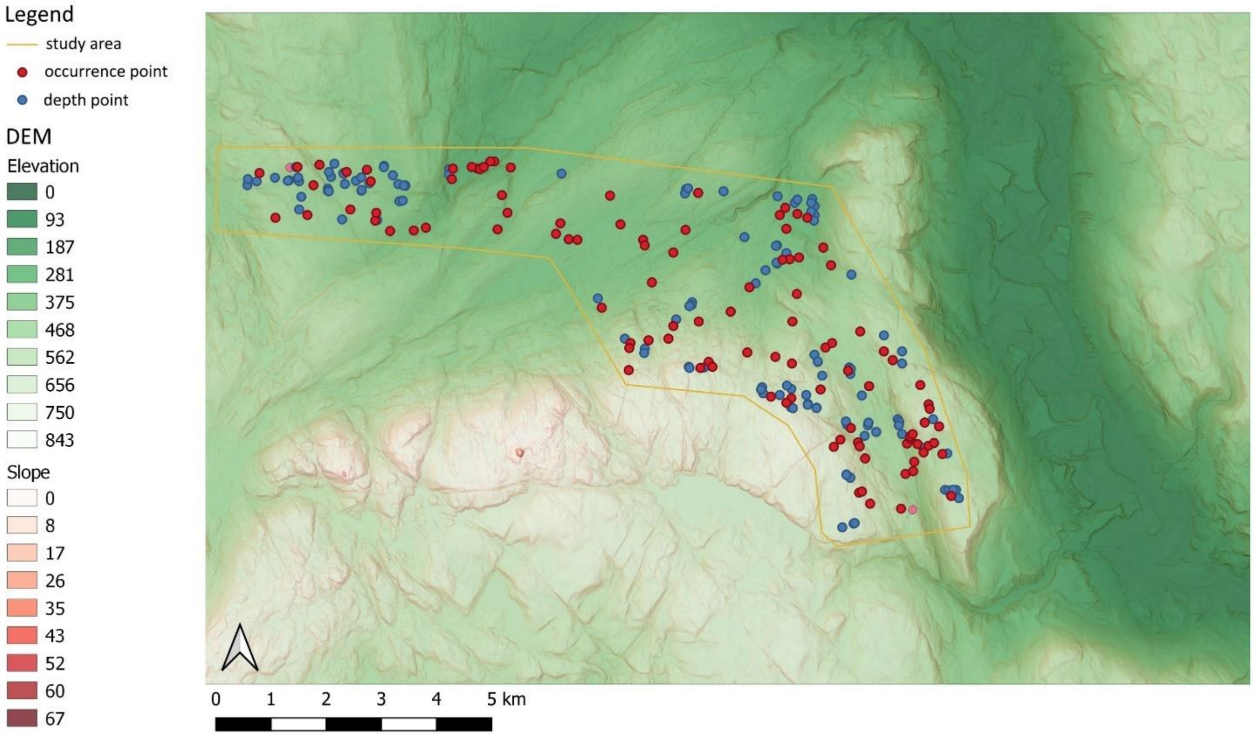


Figure 5. Digital elevation model. Topographic characteristics of the study area on a map of elevation and slope.

Topographic Wetness Index (TWI) was calculated in QGIS using the raster calculator and the "Flow accumulation" SAGA tool. The following function was used in the calculator:

$$\text{TWI} = ln\frac{\alpha}{tan\beta}$$

where α is the upslope contributing area in m^2 and β is the slope in radians. (Van der Kwast, 2016)

Heat Index (HI) was calculated in R, using the following function:

$$\text{HI} = cos\alpha_1 \times \ tan\alpha_2$$

where α_1 is the aspect difference from 202.5◦ and α_2 the slope (Parker, 1988)

Aspect favorability, which was was calculated in R using the following function:

$$\text{Aspect favorability} = cos(A_{max} - A) + 1$$

where A was the measured aspect and the max value was set on 202.5° (Beers, Dress & Wensel, 1966)

The radiometric data for Potassium, Thorium and Uranium was obtained from Norges Geologiske Undersøkelse (NGU) data portal. This data was produced with a Hummingbird^{TM} EM and magnetic helicopter survey system. Additionally, two external gamma-ray spectrometers (Exploranium GR820 and Radiation Solutions RSX-5) were used (Baranwal et al. 2013). They were calibrated accordingly to the radiation type. The predictor 'radiometric dose' was a combination of the Potassium, Thorium and Uranium data.

Radiometric dose was calculated by adding the radiation of the individual elements together using the following calculation:

Radiometric dose= $K\ (\%) + Th\ (ppm) + U(ppm) = D(nGy \times h^1)$

where the sum of Potassium (K), Thorium (Th) and Uranium (U) radiation values (ppm) form the radiometric dose. (nanoGray per hour) (Gatis et al. 2019)

2.5.Statistical Analyses

I used RStudio (version 1.4.113; RStudio Team (2021) to model the relation between the predictors and the peat occurrence data, which was in binomial form (1 for peat and 0 for no peat). The data type led to the choice of using a binomial Generalized Linear Model (GLM). I started by importing the occurrence points and predictor rasters into R from shapefiles created in QGIS. The rasters were limited to match the study area, which I did by using a simple plot to check that they were aligned properly. Then I stacked the predictors together and combined them with the occurrence data to have a common data table for the upcoming modeling. (Fig. 6)

Predictor	**Origin**
Elevation	Digital Elevation Model from høydedata.no
Slope	Calculated from the DEM
Aspect Favorability	Calculated from the aspect raster in QGIS + R
Topographic Wetness Index	Calculated in QGIS (SAGA tool)
Heat Index	Calculated in QGIS + R
Radiometric Dose	Combination of the elements below
Kalium	Obtained from NGU Geoscience Data Service
Thorium	Obtained from NGU Geoscience Data Service
Uranium	Obtained from NGU Geoscience Data Service

Figure 6. The chosen predictors and how they were obtained and created.

The preliminary results from the test plots I used pointed towards having too few positive occurrence values, only 20 out of the 106 in total. To have a larger sample of positive occurrences and improve the model accuracy, I converted the depth points we measured during the fieldwork, into occurrence points. As a result, I had a set of 225 occurrence points. On one hand, this produced an increased number of positive values for the models to determine the characteristics of what is needed for peat to occur. On the other hand, it risked tipping the scale towards positive occurrences having a greater impact than the negative. Probability of occurrence with a small bilinear data set like this can often be under- or overestimated. That is why the occurrences need to have a correct weighting in the set (Nad'o & Kaňuch, 2018). To avoid bias, I used weights to optimize the value of the new occurrence points. Since there were a total of 127 positive occurrence points, I used a 127/20 ratio to make the weights. This gave the negative occurrences more value and the positives and the negatives were equally valued by the models.

Now that all the data was sorted out properly, I ran the GLMs with occurrence against every combination of two predictors to find out how each predictor pair relates to the occurrence data. Comparing the AIC (Akaike's An Information Criterion) numbers of these models already gave an idea of which predictors had the best predictability and how the main model would be put together. AIC can be interpreted as a performance indicator that represents the fit of the model with the selected predictors (Grove, Sakamoto, Ishiguro & Kitagawa, 1986)

I also inspected FOP (Frequency of Observed Presence) plots which are a part of the R package MIAmaxent, between occurrence and each predictor. These are meant for recognizing patterns in occurrence frequency, which made them useful for this study. (Vollering, Halvorsen, Mazzoni, 2019) FOP plots also produce useful visualizations of how the different predictors affect the occurrence.

I used forward and backward selections to plot the predictors against each other. In forward selection, predictors are added until the model has reached its peak performance. The rest of the predictors are then discarded. Backward selection works backwards, starting with a full roster, and dropping predictors until the point where its performance would suffer. Forward and backward selections would often produce the same outcome, but it is recommended to do both to check for slight errors in a script or data, that the other selection would miss. In some cases, they can also produce a different outcome. (Burdon & Kumar, 2004) The results presented in the thesis are mainly from the backwards selection, but I checked both thoroughly to confirm that the results were not contradicting each other. The scripts for the selections can be found in the Appendix.

3. Results

3.1.Frequency of Observed Presence

Interpreting the FOP plots revealed the most and the least significant relationships in a visual form. (Fig 7.) According to these plots, the occurrence points in the study area correlate well with slope (Fig. 7b) and TWI (Fig. 7c). The slope graph illustrates how a flatter slope relates to increase in occurrence. A rise and decline in the TWI trend line illustrate that too little or too much wetness has a negative effect for peat accumulation. In the elevation graph (Fig. 7a), the occurrence points are scattered over a larger extent. There is a steady rise in occurrence in relation to elevation, until about 700 meters, and a decline after that. This is due to the study area not having many points over this elevation. Moreover, most of the occurrence points are situated in altitudes greater than 300 m, which is due to the characteristics of the study area and does not mean peat would not occur in lower altitudes. The heat index differs from the other graphs, because of its different working principle. The values settle close to 0 and only range from -1 to 1 by default. The FOP plot of aspect favorability did not produce a clear pattern. The profiles of the radiometric predictors seem to be in-line with each other. Out of these four, uranium (Fig. 7g) stands out with the sudden decline in occurrence as radiation levels increase.

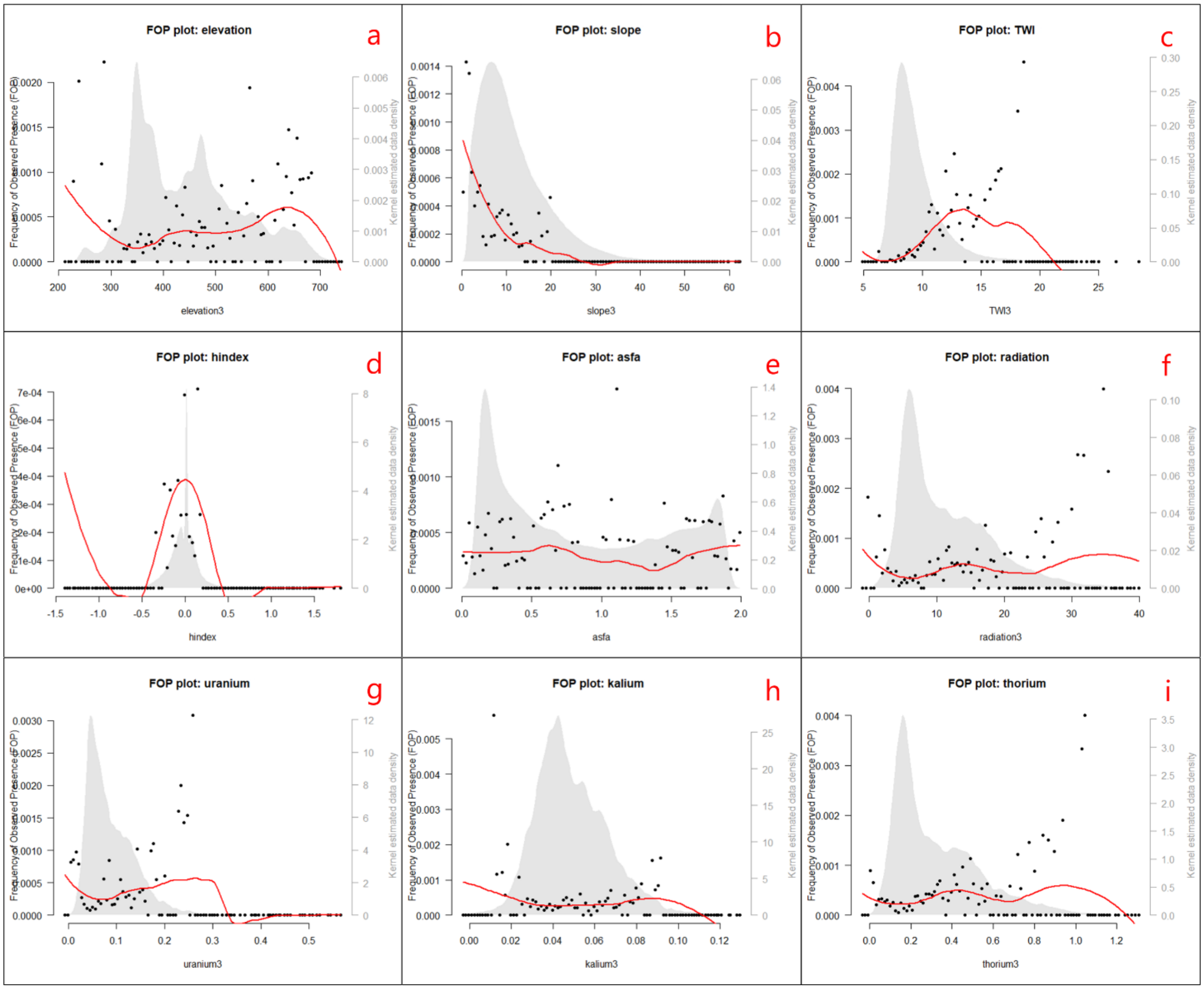


Figure 7. FOP plots of all predictors: Elevation (a), slope (b), TWI (c), heat index (d), aspect favorability (e), radiation (f), uranium (g), kalium (h), and thorium (i). The light grey mountain-shaped parts in the graphs are the most well-presented characteristics in the study area and the dots are the occurrence points. The red trend line helps to visualize the distribution of the positive occurrences according to the predictor, meaning that the line can be used to determine whether the effect of the predictor on the occurrence is positive or negative.

3.2.Modeling results

Of all the predictors, slope and TWI appeared to have the most explanatory value through the different stages of modeling. The results from single predictor GLMs added elevation to this group. These three predictors had the best performance, according to their AICs. Slope (614) and TWI (627) were considerably better at predicting occurrence than the other predictors, and elevation (662) scored better than the rest (AIC range 668-672). None of the remaining predictors stood out, which meant the differences were so small that finding them required more in-depth modeling.

3.2.1.Generalized Linear Models

Later analyses confirmed TWI, slope and elevation to be the best predictors in relation to peat occurrence. The majority of the occurrence points are distributed between the medium wetness levels, from around 6 to 14 on the x-axis of the TWI scale (Fig. 8a). Peat was more common in wet areas (TWI range 9-13) than dry areas (TWI range 7-10). This is in line with the fact that peat favors wetter conditions, although the study area does not seem to include very dry areas for comparison. Only a handful of the ocurrence points are situated at the high end of the TWI scale (15), which gives an idea of the optimal TWI range and its limits for peat deposits in the study area. The points were more evenly distributed along the slope gradient (Fig. 8b), yet the graph has a significant amount of the positive occurrences in the lower end of the x-axis, which indicates that the degree of the slope must be smaller for peat to be more likely to occur. These two show a clear connection between the predictor and the occurrence, which was not obvious with the other predictors.

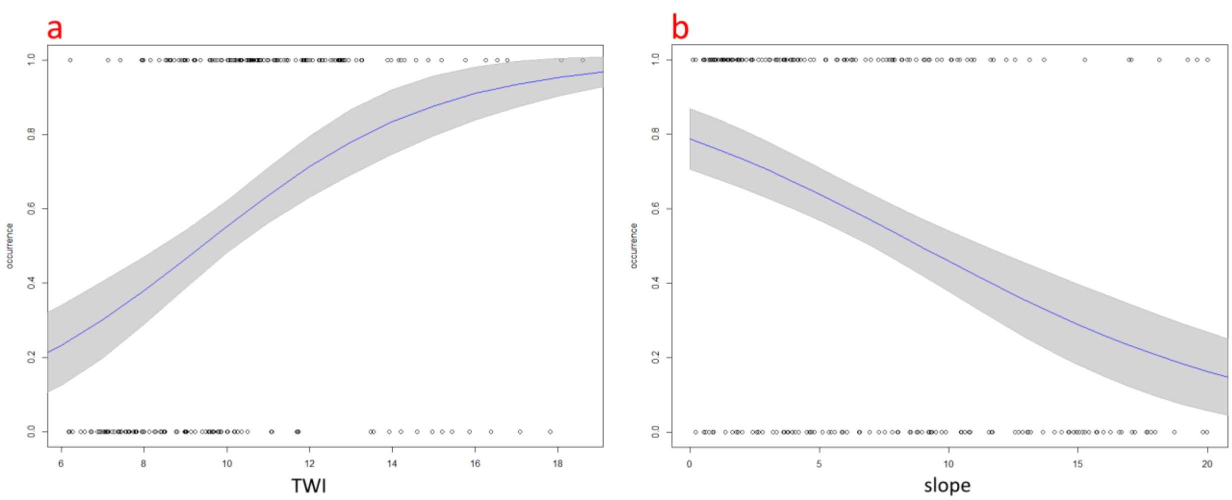


Figure 8. Results of the GLMs for Topographic Wetness Index and slope. The occurrence points are presented in the x-axis, while the trend line indicates the estimated optimal range where peat is most likely to occur, according to these variables.

Elevation and uranium were the other predictors selected for the model. The occurrence points are much more evenly distributed along the x-axis, and the trend lines go straighter. That means less predictive power than the slope and TWI had. The elevation graph still shows a clear increase in the occurrence as the elevation increases (Fig. 9a). The values in the middle of the elevation range are the most accurate, while the low and the high end have some more uncertainty. The uranium graph does not provide much information, other than uranium having a slight negative effect on peat occurrence (Fig. 9b)

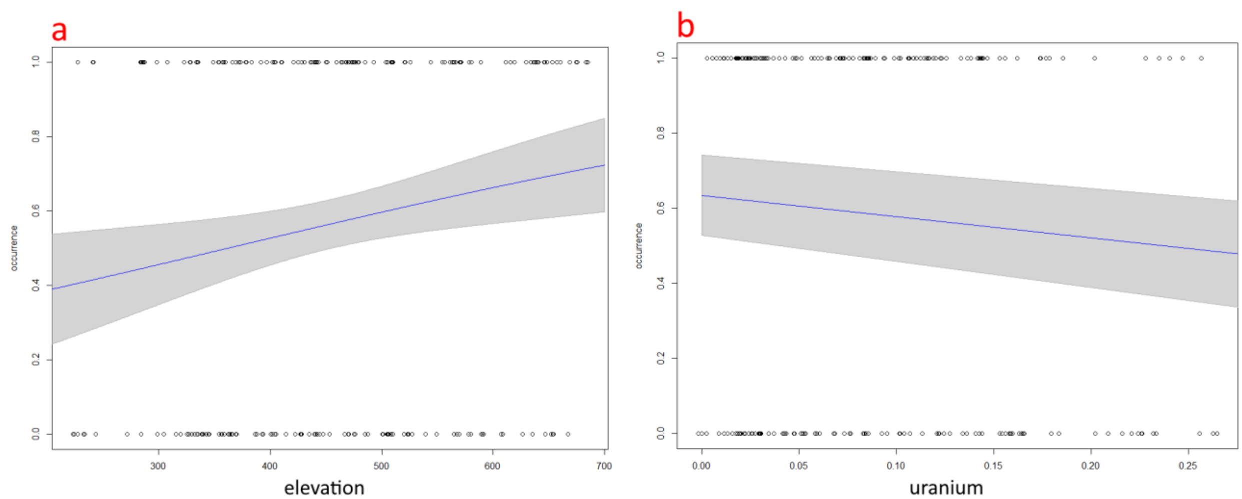


Figure 9. Results of the GLMs for elevation and uranium (radiation dose). Less curve on the line and thicker grey areas means more uncertainty in the estimation. The rest of the GLM graphs can be found in the appendix.

GLMs of the of the predictor pairings supported the results from the other analyses. Best pairs were formed from elevation with slope (AIC 571), elevation with TWI (AIC 591) and slope with TWI (AIC 605) (Tab. 1). From this result I anticipated the selection of these predictors for the final model. In the end, the result from backward selection for all the predictors (elevation, slope, aspect favorability, TWI, HI, radiometric dose, uranium, potassium and thorium) included slope, TWI, elevation and uranium.

Predictor	Rad. Dose	TWI	Heat Index	Elevation	Slope	Aspect Fave
Rad. Dose		625.01	674.51	656.09	613.31	671.48
TWI			625.58	591.17	605.8	626.7
Heat Index				663.83	612.35	648.45
Elevation					571.88	659.98
Slope						612.36
Aspect Fave						

Table 1. The AIC-numbers of the predictor pairings. Plotting them together in pairs helps in exploring the relations and understanding the process of the final selection better. AIC was the best value for comparing the predictors.

The top three predictors remained the same in the individual AIC-value comparison. Potassium, which was the last one to be left out from the final model, was very close to uranium in performance. Aspect favorability performed better than uranium, but in the end uranium had more synergy with the top three, and aspect favorability was discarded. The AIC-numbers of slope, TWI and elevation were clearly smaller, while the rest of the predictors were much closer to each other in individual performance (Tab. 2).

Predictor	Slope	TWI	Elevation	Aspect Fave	Uranium	Potassium	Heat index	Rad. dose	Thorium
AIC	614.56	627.52	662.25	668.89	669.24	669.61	671.93	671.96	672.76

Table 2. The AIC-numbers of the individual predictors from the GLMs. The lower AIC-number does not always mean that the predictor will be part of the final model. Aspect favorability lost performance when it was grouped with other predictors.

The coefficient estimates for the model confirm that an increase in TWI and elevation, as well as a decrease in slope and uranium affect peat occurrence positively (Tab. 3). The estimates are adequate, with only uranium having a slightly larger standard error. Uranium p-value also points towards slightly less significance than the other predictors. None of the predictors increase the chance for peat occurrence by a large margin. More occurrence points would be needed to find out precisely how much each predictor could influence the occurrence of peat in the study area.

Coefficients	Estimate	Standard Error	P-value
(Intercept)	-6.272	0.829	3.88×10^{-14}
TWI	0.243	0.048	3.60×10^{-17}
Slope	-0.143	0.029	7.69×10^{-7}
Elevation	0.008	0.001	2.41×10^{-13}
Uranium	-4.979	1.834	0.00664

Table 3. The coefficient distances from zero presented in a table form. The results are from the last GLM (backward selection).

3.4.Model Performance

The model performance was not as good as expected, when reflecting on the results from Gatis et al. (2019). The performance indicators for depth data and binomial occurrence data are not the same, but they provide enough information to make the comparison (Bevan, 2013). Sensitivity of the final model was 0.28, meaning that the model successfully identified 28% of the existing peat, leaving 72% of the peat undetected. Specificity was 0.96, meaning that the times the model identified peat, it was right 96% of the times. (Swift, Heale & Twycross, 2019) The conclusion from these numbers seems to be that the model was too modest; it was lacking data to make any more deductions. The model got 50% accuracy, so the classification of peat or no peat was right half of the times.

3.5.Modeled Occurrence Probability

After the modeling in R was complete, I exported the model predictions into QGIS, where a raster of the model predictions was created (Fig. 10) I call it Modeled Occurrence Probability, as it is not a clear map of where peat deposits can be found, but a result of a model estimating occurrence of peat deposits. The influence of the main topographic predictors is visible. The areas with a better probability for peat seem to be at higher elevations, have a higher TWI or a gentler slope. The effect of uranium is too faint to be pointed out from the raster.

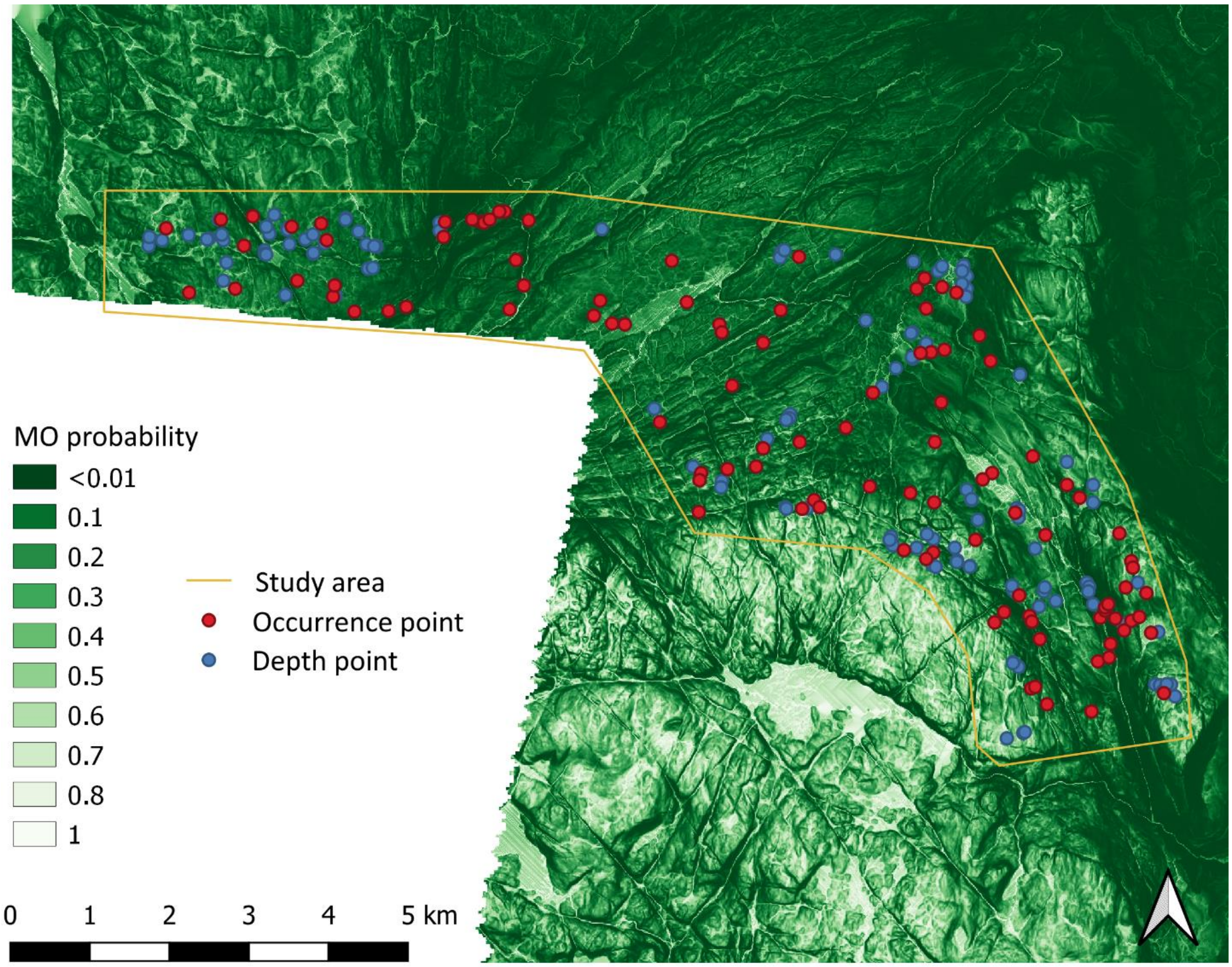


Figure 10. The final model predictions in a raster format. Modeled Occurrence (MO) Probability is the calculated model predictions from the predictors chosen for the final model (slope, elevation, TWI and uranium).

4. Discussion

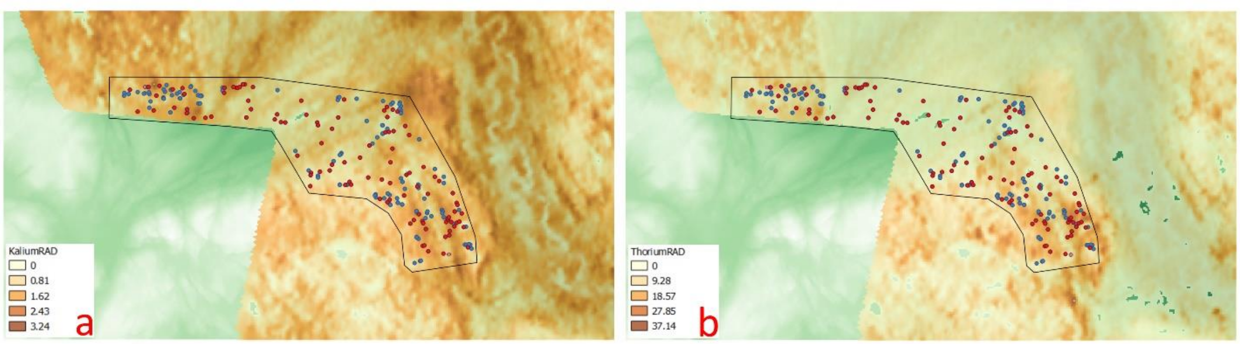
4.1.Evaluating the model

One of the reasons why the final model did not reach the expectations, is the small sample size. The predictors that performed well in the model, are likely to be correct, but the predictive power they have on peat occurrence is still somewhat inaccurate. Especially with a binomial data set, having a larger sample could boost the performance of the model greatly (Bevan, 2013). The characteristics of the study area in Skrimfjella are not represented well enough by the 106 original occurrence points. For example, elevation range of roughly 500 meters is only covered by 21 points per 100-meter difference. This occurrence data is not directly comparable to the depth data from Dartmoor (Gatis et al. 2019), but with fewer radical changes in the landscape, the depth points there have less individual value, making them represent the study area better. Gatis et al. (2019) also produced a map of modelled peat extent, which can be compared to the raster of Modeled Occurrence Probability. (Fig 10.) The basic principle is the same, but the one from Dartmoor was made using more confirmed peat values, while my “map” is based on estimations from a less representative dataset. An optimal result from a study focusing on occurrence would produce a similar raster, but with clearer contrast of possible peat deposit presences and absences.

4.2.Evaluating the predictors

The predictors chosen for this study are inspired by the research from Gatis et al. (2019), with some exceptions. My chosen predictors included heat index and aspect favorability. The fact that these two did not perform as well as expected, does not mean they should be discarded in the future studies right away. The main reason for using these in a study would be to measure the effect of solar radiation on peat formation, which could also be a predictor of its own. Additionally, aspect has been used to produce some decent values on other studies (Chico et al. 2020). However, the strong performance of slope makes an argument against heat index and aspect favorability. If peat favors flat terrain, then predictors based on aspect lose some of their significance, because flat areas are exposed to sunlight in the same way throughout the day. There might be mountains blocking certain directions, but this is hard to include in a model.

Radiometric dose did not have such an impact it had on the Dartmoor study, where it was clearly the most predictive one of the predictors (Gatis et al. 2019). In my study, radiometric dose failed to contribute significantly to the modelling of peat occurrence, and was left out of the final model. Only uranium had the predictive power to be selected for it. Of the rasters created in QGIS, uranium was also the radiation type that seemed to be the weakest in the study area, compared to the other types of radiation. (Fig. 12) That could be one of the reasons for its best predictability, considering the overall weakness of the radiometric data for this area. If higher radiation leads worse results, then the best radiometric predictor would logically be the one that has the smallest radiation value.



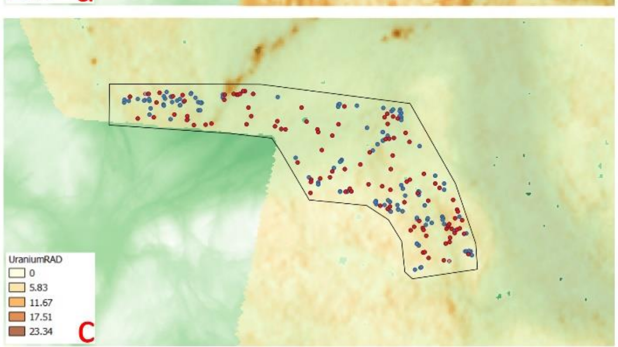


Figure 10. Potassium (a), thorium (b) and uranium (c) radiation values in the study area. The change of bedrock type from granite to limestone is visible in the upper left corner of the thorium (b) map, hinting that the bedrock could have a major role in the performance of the radiometric predictors. The boundaries of available radiometric data for the area can be seen in the lower left corner of the rasters.

Topographic predictors fared better than those derived from the radiometric data. This could be due to the great variability in bedrock types in the area (Fig. 2). Since the radiometric signal behaves differently in different bedrock and soil types (Rawlins et al. 2007), greater radiometric predictor accuracy would require calibration for each bedrock type separately (Gatis et al. 2019). The equipment that was used to measure the radiation in the study area was calibrated for each radiation type (Baranwal et al. 2013), but for the purpose of having radiation as a predictor in this kind of a study, calibrating the measuring tools for different bedrock types would be essential. Another thing affecting the radiometric data, is the seasonal variability in the area. In northern Europe, where the seasons are very different from each other, the time of the data extraction should be considered carefully. The radiometric data of the target area were measured during May and July 2011. Other regions that were part of the same survey, were measured between 2008 and 2009, during the summer and autumn months (Baranwal et al. 2013). The measurement period is long, but conditions are also the most similar between the five warmest months. Nevertheless, temperatures and precipitation can change considerably between months and years. To minimize the effect of the seasonal variability, the conditions of measurement days should be noted, so they can be used in the interpretation of the results, if there seems to be some difference to the expected radiation values.

Remote sensing is developing rapidly and calibrating the spectrometer for different bedrock types would still be less work than going to the field with the depth measuring gear. Skrimfjella has multiple bedrock types (Fig. 2)(NGU, 2020), so for the purpose of developing the method and increasing the international knowledge about the relationship between bedrock and the different radiation types, I would choose a future study area with one or two bedrock types. The topography in Skrimfjella also varies more than that in Dartmoor, which raises questions about the topographic predictors. Would flatter topography and less bedrock types make radiometric predictors perform better than topographic ones in comparison? The characteristics of the area could have a notable impact on how the predictors perform, especially when the sample size is low. Additionally, remote sensing seems to work better with flat-bottomed peatlands (Vernimmen et al. 2020).

Slope and TWI were the best predictors for the area by a clear margin. When there are plenty of slopes in the environment, it becomes more visible that the model will see the flat areas as superior to the steep ones. The same is true for the TWI, as it also relies heavily on slope. The precision of these two predictors benefits from a more radical topography. With elevation, the link between altitude and peat formation is not as direct. (X1) Peat needs still water to occur, and in areas with high elevation, many parts are too steep to hold water or peat. This limits the chances for peat deposits. Peat occurrence in mountainous areas has not been studied extensively, but the forming of peat does not seem to suffer from higher altitudes (Llanos et al. 2017). The results from the GLM demonstrate a positive relationship with peat occurrence and higher elevation. A result like this can be due to peatlands in lower altitudes being dried for agriculture or forestry, among other purposes. When a peatland is located high enough, it is much less attractive a target for exploitation, and thus so many of the peatlands in the region have been spared from drying. The lack of roads and other infrastructure do not make it optimal for agriculture or other long-term projects. Drying requires digging, which comes with obvious logistical problems, despite the purpose of drying the peatland. Lately, this kind of regions have been considered for new wind park projects or cabin building. A part of Skrimfjella was also briefly included in a plan charting possible wind power locations, which makes investigating peat occurrence there useful and timely (Jakobsen et al. 2019).

4.3.Future Research on Peat Occurrence

For future studies working with peat occurrence, it is important to establish some guidelines for the fieldwork. The fieldwork should be done in a time of the year that the ground is melted, and it is possible to dig. Having a GPS-device with at least a three-meter accuracy is also recommended. Many of the occurrence point locations required digging, as the sphagnum growth indicated the possibility of peat, even when the surroundings were dry. There were some visible peat pouches around many of the point locations, but the occurrence points rarely happened to be situated on them. In many cases, the GPS led me to a place that was mossy or looked otherwise suitable but did not contain peat. Sometimes identifying the peat was hard, as the peat I found was in different phases of decaying. The Von Post scale defines ten different states of decay for sphagnum peat, which can make peat classification in the field difficult. (Laine et al. 2018) There was no clear pattern to be visually identified with the peat deposits while visiting these points during the fieldwork.

Windmills and cabins are an exception in a sense that they are not as demanding on the land as agriculture or forestry, which are the main reasons for historical peatland draining (Joosten & Clarke, 2003). The land does not have to be productive or nutritious for either structure. It just has to be dry enough for the building site to be established. Then it is up to the cabin owner if they want to live on a peatland, as long as the cabin is built on a sturdy spot. Wind turbines can be situated in any type of terrain if it is physically possible to build them there. The construction of a wind turbine is the most damaging part for its surrounding land area. A study by Heal et al. (2019) revealed a change in the macronutrient concentration (mainly dissolved organic carbon and soluble reactive phosphorus) in a catchment area mostly covered by blanket peat, due to forest felling, borrow pits, turbine base and road construction. Furthermore, operating wind turbines seem to affect the peatland environment, by slightly altering the temperature of the ground-level microclimate. Soil, soil surface and air temperature at a Scottish wind farm experienced up to 0.18°C increase, when the turbines were on (Armstrong et al. 2016). Although not very drastic of a change, it could affect the ecosystem respiration and thus the CO^2 intake of the mire (Ward et al. 2013). Additionally, a study on wind parks on undegraded peatlands by Smith, Nayak & Smith (2014) claims, that peat is more valuable for the climate, than the wind power generated from the turbines built on the peat deposit would be.

The world has come a long way from the old days, when peatlands were drained out of necessity, like they were in Finland before the urbanization (Turunen, 2008). Historically, the amount of drained peatland has steadily decreased, the closer to the present day we look. It might seem like we have already caused irreversible harm to our ecosystems and climate, but there are still uncharted peatlands in the world, that can be preserved (Joosten & Clarke, 2003). As the technology related to peat mapping continues to develop, all these yet-to-be-identified peatland locations have a greater chance of being taken under the wing of some international agreements set to improve natural values (Stoneman et al. 2019).

5. Conclusion

Peat occurrence in the Skrimfjella study area (40 km^2) was modeled with predictors inspired by the study Gatis et al. (2019) did on Dartmoor. The final model included slope, elevation, TWI and uranium (dose). The role of the radiometric data in this study was diminished, likely due to the great variation in topography, but especially bedrock. The spectrometer used to measure the radiation should be calibrated accordingly for each bedrock type beforehand to improve the estimated accuracy of the data type. The model accuracy was only 50% with a sensitivity of 0.28 and specificity of 0.96. A future study following a similar modeling pattern, should take sample size into account and ensure enough positive and negative occurrences to cover all the characteristics of the study area properly, thus avoiding bias due to regional differences. The role of remotely sensed data in estimating peat occurrence is promising but requires some *a priori* knowledge and planning, when selecting the study area and sample size. It is highly recommended to do both occurrence and depth modeling simultaneously, as having data from both measurements can provide more relevant and applicable spatial information. Having access to both peat depth and extent from the same study area can be useful in a larger scale, than the individual results. It would also reveal more about the current state of the area, which could be used in protection of the peatlands.

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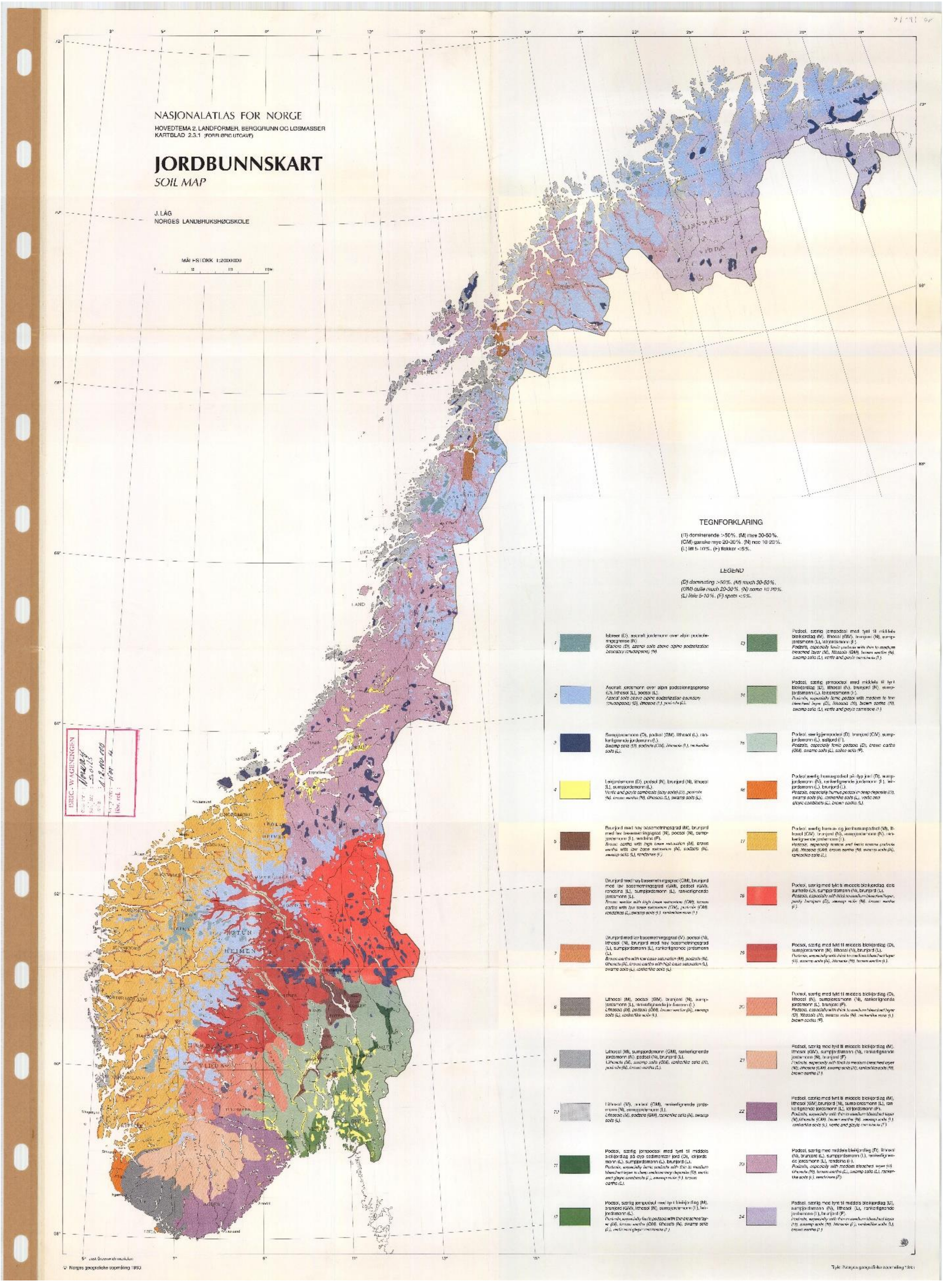
7. Appendix

Appendix A - Maps

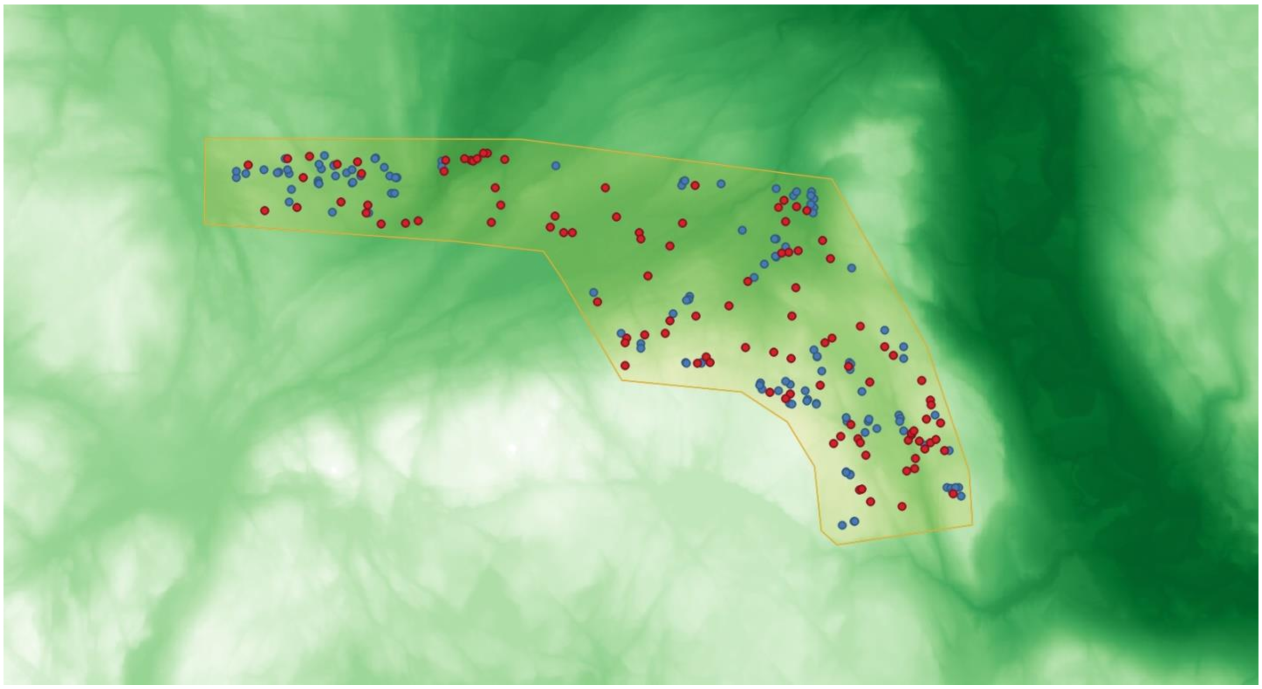
Soil map of Norway

(next page)

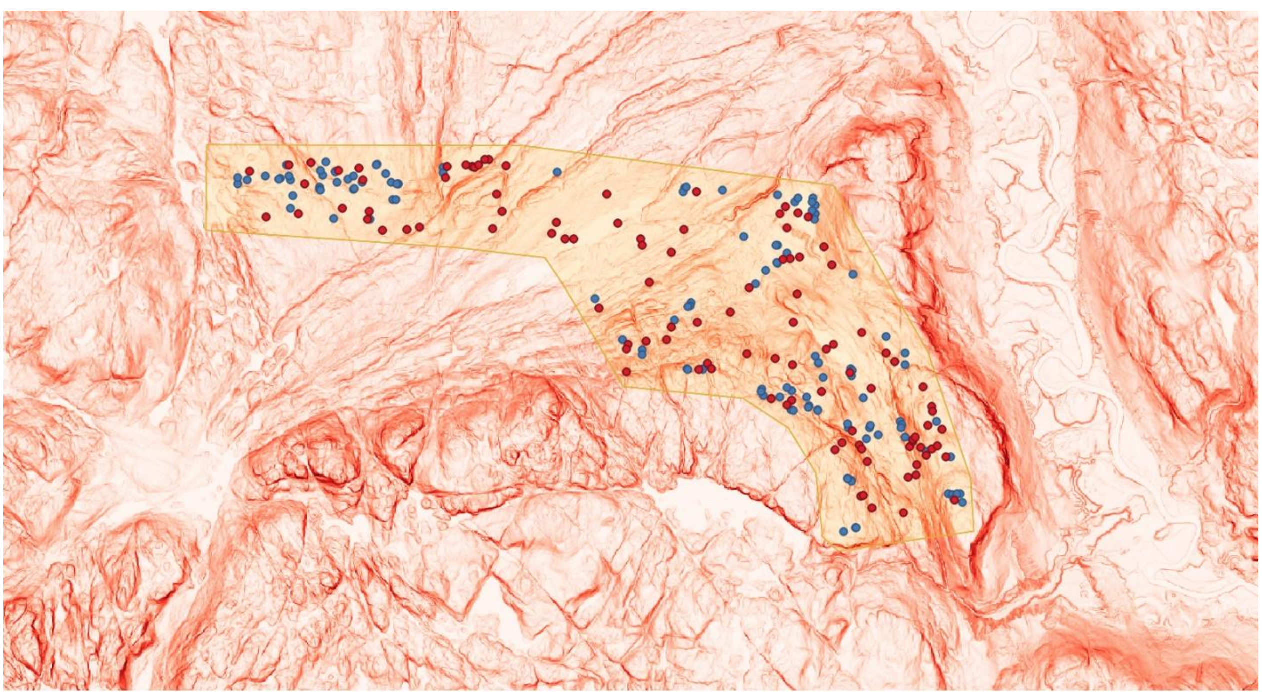

NASJONALATLAS FOR NORGE
HOVEDTEMA 2. LANDFORMER, BERGGRUNN OG LØSMASSER
KARTBLAD 2.3.1
JORDBUNNSKART
SOIL MAP
J. LÅG
NORGES LANDBRUKSHØGSKOLE
TEGNFORKLARING
(M) mye 30-50 %.
(GM) ganske mye 20-30 %. (N) noe 10-20 %.
(F) flekker
LEGEND
(D) dominating >50 %. (M) much 30-50 %.
(GM) quite much 20-30 %. (N) some 10-20 %.
(L) little 5-10 %. (F) spots <5%.

Appendix B – Predictor Rasters

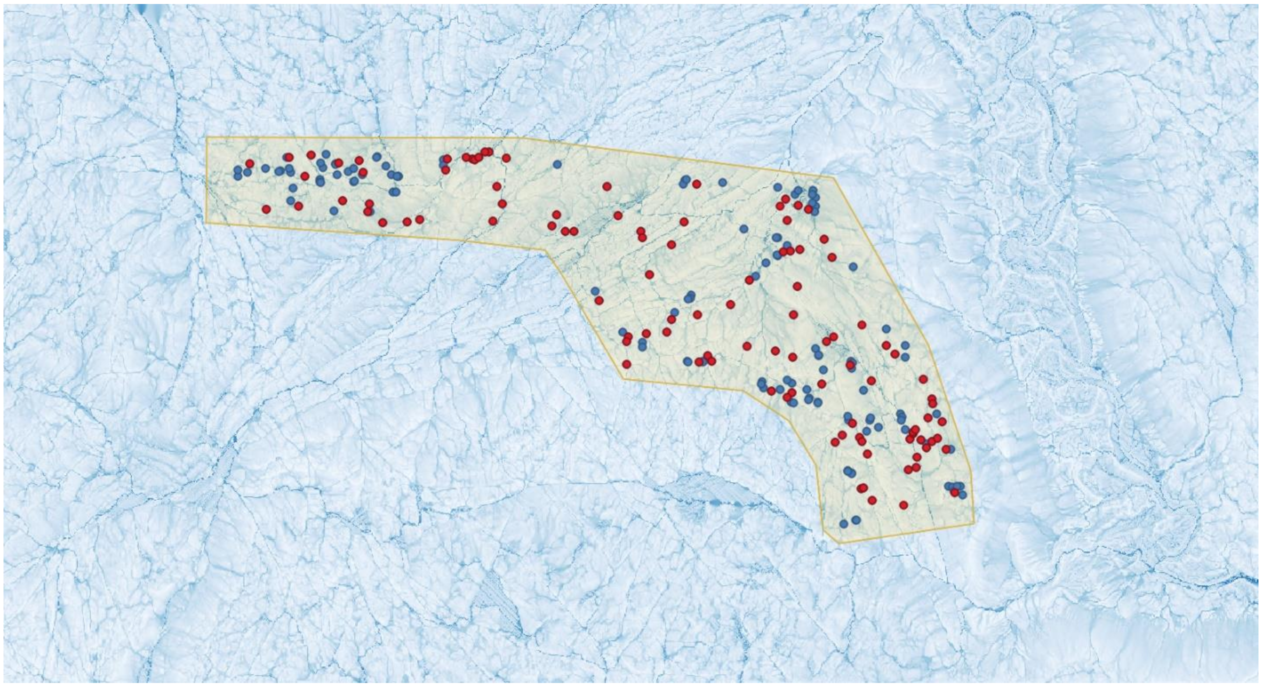
B-1. Elevation Raster



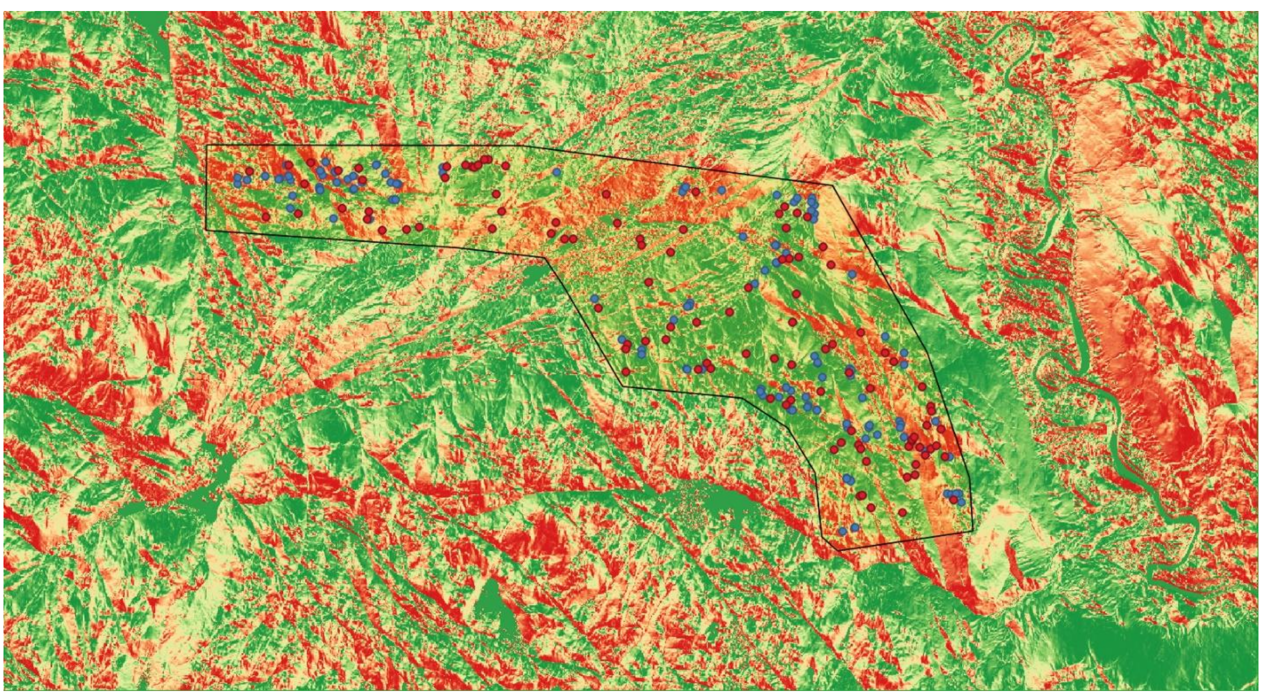
B-2. Slope raster



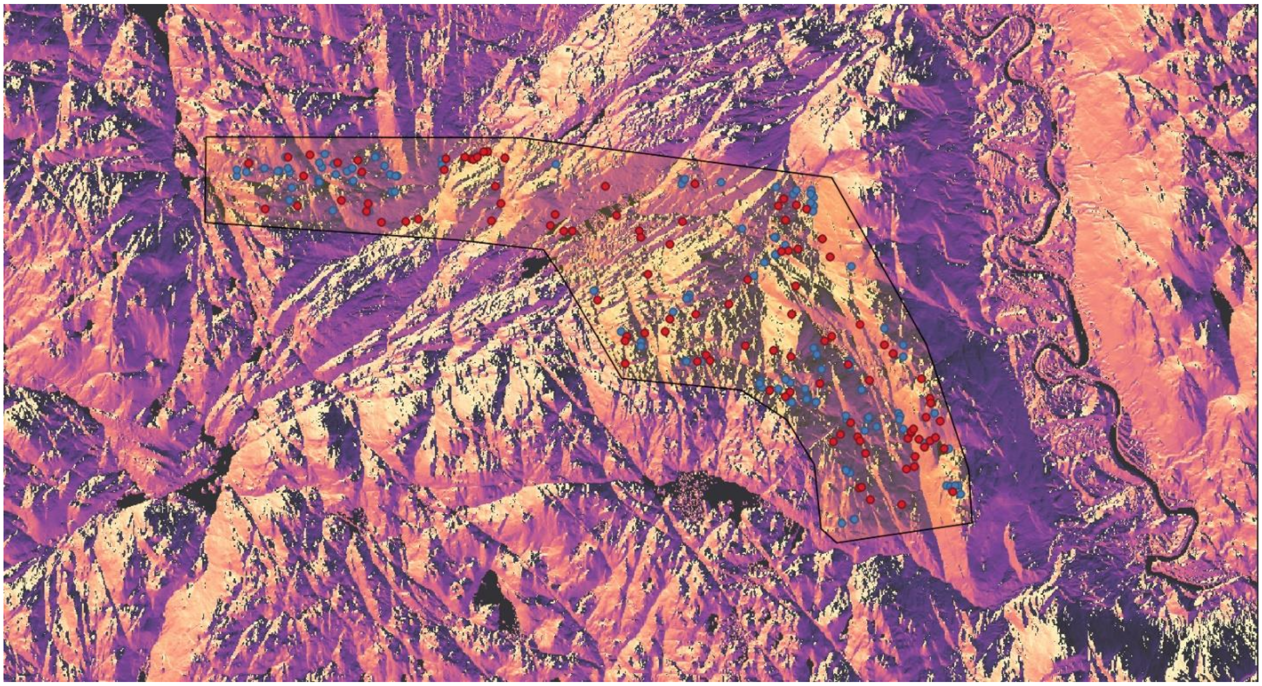
B-3. Topographic Wetness Index raster



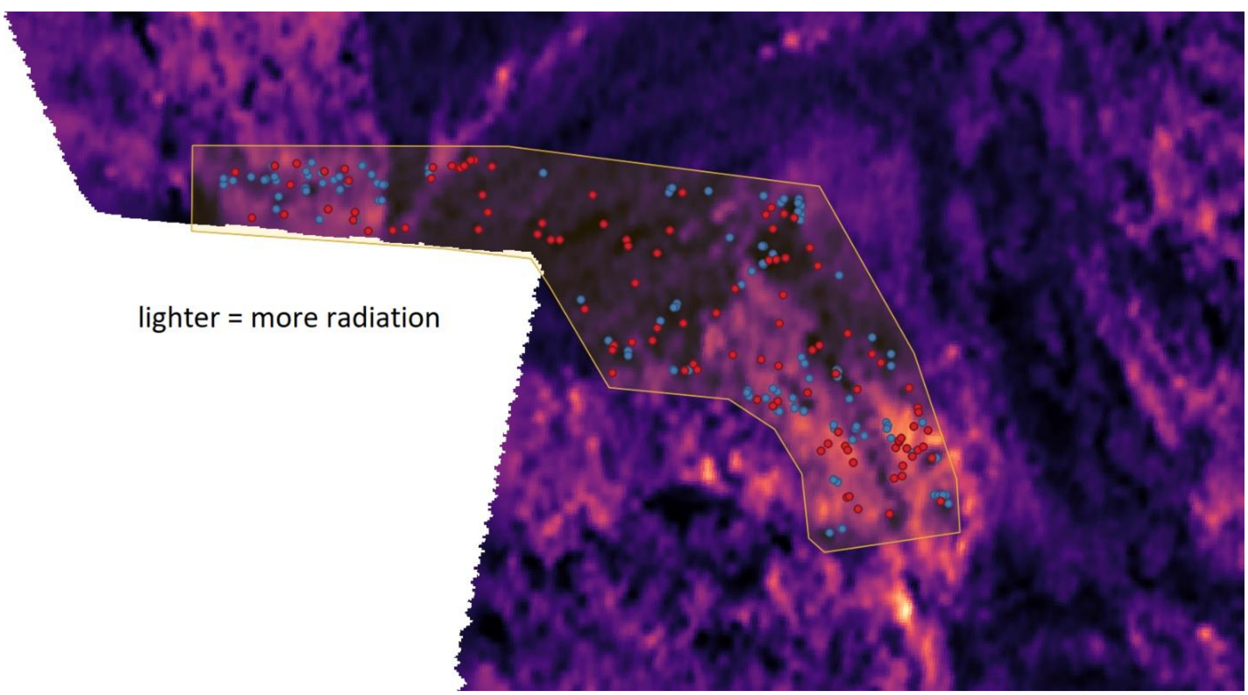
B-4. Heat Index raster



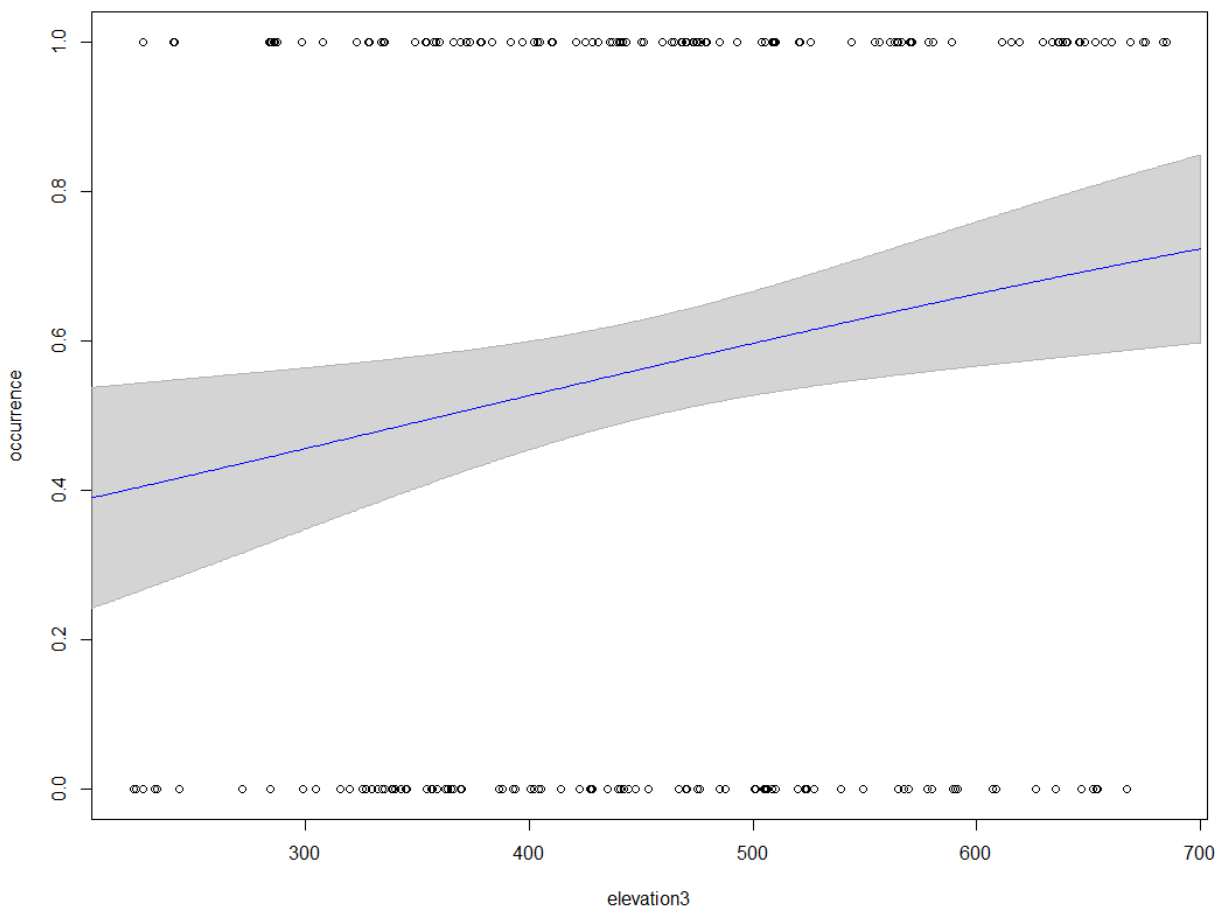
B-5. Aspect raster

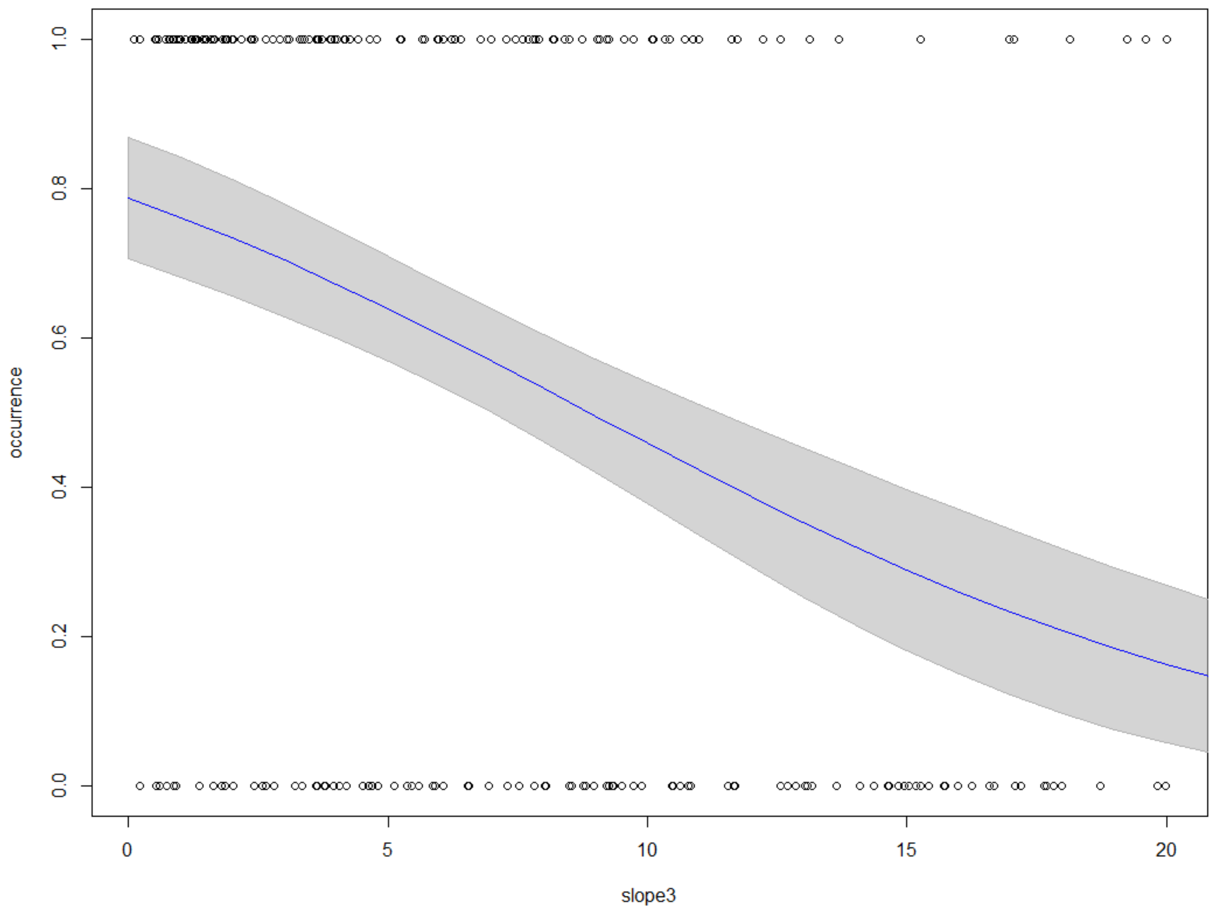


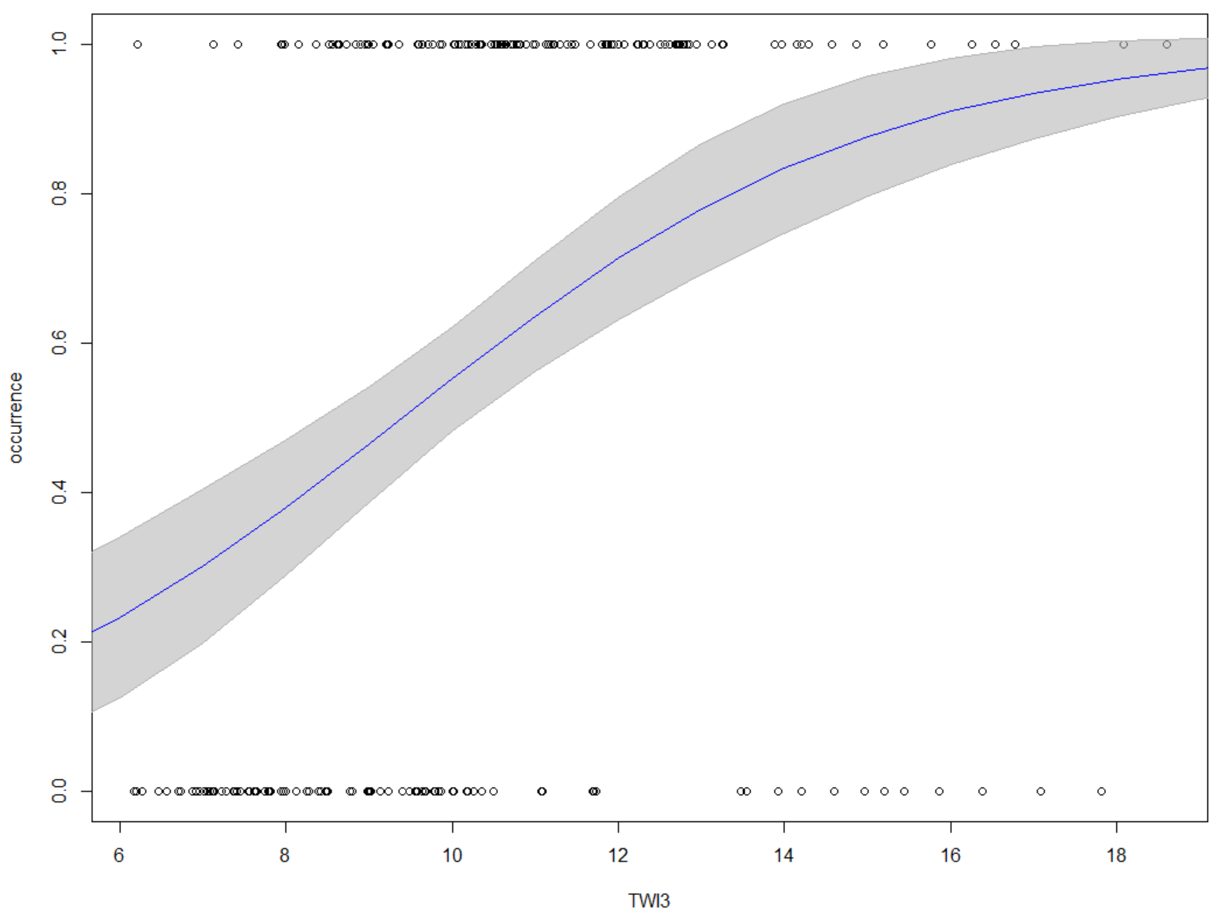
B-6. Radiometric dose raster

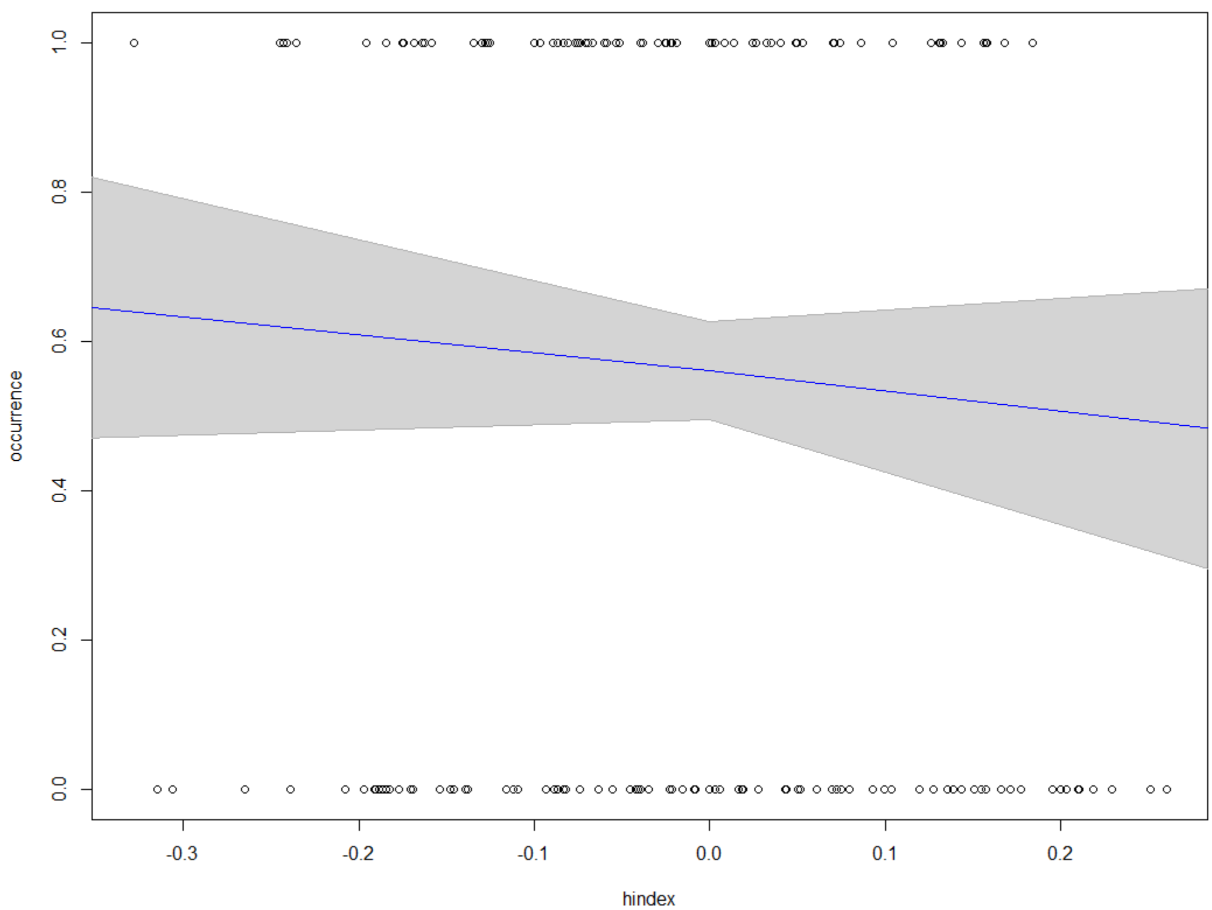


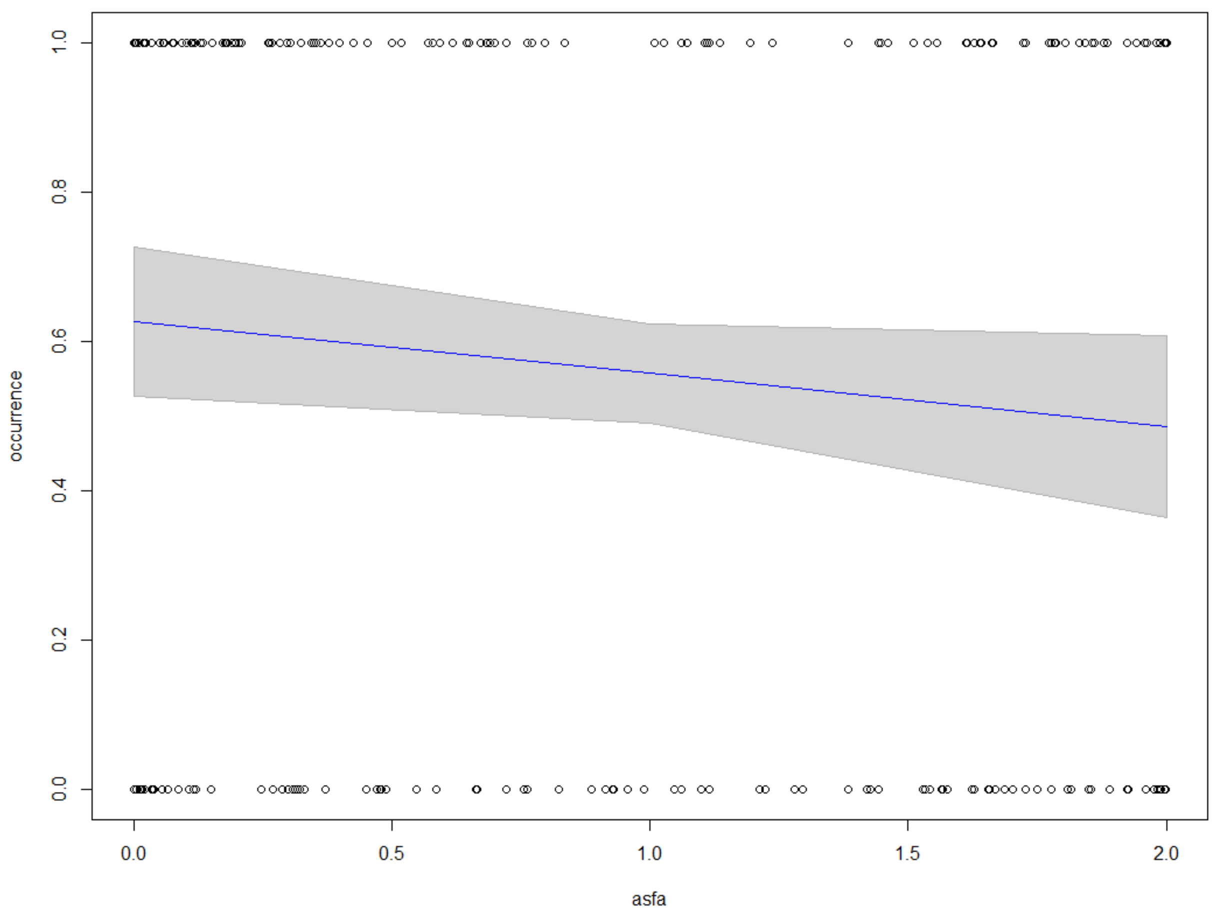
Appendix C – GLM Plots

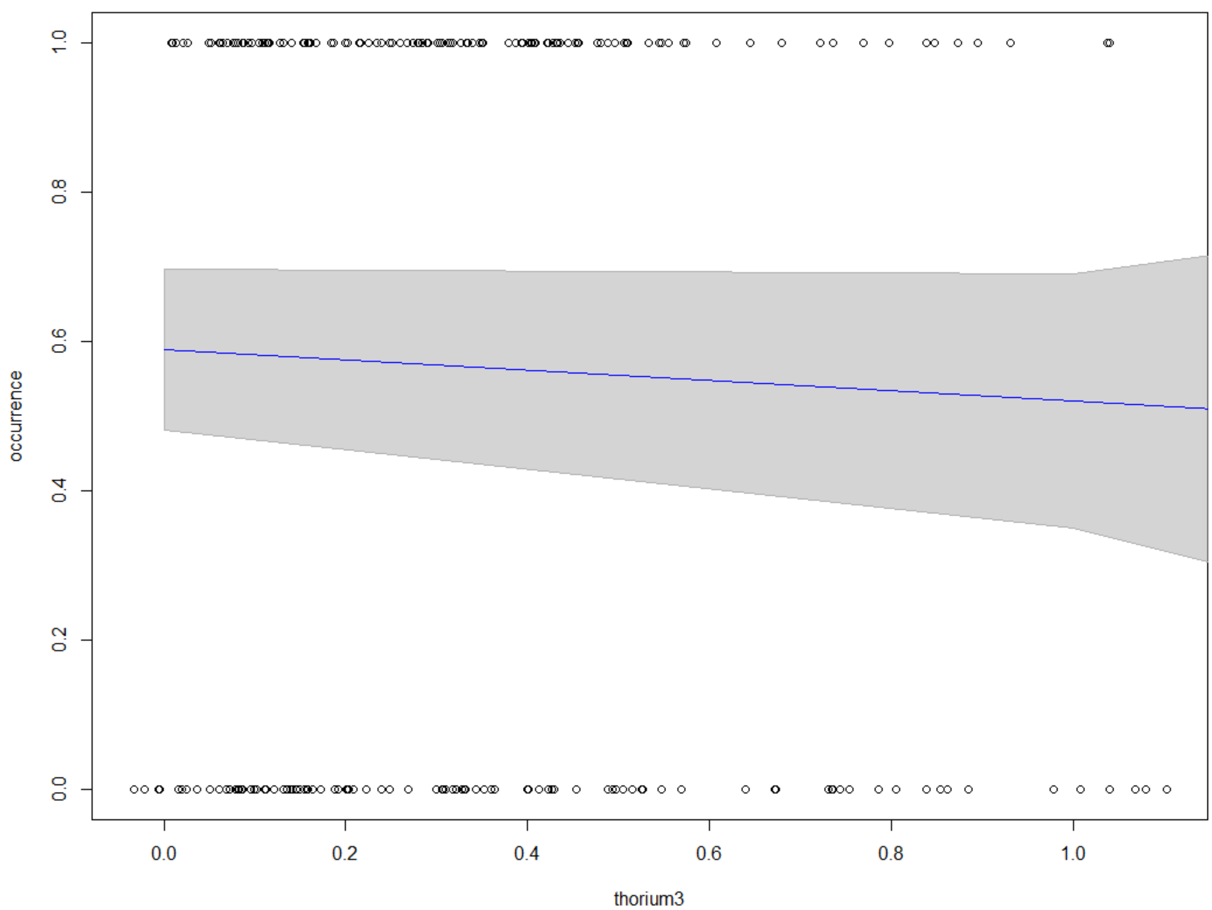


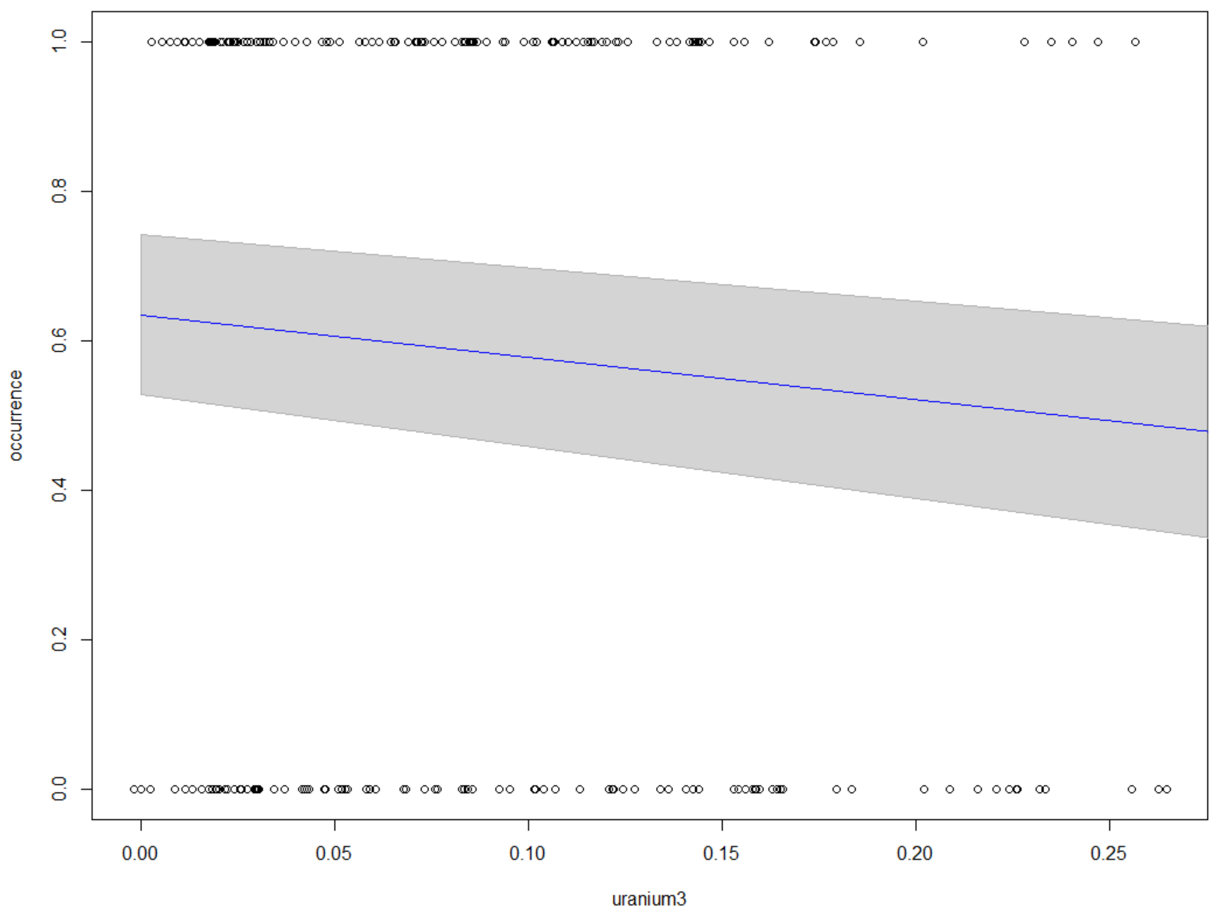

occurrence
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20
slope3

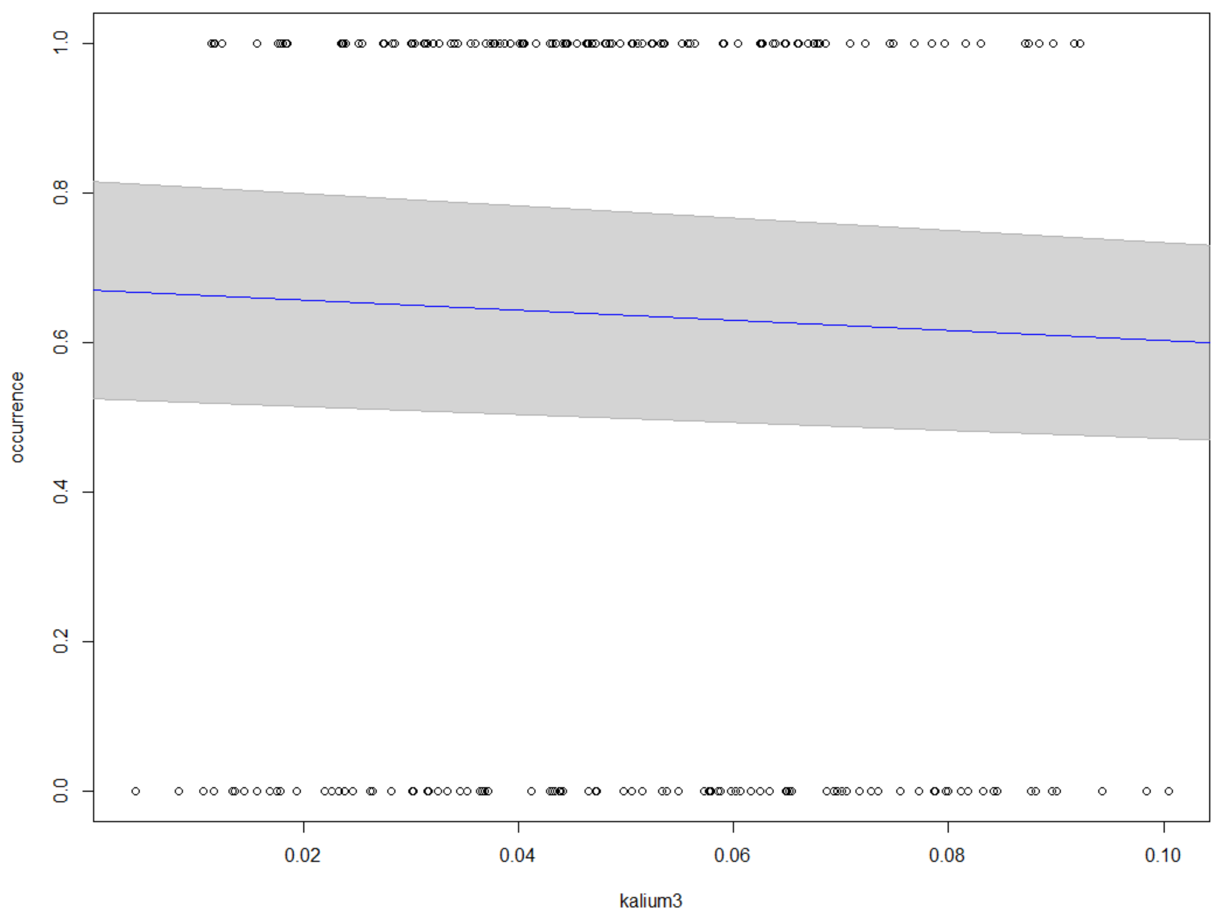

occurrence
0.0
0.2
0.4
0.6
0.8
1.0
6
8
10
12
14
16
18
TWI3

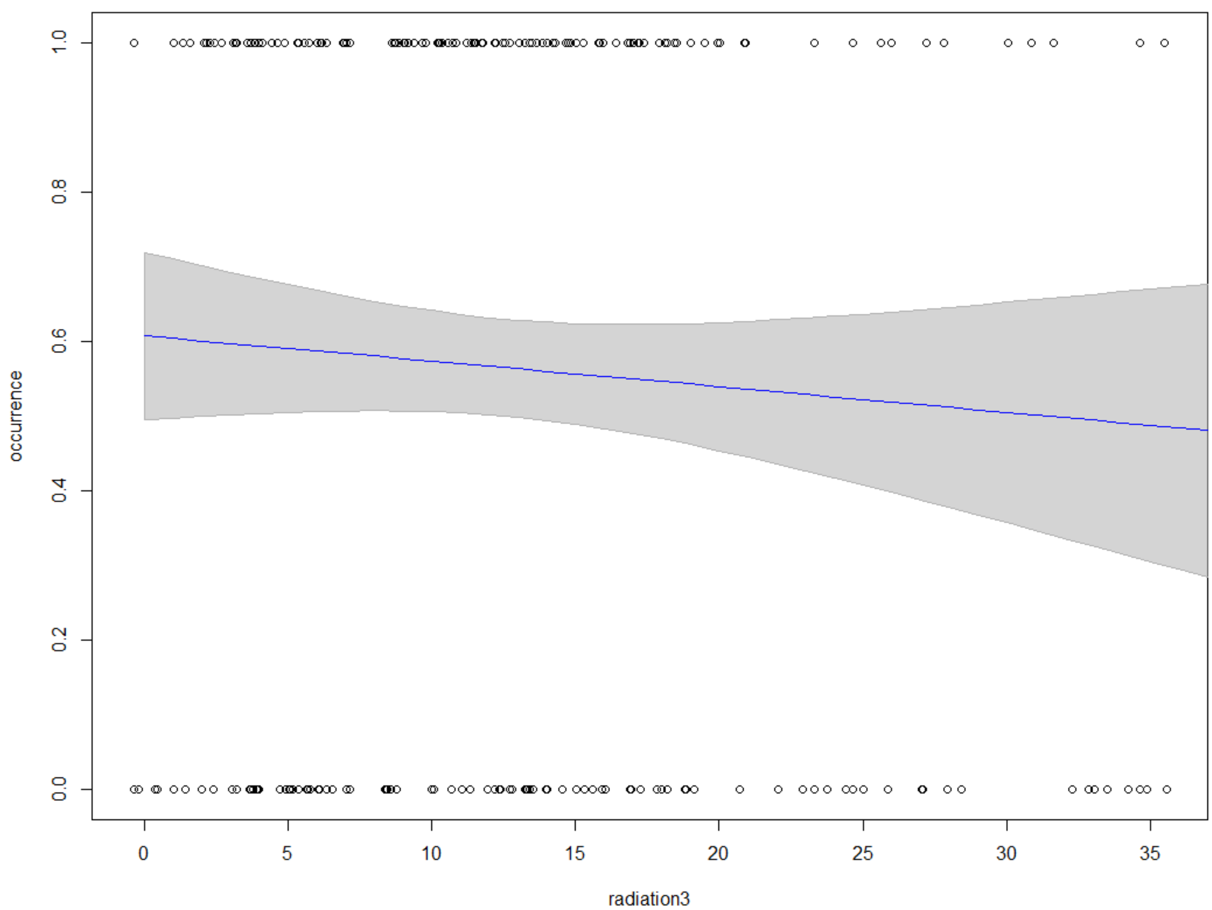

1.0
0.8
0.6
0.4
0.2
0.0
occurrence
-0.3
-0.2
-0.1
0.0
0.1
0.2
hindex


1.0
0.8
0.6
0.4
0.2
0.0
occurrence
0.0
0.5
1.0
1.5
2.0
asfa


occurrence
thorium3
0.0
0.2
0.4
0.6
0.8
1.0


1.0
0.8
0.6
0.4
0.2
0.0
occurrence
0.00
0.05
0.10
0.15
0.20
0.25
uranium3


1.0
0.8
0.6
0.4
0.2
0.0
occurrence
0.02
0.04
0.06
0.08
0.10
kalium3



occurrence
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20
25
30
35
radiation3