MODELING GRASSLAND TRAITS USING UAV-BASED RGB AND MULTISPECTRAL IMAGES.

ZEESHAN UMAR
August, 2020

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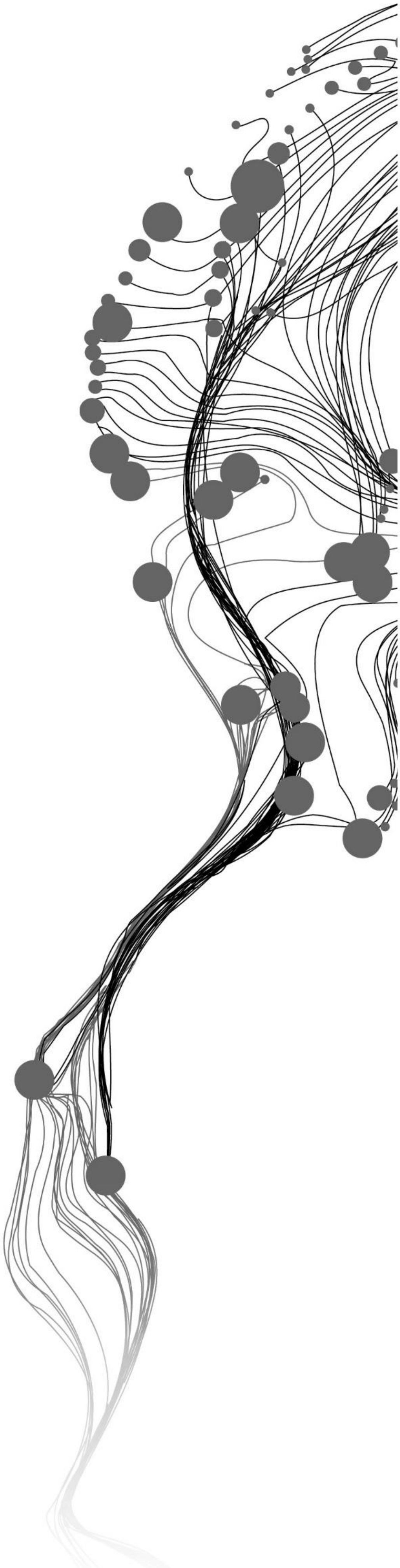

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ZEESHAN UMAR
Enschede, The Netherlands, August, 2020

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
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ABSTRACT

Dry matter predictions provides farmers with important information about the nutritional quality of the grasslands. The assessment of spatial distribution of dry matter in grass provides farmers with useful feed information for dairy animals. However the existing remote sensing near real-time techniques, which involves unmanned aerial vehicle (UAVs) mounted with high resolution multispectral sensors to compute the multispectral vegetation indices (MI) is expensive. To address this problem, there is a need of using cost effective Red, Blue, Green based Vegetation indices techniques (RGBVI) for the prediction of dry matter. Therefore, the main objective of this research is to compare the dry matter prediction for both RGBVI and multispectral vegetation indices (MI) acquired via a UAV. The sequoia sensor time-series VI (i.e. RGBVI & MI) dataset are compared using linear and non-linear random forest regression model. This research investigate the impact of time-series dataset of multiple UAV flight to further optimize the model prediction performance. The linear regression model with selected metrics (i.e. RMSE, r-square, MAE) perform better for Kieftenweg using the RGBVI dataset compare to the Vonderweg. The non-linear model using the same metrics perform better for Vonderweg using the RGBVI dataset compare to the Kieftenweg. However, the two models perform almost similar for types of VIs (i.e. RGBVI and MI) combined datasets for two grasslands. The VI's calculated from the timeseries dataset were also ranked to analyse them for their importance to prediction results. The last two flights means and cumulative values of VIs were ranked the highest based on their contribution to the final results of prediction of dry matter for Kieftenweg using the RGBVI datasets. The commutative and mean of last two flight based VIs were ranked second highest for Vonderweg and two fields combined dataset of RGBVI. The spatial distribution of the dry matter were also analysed using the surrounding pixels around the ground observation. The Kieftenweg and Vonderweg predictions maps displayed predictions result within a certain range beyond which the model couldn't predict.

The present study finds out the RGBVI can produce better results for the individual grasslands. However, the RGBVI produce almost similar to MI for the two fields combined dataset.

Key words: UAV, variable importance, precision manure management , remote sensing , RMSE, r-square, MAE

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1. INTRODUCTION

1.1. Motivation

Grasslands are part of the earth's surface covered with grass (Blair, Nippert, & Briggs, 2014). Earth's surface is comprised 40% of grasslands (Lussem, Bolten, Menne, Gnyp, & Bareth, 2019a). Grasslands have a multifunctional role in the earth's ecosystem. However, the necessity of people to support themselves, transform these grasslands to pastures for their livestock to acquire benefits in the form of dairy products and meat (Salmon et al., 2018). The yield from the grasslands to ensure food security is significantly increased with the latest technological advancements in the field of agriculture(Wrigley, Batey, & Miskelly, 2017)). The modern age agriculture equipped farmers with new technologies (e.g. Remote Sensing, GPS) to support farming.

Remote sensing is the science of getting information about an area, body or phenomena without getting in physical contact (Jabalpur, 2011). Modern agriculture is facilitated with remote sensing to make site-specific decisions. For instance, the farmer can use the information related to the deficiency of nutrients to decide site-specific provision of manure in the grassland. This is possible with the approach of remote sensing to collect data to assess the grassland in a cheap and less time-consuming way, which is the reason for remote sensing gaining popularity among the farmers. One way of using the science of remote sensing is the collection of multispectral imagery. Multispectral imagery is a representation of the received electromagnetic radiations in the visible and the near-infrared band in the form of an image (Ose, Corpetti, & Demagistri, 2016). They were used in the past to get an insight into the landcover and land use information. Nowadays, the newest research is aiming to explore further cost-effective RGB based images to monitor the quality of the vegetation cover (Lussem, Bolten, Gnyp, Jasper, & Bareth, 2018). The RGB (i.e. Red, Blue, Green) images receive electromagnetic radiations in the visible spectrum RGB (i.e. Red, Blue, Green). The RGB in combination with the near-infrared (NIR) bands based methods discussed can be useful for observations of grasslands and examine the factors (e.g. dry matter, rainfall, temperature) responsible for affecting grass. The information in the RGB and NIR is useful for predicting dry matter in grass. The prediction of dry matter yield can help the farmers for better management practices to take actions against the yield-reducing agents(e.g. Climate change(Blair et al., 2014).

Different methods have been previously used to predict the dry matter. Dry matter can be defined as “ the contents of grass after water is removed (Yoottasanong, Pholsen, & Higgs, 2015). The dry matter prediction provides the farmers with important information about the nutritional quality of the grasslands. Previously, a number of linear and non-linear regression models were used to predict the dry matter yield of the grass (Bendig et al., 2015). Linear regression method studies the relationship of two or more dependent variables with one independent variable (Sellam & Poovammal, 2016). The linear regression models were preferred for their straightforward interpretations (Backus & Wild, 2013).They are best fitted in situation when there is a linear relationship between the variables. Unlike the linear equations the non-linear method are more complicated to implement, but they are more flexible compared to the linear regression method based on the reason it can adapt quickly to any curve (Walmsley & Lowe, 1985). There is very limited study about the random forest regression models in the context of information in the RGB spectrum for dry matter prediction (Xing, Pittman, Inostroza, Butler, & Munoz, 2018). The random forest model is combination of decision trees and where each decision tree is constructed from random number of subset selected from data used to train the model(Liaw & Wiener, 2002; Pavlov, 2019)

Problem Statement

The prediction of dry matter is very important to assess the nutrients availability in the grass. Using multispectral vegetation indices (MI) for dry matter prediction is expensive(Lussem, Bolten, Menne, Gnyp, & Bareth, 2019b). There is a need for a cheaper means of dry matter prediction for which the predictions quality are identical to MI based dry matter prediction results. RGBVI are a cheaper means of dry matter predictions in grass (Lussem et al., 2019; Kamilaris & Prenafeta-Boldú, 2018; Liakos, Busato, Moshou, Pearson, & Bochtis, 2018). However, the correctness of RGBVI in grass needs further investigation to compare it with MI dry matter prediction results(Zheng et al., 2018).

1.2. Research Objectives and Research Questions:

1.2.1. Main Objective:

The main objective of this MSc thesis is to compare the dry matter prediction in grassland with both RGB and MI VIs acquired via a UAV.

1.2.2. Sub-Objectives guiding the research question:

I. To compare the dry matter prediction performance of linear and nonlinear machine learning based regression models.
Respective research question: Which of the linear and nonlinear regression models is better for dry matter prediction with less errors in the grass using RGBVI?

II. To compare the dry matter prediction performance for two data sets, RGBVI and MI.
Respective research question: How is the performance for the two data sets (i.e. RGBVI and MI) analysed via the prediction error?

III. To improve dry matter prediction accuracy in grass using time-series remote sensing data.
Respective research question: What is the impact of time-series remote sensing data on dry matter prediction in grass?

1.3. Conceptual Framework

Conceptual framework is summarized in Figure 1, that describes the main concepts of this research. This gives a broad picture of the grassland system. Figure 1 Conceptual frameworkalso display the different parameters of the grassland system. The variation in which affects the final output of the grassland system in the form of dry matter within the grass. It also describes the relationship between the different concepts of this research. The conceptual framework consists of input, output, processing, data parameters. Remote sensing is a process to monitor the grassland with the help of sensors mounted on UAV to create orthomosaics. The orthomosaics are further processed for the calculation of Vegetation indices (VI) for prediction of dry matter within the grassland. The VI calculated from the orthomosaics are divided into types RGBVI and MI. The VI's using the red, blue and green bands are categorized as the RGBVI. The VI's using RGB in combination with the near-infrared are categorized as MI. The sensors required for multispectral imagery are expensive compare to the sensors needed to record information in the RGB bands. The soil texture information is also available for dry matter prediction analyses. The soil texture information of the grasslands is based on the combination of sand, silt and clay. This information is very important to understand the fertility and water absorption in soil. Furthermore, the overall grassland is distributed in to manure zones. The manure treatment of the grassland is also an important factor the assess the dry matter distribution in the grassland. The precision manure management concept is used to apply different percentages of manure to the grassland. The precision manure management ensures there is less waste of resources. The overall cost of manure provision to the grassland is also reduced.

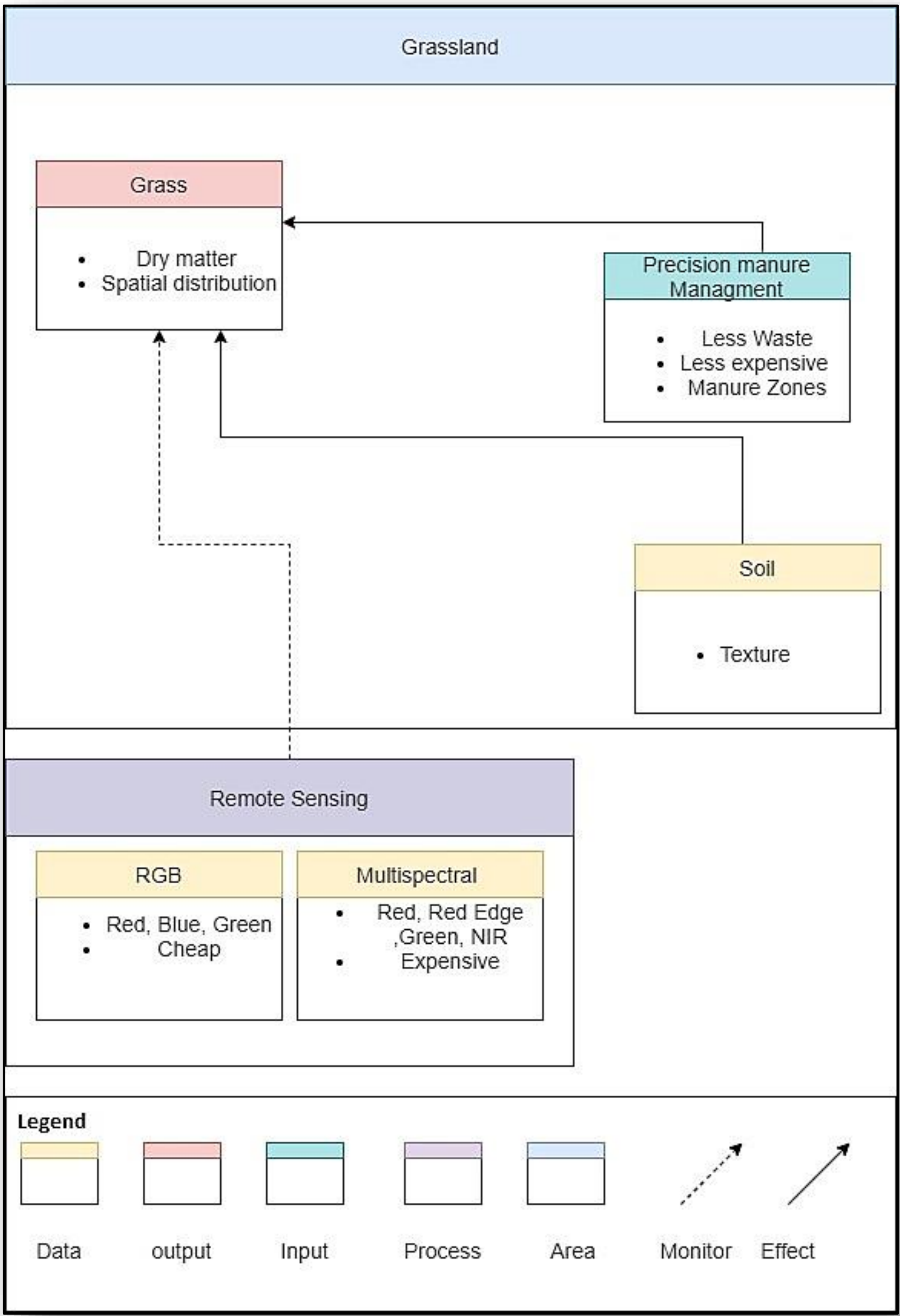

Figure 1 Conceptual framework

1.4. Aimed Innovation:

Previously, the RGBVI has been used to predict dry matter in a single grassland with varying percentages of manure. This research will consider two grasslands with same manure treatment for dry matter prediction. Previously, linear regression model is used for prediction of dry matter. This research is considering comparison of linear approach to a non-linear method of prediction, which is more flexible approach to predict the dry matter in two grassland with same manure provision plane. The flexibility of the model defines the model learning influenced from the variation in the dataset. Unlike Lussem et al. (2019), this research is also considering time-series analysis for recorded data from multiple UAV flights conducted during the growing season of grass. The same research also suggests the generalization of linear regression model results of dry matter to multi-site grasslands with difference in soil texture using same precision manure setup. This research uses both linear and non linear regression model to optimize the dry matter prediction results for the two grasslands.

2. LITERATURE REVIEW

2.1. UAV applications for precision agriculture

UAVs also commonly known as drones, are flying robots and their usage encompasses diverse applications in the modern world. However, this study focuses on the UAV's range of applications related to precision agriculture. For instance, UAV's applications related to precision agriculture ranges from monitoring climate affect, periodic crops growth, feeds intake for livestock, health of livestock and nutrients quality level assessment.(H. Wang, Mortensen, Mao, Boelt, & Gislum, 2019). UAV's hold potential benefits for farmers, when it comes to precision agriculture to monitor agricultural productivity using ultra high resolution imagery (e.g. in centimetres), low operational cost and acquire data almost near real time(Zheng et al., 2018). UAV's can be defined as "UAV's are aircrafts, which needs no support of onboard pilots for flying"(Narayanan & Ibe, 2015). Figure 2 Types of UAV's for precision agriculture (Adiloğlu et al., 2012). different types of UAVs used for precision agriculture, which can be categorized into multirotor, fixed wings , single rotor and fixed wing multi rotor hybrid UAV"s(Adiloğlu et al., 2012).

Figure 2 Types of UAV's for precision agriculture (Adiloğlu et al., 2012).

The multiple quadcopter are preferable for small farms for the reason most of their energy is utilized against the gravity and wind to hover. Multirotor UAV's have slow flight speed compare to their other types of UAV's. The fixed wing drones are preferred for large farms for the reason of higher speed and longer flight duration compare to multiple rotor drones but their main disadvantage is not having the capability to hover. The single rotor UAV is a more stable version of the previous two types with all the good qualities of both. The single rotor drones have two rotors. One is used for the control and the other one is used for thrust. They are highly manurable UAV's with more airborne time. They are mostly use for precision spraying within the field. The main disadvantage of using single rotor drones comes with complicated flying procedure, cost, risk of fatality for its large propeller size capable of providing more thrust and long endurance flight. Fixed wing multirotor hybrid drones also known as hybrid VTOL (vertical take off and landing) drones, combines the best features of multirotor and fixed wing drones. Which makes it an ideal choice for precision farming. They can be used for long endurance flights for long farms. They easily monitor the health, dry patches within the crops , pests and fertilizers (manure for this research).

The observed grasslands related to this research uses the concept of precision manure management. Precision manure management can be defined as "practice of avoiding intensive farming methods to utilize manure according to the needs of the crops in a more sustainable manner" (Moshia et al., 2014). Precision manure management take into account the best features of both the agronomics and Precision agriculture (Moshia et al., 2014). Precision agriculture takes into account the site specific data from different sources (i.e. sensors) to optimize yield(Chmielewski & Potts, 1995).The science of remote sensing provides non-destructive and rapid methods for useful management practices for manure provision at the right location, at right rate and right time(Fajardo et al., 2016). UAV based remotely sensed collected information can be used to monitor the nutrients quality assessment in terms of dry matter contents of the crops(i.e. grass). Dry matter information is very important for manure management to ensure sustainability with avoiding waste of resources (Jones et al., 2017).

Table 1 List of selected VI

Type	VI's
RGB	NGRDI
RGB	MGRVI
MI	NDVI
MI	EVI2 (Two band)

Table 1 List of selected VI a list of VI's used for prediction of dry matter in grass. This research uses the previously considered VI's shows strong relationship to dry matter content within the grass (Ashapure et al., 2019; Lussem, Bolten, Menne, Gnyp, & Bareth, 2019; Zheng et al., 2018; Jannoura, Brinkmann, Uteau, Bruns, & Joergensen, 2015).The considered VI's can be categoirzed into two types based on the creation of rasters using only the bands lies in the visible part of the EM spectrum (i.e. RGB) and rasters in combination of both RGB and near-infrard (i.e. NIR) bands of the EM spectrum (Jannoura, Brinkmann, Uteau, Bruns, & Joergensen, 2015). Previously, the cheaply available RGBVI to predict dry matter was used for one site within a precision manure management setup. Further research is need to evaluate the performance of the two types of VI's selected for multi-site grasslands to predict dry matter(Liang, Shi, & Zhang, 2018; Lussem et al., 2019a). The results can be further optimized using the time-series data acquired for the multi-site grasslands(Jannoura et al., 2015; Xing et al., 2018).

2.2. Review of analytical methods for dry matter prediction in grass

Nowadays, precision agriculture is reshaping the conventional farming methods based on the collected data from farms using remote sensing. Which helps the farmers in making useful agronomics decisions based on what happened , what is happening and what will happen. Agronomy also know as agronomics can be defined as " the science of increasing productivity with improving the use of soil". The prediction of dry matter in grass can help farmers in making good agronomic decisions based on the spatial distribution of the dry matter in grass. A number of analytical methods exists to acquire the spatial distribution of dry matter information. However, these methods works with collection of ground observation to validate the analytical methods findings. These ground observations from the fields require expensive laboratory tests to find the exact percentage of dry matter in grass. Reducing the number of samples to minimize the cost of laboratory means selection of analytical methods, which can work efficiently with less ground observation. (Grömping, 2009) suggests the random forest (i.e. RF) and linear regression model perform better than any other analytical method based on the required ground observation to predict dry matter spatial distribution in grasslands. The same research suggests the use of RF models for predictions is more suitable for high dimensional data for prediction compare to using LR model. However, the LR model is robust model in situation where the number of ground observation are more than the number of predictors. If the number of observation is less than the number of predictors available for the model for prediction the LR model performance decreases drastically. The two RF and LR models are different approaches to analyse the dry matter spatial distribution in grasslands. The linear regression can perform prediction of dry matter in grasslands if there exists a linear relationship between the target variable (i.e. dry matter) and the predictor. However, if there is no linear relationship the LR model prediction performance results into large values for selected error metrics. The RF based regression model has non-linear nature, which makes it more flexibility to fit any curve of the provided dataset.

Lussem and collabrators (2019b) predicted dry matter within a grassland with precision manure management setup using linear regression model for two types of VI's(RGB and MI). However, the same research suggest this method need further investigation for generalization the results to multi-site grasslands. This research can be further optimized using the time-series data of multiple UAV flights during the growing season of grass. Previous research suggests the VI's values fluctuates in time (Li, Yang, Liu, Liu, & Shi, 2015). The reason for fluctuation in the VI's can be recorded within weeks(Zhang et al., 2018a). For instance, the reason can be the variation in the availability of water and radiation energy (Zhang et al., 2018b). One aspect of this research will investigate the impact of using the mean and cumulative values of the selected VI's impact on the prediction error for dry matter. The spatial patterns of the dry matter within the grasslands can be further validated the model findings for nearby pixels surrounding the ground observations.

3. STUDY AREA AND METHODS

3.1. Study area

The study area consists of two grasslands located in Bentelo. Bentelo is part of the Overjissel province of Netherlands, which is a small farming village, where the surface is mostly sandy soil. Bentelo is comprised of swampy meadows. The land is mostly used as pastures, which helps in supporting cattle and dairy farming in the region. The climate information for the months February , March and April were collected for the reason that the UAV flights were conducted for the study area in this time of the year (KNMI, 2019). The average temperature in Celsius scale of 13.8 for February, 19 for March, 24.3 for April The average precipitation are also acquired from the same source 51.1 mm for February , 65 mm for March and 45.2 mm for April. The two grasslands for identification are named Kieftenweg and Vonderweg. The two grasslands are displayed Figure 3: Study area: two grasslands Vonderweg (Left) and Kieftenweg (right) , Kieftenweg on the right and Vonderweg on the left side. The two grassland are 1858.6 meters apart from each other. The two grasslands Kieftenweg and Vonderweg cover an area of 2.6811 and 3.611 hectares. The two grasslands are planted with seeds of English grass. Kieftenweg has been used continuously as grassland for nine years. Unlike the previous (Kieftenweg), Vonderweg has been used as grassland for two years. The soil type of Vonderweg is a combination of loamy and sandy, while the soil type of Kieftenweg is mostly sandy.

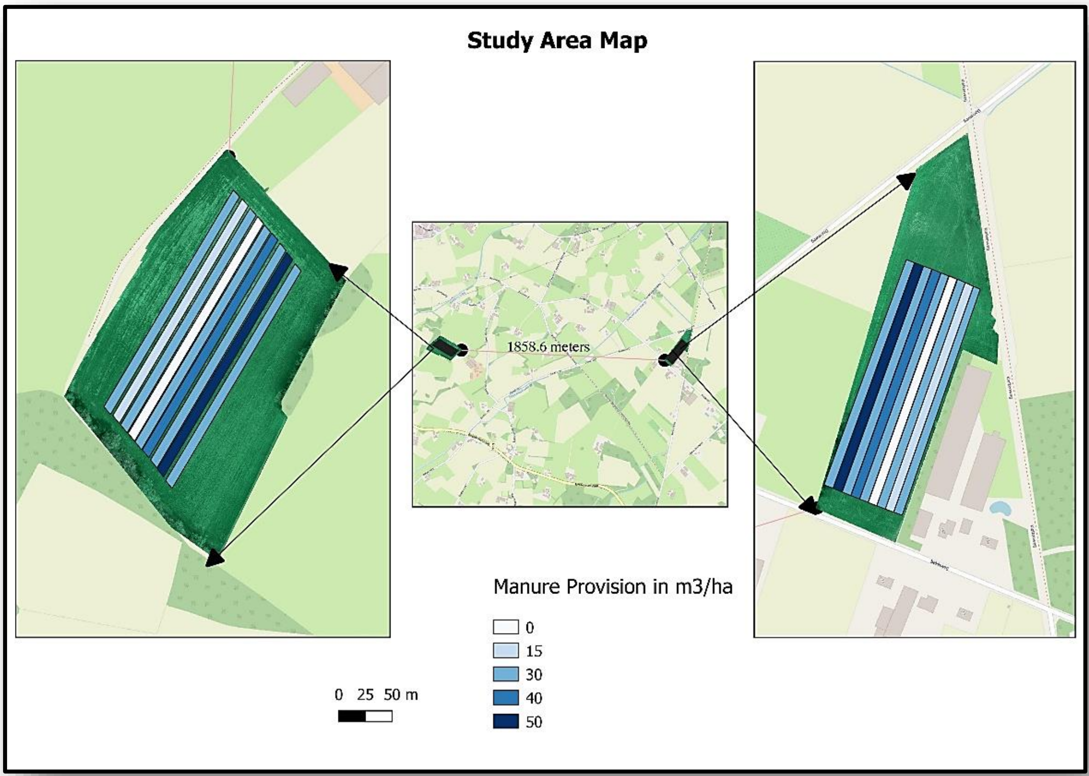

Figure 3: Study area: two grasslands Vonderweg (Left) and Kieftenweg (right)

The two grassland uses similar manure provision plan. Each grassland is divided into five different manure zones. The quantity of manure supplied within each manure zone is 15 m3/ha, 30 m3/ha,40 m3/ha, 50 m3/ha, and no manure at all respectively in (Figure 3: Study area: two grasslands Vonderweg (Left) and Kieftenweg (right).

3.2. Data Description:

The data to research dry matter in the two grasslands, include the UAV mounted parrot sequoia sensors images and the ground observations (see table 2). Private companies Gebr. Fuite B.V and Veelers Melkgeitenbedrijf B.V, based in Netherlands collected these datasets. The companies responsible for the provision of the UAV mounted parrot sequoia sensor imagery and ground observations along with flight specifications are listed in table 2.

Table 2 UAV flight details

Grassland	**1st flight**	**2nd flight**	**3rd flight**	**Altitude (meters)**	**Service providing companies**	
					UAV imagery	**Ground observations**
Kieftenweg	19/03/2019	07/04/2019	30/04/2019	40m	Robor Electronics BV	Gebr. Fuite B.V
Vonderweg	17/02/2019	19/03/2019	30/04/2019	40m	Robor Electronics BV	Veelers Melkgeitenbedrijf B.V

During the grass growing season the UAV mounted parrot sequoia imagery were recorded for three instants of flights. The dates of those flights for the both grasslands are specified in table2. The altitude of UAV flights were conducted at forty meter for the reason parrot sequoia sensor capture the imagery at uniform height.

Sequoia is a combination of multispectral and sunshine sensor. The sequoia sensor imagery uses absolute reflectance measurements, which doesn't require radiometric calibration. Sequoia sensor capture imagery using the red (640-680 nm), green (530-570 nm), red edge (730-740 nm) and near-infrared band (770-810 nm) of the EM spectrum. The sequoia sensor is also incorporated with an internal GPS, which makes the imagery collection more efficient in terms of the recorded altitude, speed of flight and spatial-position accuracy. The sequoia is a light weighted sensor, which makes it suitable for any model of UAV.

The orthomosaic resulted from the sequoia imagery for the two grasslands have a ground sampling distance value of 5.02 cm/pixel. The GSD was calculated using the reported dimensions of the orthomosaic from Pix4field 3000x4000 (i.e. width x height), sensor width (6.17mm) and the focal length (4.88mm). The GSD of the orthomosaic is used to present the area of grassland in centimetres the pixels presents. The bands information to compute the selected VI's from the orthmosaics represents the vegetation properties. The bands combination information is listed in table 3, which are used to study the dry matter in the two grasslands.

Table 3 VI calculation using bands specific information

Type	**VI's**	**Formula for calculation**
RGB	NGRDI	$\frac{Green-Red}{Green+Red}$
RGB	MGRVI	$\frac{(Green)^2-(red)^2}{(Green)^2+(red)^2}$
MI	NDVI	$\frac{(Nir-Red)}{(Nir+Red)}$
MI	EVI2 (Two band)	$\frac{2.5*(Nir-Red)}{(Nir+2.4*Red+1.0)}$

The collection of sequoia imagery analyses the dry matter in grass using ground observations for validation. The validated prediction results is useful source of information to analyse nutritional level of the grass feed for dairy animals. The total number of 23 dry matter ground measurements were collected for each field. The ground measurements were collected at the end of the grass growing season before the mowing of the grass, which can be seen as buffer features in Figure 4 Ground observation plotted on grasslands maps. The dry matter measurement were performed using the conventional oven dry method (Brahmakshatriya & Donker, 1971). The samples were kept in the oven at 70 to 80 centigrade overnight for more than 4 hours.

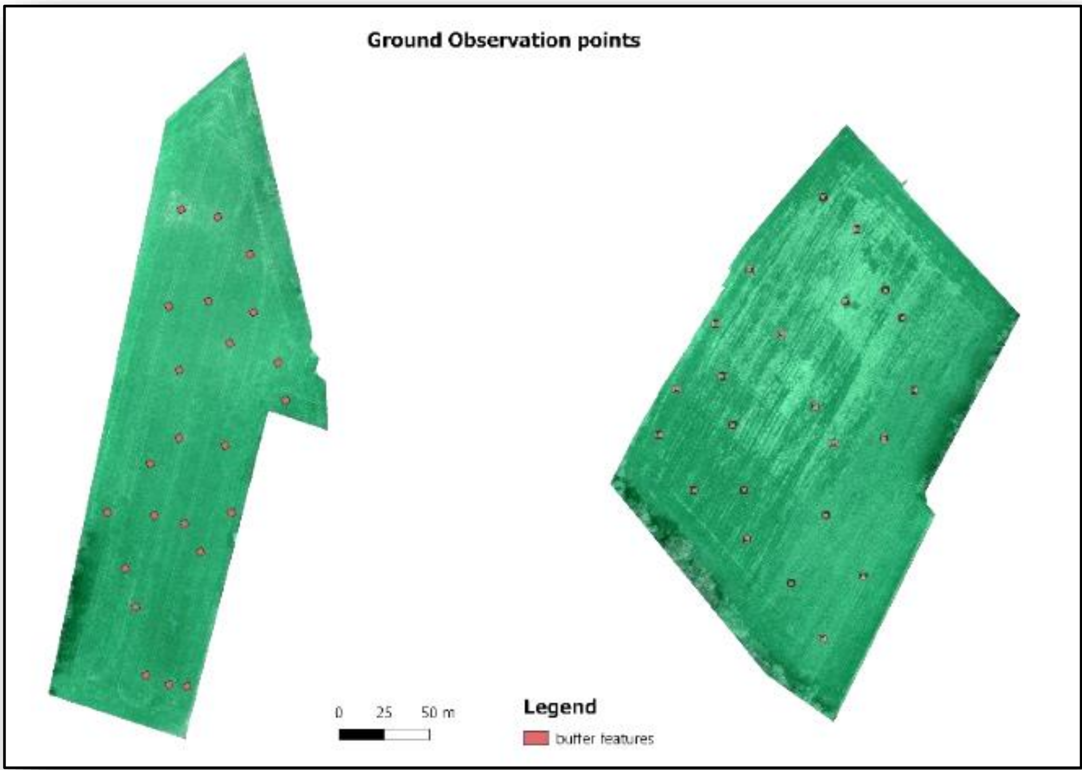

Figure 4 Ground observation plotted on grasslands maps

3.3. Data Preparation:

The data preparation started with creation of orthomosaics with stitching the UAV mounted sequoia sensor tiff formatted imagery. Pix4field is a photogrammetric aerial images processing software, which facilitates the precision farming by stitching UAV mounted Sequoia sensors imagery. All the provided images can be uploaded to the pix4field software, the captured Sequoia images have a specific geo-location. The stitching starts with first identification of the initial position of the UAV flight over the grassland in Figure 5 Initial point setup Pix4field (Carneiro et al., 2014), which is presented with a large blue dot. In the next step the tie points are identified for the provided images. The images tie point is decided based on the ground control points , initial position and computed position. The images at these points are overlapped to form one orthomosiac. As discussed previously, the sequoia datasets doesn't require a radiometric calibration. Pix4d ensure the quality of the orthomosaics with geometric and rig relative calibration to minimize distortion and missing pixels values. Pix4field software also facilitate computation of vegetation indices with the index calculator. The selected vegetation indices in Table 1 List of selected VI were calculated using the index calculator in Pix4field. The computed VI's were saved as tiff formatted raster files. The raster values were extracted for the area of the raster's overlapping the area of the field for which the ground measurements of dry matter were recorded.

Figure 5 Initial point setup Pix4field (Carneiro et al., 2014)

A buffer square feature of 2x2 m^2 of were created around the ground observations in QGIS, which is a open source software use for geospatial information visualization, editing and processing. The reason for keeping the buffer size equal to the ground observation for validation purpose, If the buffer is selected outside the area for which ground observation samples are collected the dry matter predicted values cannot be validated. The buffer square feature was overlaid on the computed raster files in R-studio to extract the mean raster values for the ground measurements . The ground measurement coordinates were first re-projected into a similar coordinate system of the orthomosaic created in Pix4field. The coordinate system used for the reprojection of the points was EPSG:32632 - WGS 84 / UTM zone 32N. The extract function in R-programming language is used to acquire the VI's raster values for the target ground observations in the two grasslands. The VI's values were collected for the target ground observations areas.

3.4. Workflow:

The order of activities involved in achieving the objectives are visualized in the Figure 6 Workflow. The first task involved the transformation of the UAV imagery to orthomosaics, which is the process to stitch imagery acquired for multiple flights of UAV into raster format files. The raster format files are pre-processed to enhance the quality of the imagery with rig-relative calibration and geo-referencing. The generated raster are further processed for uniform resolution and raster extent using the resample function for raster in the rasterio library in R programming language. Furthermore, the exploratory data analysis is used as a tool to look for patterns within the provided input data to the two regression models. The next step involves the calculation of the selected VI's in Table 1 List of selected VI using the formulae based on the band specific information. The VI's values extraction process provides the predictors values for prediction of dry matter. The VI's values are provided to the model as input to train the model and predict the dry matter values. The results are validated with the ground observations. The feature importance is the last step involved in the workflow to rank the predictors of the two models. The prediction results of the two models are analysed to assess the objectives are achieved with guiding research questions.

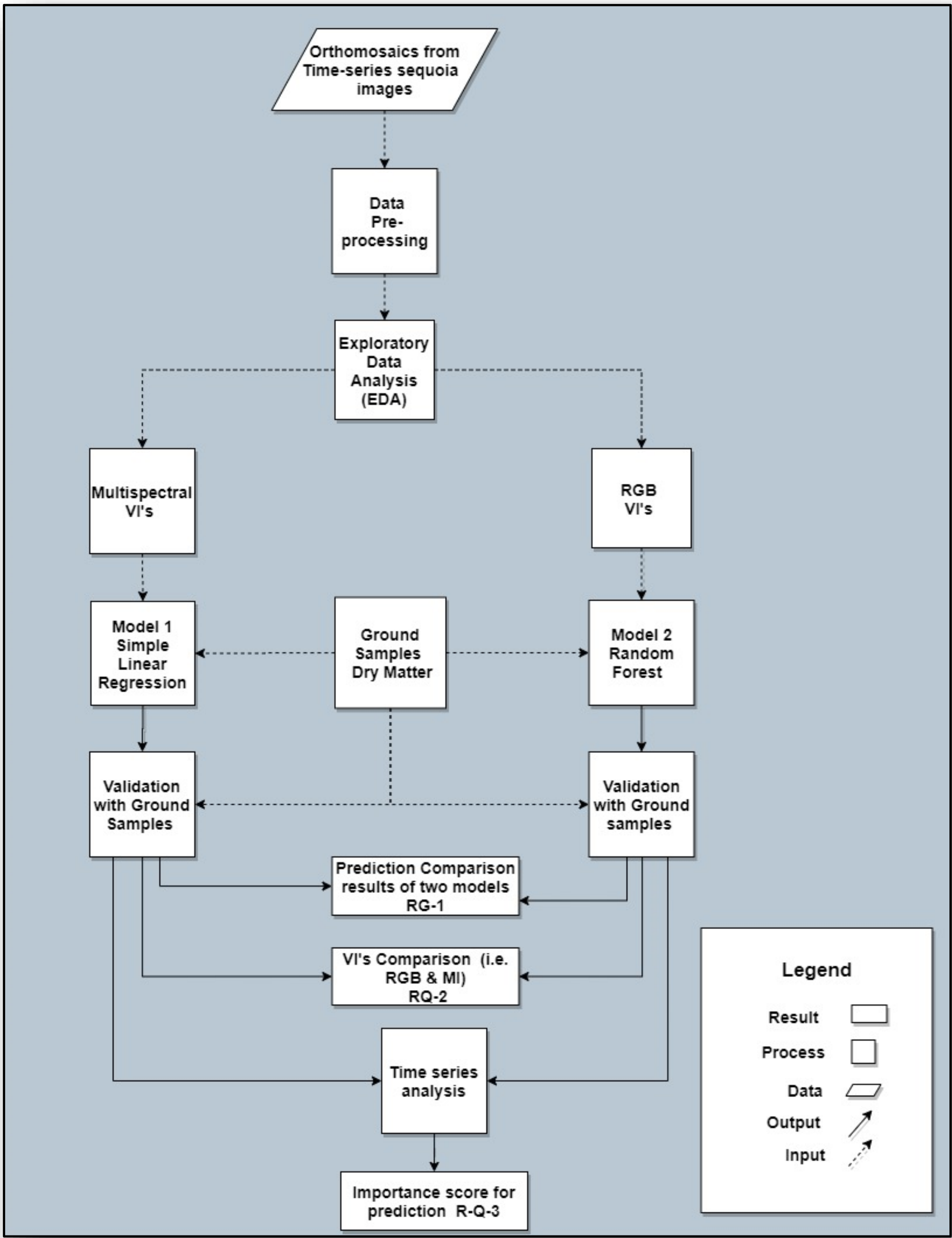

Figure 6 Workflow of the Methodology

3.5. Exploratory data analysis.

To perform exploratory data analysis the first step is the identification of highly correlated variables to perform prediction of dry matter. This research considers multiple VI's to predict dry matter, which is the reason for multivariate analysis to be performed on the predictors(i.e. VI's) data. The multivariate analysis uses graphical and non-graphical methods for exploration of data. The exploratory data analysis is performed visualizing correlation matrices and outliers detections graphs. The exploratory analysis uses the VI's values for the two fields individually and combined. The environment used to analyse the data is R-programming language.

The detection of outliers is very important before feeding the data to regression models. A number of method exists for outliers detection. This study uses the boxplot method for outliers detection. The boxplot is considered a robust method of outliers detection (Nkechinyere & I, 2015). Unlike, the standard deviation method using mean value which can easily affected from the extreme values(Nkechinyere & I, 2015). The boxplot method uses the robust median rule for outliers detection. The results from the model may not represent all instants of data if influenced from mostly from extreme values (i.e. outliers). Outliers can be defined as " those instants of the data deviating from the overall distribution pattern"(Casalegno, Sello, & Benfenati, 2008). The occurrence of the outliers is usually caused from error in measurements for the reason of an extreme event. Outliers are removed from the datasets for disturbing the overall distribution patterns (Martin, 2007). The outliers in the exploratory data analysis are detected using the R-programming language internal function boxplot. The boxplot divides the data into four quartiles, each represent 25 percent of the total instants of data(Choonpradub & McNeil, 2005). The boxplot identifies the outliers using the interquartile range of the spread of the variable values. Figure 7 boxplot display the interquartile range which represents the middle 50 percent of the data from lowest to highest in order (de San Buenaventura Colombia Cousineau, 2010). The intended variable for identification of outliers distance from the interquartile is determined. The data instants which lies about 1.5 of the interquartile distance above the upper quartile and the data instants which lies about 1.5 times the interquartile distance below the lower quartile are specified as outliers (Choonpradub & McNeil, 2005). The identified outliers common for all the predictors were removed from the input dataset prepared for the two models. The outliers identified for individual VI dataset was replaced with the mean value of the predictor of the specific column within the datasets(Cousineau, 2011).

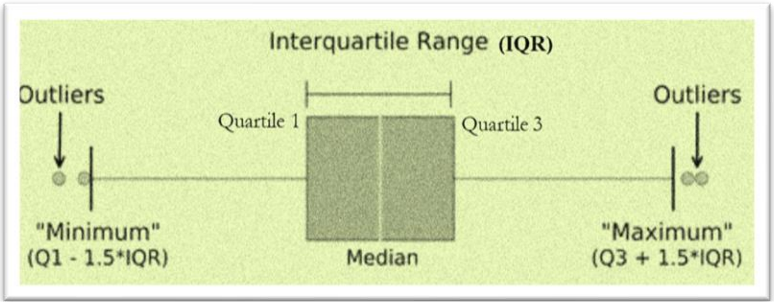

Figure 7 boxplot (Choonpradub & McNeil, 2005)

The applied boxplot method to represent outliers from all the applied VI's. The data to the boxplot is provided in vector or matrices form to the boxplot function. The boxplot function results can be displayed in different ways in graphs. For comparison of the two types VI's (i.e. RGBVI and MI) all the variables are accommodated in one boxplot graph horizontally. The y-axis represent the names of the predictors and the x-axis of the graphs represent the range of VI's values. Prior to the execution of the boxplot function the par function in r programming language is used for a multi-panel plot for specifying the rows, columns, width and height of the plot. The common outliers within the rows of the datasets were identified from the boxplot function execution and removed to reduce the prediction errors for the regression model.

linear regression model assumes linear relationship among the predictors and the response variable (Casson & Farmer, 2014). The linear relation between predictors and response variable is investigated using Pearson correlation, the results are visualized for individual grassland dataset and the two grassland combined dataset(Schober & Schwarte, 2018). The Pearson correlation coefficient represent with ρ for individual predictor represented with x and response variable represented with y is computed using the covariance and standard deviation of the respective predictor and response. The covariance represented with $cov(x, y)$ refer to the joint variation of the two variables x and y , if predictor value increases the response variable values increases accordingly and the same for decreasing of the two variables values. The standard deviation represented with σ refer to the spread of the values away from the mean values. The Pearson correlation coefficient can be calculated using the equation 2. The correlation matrix is generated using the library corrplot. The function corrplot named similar to the library name is used to create the correlation matrix. The upper visualization method to display the correlation plot is used to see the relationship of the predictor with itself and all the other predictors.

Equation 1

$$\rho = \frac{cov(x, y)}{\sigma x \sigma y}$$

3.6. Linear vs non-Linear models using two types of VIs

As discussed in the previous section 3.5, the data used in the models is pre-processed for the identification of outliers. The results from the exploratory data analysis is used for removal of outliers from the datasets of two grasslands. The process that lead to the removal of outliers is explained in details in section 13.5. The remaining dataset without outliers for Vonderweg consist of only 22 observations and 19 observations for Kieftenweg. The combined dataset of the two fields As discussed in the section 3.2, the two grasslands Vonderweg and Kieftenweg combined dataset of 41 observations was also used for dry matter prediction . The dataset of 19 ground samples were used for training the model for Kieftenweg field and dataset of 22 ground samples were used for training the same model for Vonderweg grassland. As discussed in section 3.2, the ground observations collected for the two fields are 46. However, after the removal of outliers detected within each fields leave us with only 41 observations. The two linear and non-linear models are also tested for prediction using the 41 observations of the two fields combined.

Error! Reference source not found. The predictors are named based on the selected VI, UAV flights information and the method of combination for multiple UAV flights based VIs values (i.e. cumulation and mean). The first two flights at the start of the growing season using the mean or cumulative method of combination for VI values are used to make the set of 4 predictors. The last two flight based VIs values are combined using mean and cumulation for making another 4 predictors. The three flights all togather mean and cumulative of selected VI make another 4 predictors. The VI's calculated for two flights with coinciding dates (i.e. 30/014/19, 19/03/19) makes more 4 predictors. All togather makes a list of 16 predictors for the two linear and non linear models as shown in Table 4.

Table 4 Predictors for the two models

RGBVI	**MI**
All three flights Mean-MGRVI	All three flights Mean-EVI2
All three flights mean-NGRDI	All three flights mean-NDVI
All three flights cumulative -MGRVI	All three flights cumulative -EVI2
All three flights cumulative-NGRDI	All three flights cumulative -NDVI
30/04/19-MGRVI	30/04/19-EVI2
30/04/19-NGRDI	30/04/19-NDVI
19/03/19-MGRVI	19/03/19-EVI2
19/03/19-NGRDI	19/03/19-NDVI
Ist two flights mean-MGRVI	Ist two flights mean-EVI2
Ist two flights mean-NGRDI	Ist two flights mean-NDVI
Ist two flights cumulative-MGRVI	Ist two flights cumulative-EVI2
Ist two flights cumulative-NGRDI	Ist two flights cumulative-NDVI
Last two flights mean-MGRVI	Last two flights mean-EVI2

Last two flights mean-NGRDI	Last two flights mean-NDVI
Last two flights cumulative-MGRVI	Last two flights cumulative-EVI2
Last two flights cumulative-NGRDI	Last two flights cumulative-NDVI

3.6.1. Linear regression model:

As discussed in section 1.1, linear regression is a statistical method based on relationship between two variables. We can define linear regression as "Predicting scores for one dependent variable based on the scores of the independent variable"(Dupuy, 2018). The linear regression is implemented using caret library for R programming language. The linear regression model uses the leave one out cross validation method for dry matter prediction. The leave one out cross validation method is used to optimize the performances of the selected metrics to calculate prediction error. leave one out cross validation method approach is very useful approach for small data sets. The data sets of the two grasslands consist of only forty six samples. The datasets are even further reduced with the removal of outliers. (Menze & Ur, 2014; Peter et al., 2014) consider leave one out cross validation (i.e. LOOCV) method very useful for small datasets to avoid overfitting in the assessment of the regression models. The regression model using LOOCV leaves one value of the target variable and uses the rest of the values to predict dry matter. This process continues for all the values in the dataset.

The mathematical expression for linear regression can be described using Equation 2. The parameters the equation is composed of are the y-intercept , slope , dependent and independent variable. β expresses the slope of the fitted regression line in the scatter plots. The slope tells the expected change in the predicted value of the dry matter with respect to the change in the VI's value. The slope is the most significant parameter to see the relationship between the two parameters. The relationship can be negative, positive or no relationship at all. The positive value of slope means that an increase in the value of the VI's would result an increase in the dry matter value. The negative value of the slope means that a decrease in the value of VI's means an increase in the dry matter. In the case of slope equals to zero the VI's have no effect on the dry matter at all. For any regression analysis the underlying hypothesis is that the slope is not equal to zero.

Equation 2

$$y = a_1 + \beta x_1$$

3.6.2. Random Forest model:

Random forest is non-linear regression model, which can be used for regression for prediction of dry matter in two grasslands. To understand random forest regression model, It is important first to understand the concept decision tree based models. The reason is random forest based models are combinations of decision trees. The decision trees are comprised of Nodes, decision nodes, split and leaves.

Random forest start training the model from the root node, which is displayed in Figure 8 Parts of a single tree in Random forest (Peter et al., 2014). The root node is the node provided with the entire data set/population of samples. Split represents the decision taking place at each node. which divides a nodes into two or more sub-nodes. The nodes not splitting into further nodes are called leaves. The nodes between the leaves and the root nodes are called decision nodes. The decision trees are supervised methods, which can be used for prediction of continuous values to solve regression problems. The variance reduction algorithm based decision trees are used for regression problems. Using this algorithm variance at each split is measured. This algorithm test the homogeneity of data at each split. The tree keeps growing until all the data is separated at leaf node. However, this could cause overfitting for real regression problems. Constraining tree growth at each node using the mtry (i.e. the number of variables available at each node) values can help in avoiding this problem. The random forest based models were introduced to avoid the overfitting problems with the decision trees based models.

As discussed in section 3.6.1, the random forest regression model uses the same data and LOOCV method for dry matter prediction. The random forest based models is a popular approach to solve the regression problems in a more efficient way. The random forest based model was build using caret package in R. The two functions from the caret package were used to build the model. The trainControl function from the caret package was used to specify the cross validation method and hyperparameters tuning. The trainControl function randomly change the hyperparameters with random values to predict dry matter. This is performed with changing the mtry (i.e. the number of variables available at each node) values for the model. The mtry is considered a central tuning parameter more capable to improve results compare to other parameter (Probst, Wright, & Boulesteix, 2019). There are other hyperparameters but the number of trees and mtry values are consider to impact more the final results (Z. Wang, Wang, Zeng, Srinivasan, & Ahrentzen, 2018). The RF based regression model uses only mtry and number of trees tuning for dry matter prediction. The caret package provide the semi-automatic method of tuning the mtry hyperparameter tuning. The hyperparameter tuned for getting optimized results for dry matter predictions include the mtry and number of trees. The model runs multiple times with different mtry values and the best three results based on error metric (i.e. RMSE) are returned. The caret package in R programming language provides this semi-automatic method for hyperparameter tuning. TrainControl function argument uses "random" to test the model with random values of hyperparameters. The train function is used to specify the regressor, predictors and the target variable for dry matter prediction. The mtry values and the resulted prediction values with the lowest prediction errors values from the selected regression metrics can be accessed using the modelFinal function in the same package (i.e. Caret) in r programming language.

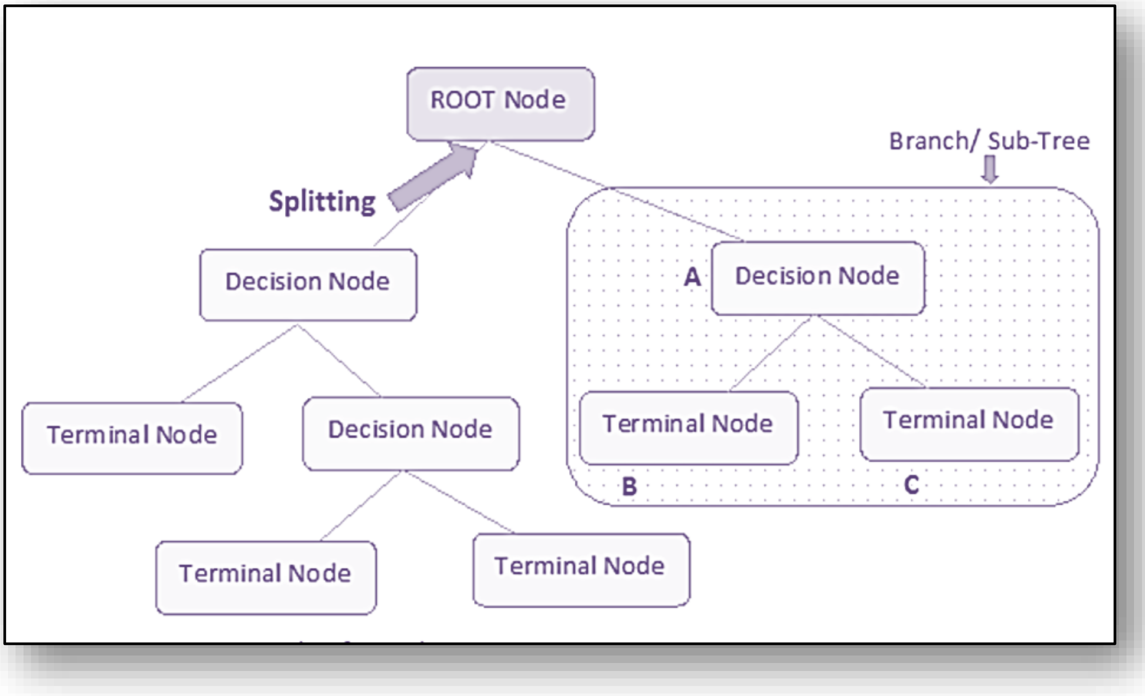

Figure 8 Parts of a single tree in Random forest (Peter et al., 2014)

3.6.3. RF and LR Models performances for RGBVI and MI

The linear regression model and the random forest regression model were provided with pre-processed data. The two regression models were compared using the three metrics coefficient of determination (i.e. r-squared) , mean absolute error (i.e. MAE) and root mean square values (i.e. RMSE).

The root mean square error is used for the validation of the predicted values from the model. This is performed by taking the difference in the observed ground truth (i.e. dry matter) and the predicted values to determine the residual value. The results from the root mean square error shows how far the predicted dry matter differs from the actual ground observation. The lower values of the root mean square indicate a better fit of the model for the dry matter prediction.

The coefficient of determination is also called R-squared values of the regression model. These values tells us about the degree of fitness of the model for the dry matter ground data and the VI's. The coefficient of determination maximum value is one. The r-square value of one would mean the variation in the dry matter ground observation are completely explained by the regression model. The value of the coefficient of determination varies between 1 and 0. The r-square values represent the range of variation in the dry matter ground samples, which can be explained with the help of the model.

Mean absolute error is another metric used to compare the dry matter prediction results of the two models. The mean absolute error (MAE) uses the difference between the predicted values and the actual values observed on the grounds. The final MAE value is acquired taking the average of errors for all the instances of prediction.

During the LOOCV for individual target variable the model saves the predicted value for each iteration. The predictions values can be accessed using the pred function in association with the model name (e.g. Fit$Pred). The predicted values from the model for each ground observation can be acquired using the model$Pred command. The final step of the model comparison include visualization of the results using the plot function to plot ground observation against the predicted values.

The two models LR and RF are provided the two types of VI's (i.e. RGBVI and MI) to acquired dry matter prediction results for comparison. The LR model performance is first assessed for the RGBVI for individual grassland and combined datasets of the two grasslands. Then the same model performance is assessed for MI for individual grassland and then combined datasets for the two grasslands. The next step involves using the RF regression model first for the RGBVI dataset for individual and the datasets for the combined two grasslands datasets. The RF regression model is also used for MI datasets for the individual and then the combined datasets. As earlier described the two models works wit the same metrics and LOOCV method for validation of the results.

3.7. Time Series Analysis:

The time series analysis is carried out for the VI's computed for all the three flights of the UAV before the mowing of grass. The UAV flights coincides in time are used for this analysis of the two grasslands. The time series analysis works with the means and cumulations of VI's values for the UAV flights around the ground observation. The means and cumulation of VI"s are calculated for all the three flights togather. Then the mean and cumulation values of the VI's are computed for the first two flights recorded at the start of season. The mean and cumulation of VI's values are computed also for the last two flights at the end of the season. As discussed in section 2.2, the mean and cumulative values for the multiple flights of UAV impact is also investigated for prediction error in dry matter for the two grasslands.

3.7.1. Features ranking and selection:

The time-series dataset based on the multiple UAV flights is used for dry matter prediction can be investigated further for its importance for dry matter prediction. A number of methods exists to select the most relevant features important to evaluate the prediction performance of model. To achieve the third sub-objective a function varImp is used to find the most important feature contributing to the prediction of dry matter in the two grasslands. The varImp is a wrapper function, the function wraps the importance function in the random Forest and party package in R-studio. As we discussed the two models uses the leave one out cross validation method to validate the results for the two models. Their can be biasness in the important feature selection, which means the assigned score to rank the predictors would overfit..

As feature importance is performed in previous research (Huang & Boutros, 2016; Zhong, He, & Chalise, 2020), this research uses the same embedded function varImp to assign importance score for ranking predictors. A nested loop approach is considered for feature selection in current setup of using the leave on out cross validation method. There are two loops are used for the feature selection. The inner loop is used for the individual model involved in the LOOCV for based feature selection. The outer loop combine the feature selection results from all the models resulted from the LOOCV. An average mean square error for individual model on bases of OOB (i.e. out of the bag) data is calculated. The same process is repeated for the rest of trees in individual random forest model. The resulted features based on importance for prediction are ranked in decreasing order.

3.8. Prediction validation maps:

The dry matter predictions for the two grasslands are further validated using the raster values of the predictors around the ground observation. The predictors values around the ground observations are compared to analyse for anomalies to validate the model predictions. This is performed using the predict function of the library "Raster". The arguments of the function include the train model name and the predictors names. However, this research works with sixteen predictors and one target variable. As explained in section 3.2, the predictors used are the combination of three UAV multiple flights for which 4 VIs are calculated. The mean and cumulation of the different flight in time values for the 4 VI's make in total 16 predictors. The 16 predictors using the time-series UAV flights based VIs dataset are used for the reason to further optimize the dry matter prediction in the two grasslands. The stack function in the raster layer is used to make a collection of raster layer objects for all the predictors. The raster stack is provided to the prediction function in the argument as an object. The prediction validation map is created for the model with high prediction accuracy in terms of the metrics used to assess the performance of the models.

4. RESULTS AND DISCUSSION

This chapter presents the results of the methods, which are used for prediction of dry matter using the two models (i.e. LR & RF) working with two types of vegetation indices (i.e. RGBVI &MI). The first part of the chapter explains the results from the exploratory data analysis performed on the data collected for the two grass fields. This analysis investigates the anomalies within the data provided for prediction models. The second part of the results chapter is about the comparison of results from the two models for the two types of VIs. The final part of the results chapter analyses the importance of time-series data collected from multiple UAV flights for dry matter predictions.

4.1. Exploratory data analysis (EDA):

In this section, the exploratory data analysis results for outliers detection and correlation matrix are visualized. The results for the EDA are structure based on the type of VI (i.e. RGBVI and MI) and datasets of the two grasslands. The datasets used for the outliers detection and correlation involve the individual grasslands(i.e. Vonderweg & Kieftenweg grassland) observation values and the two grasslands combined observation values.

4.1.1. Outliers:

The two grasslands are treated with non-uniform distribution of manure, which makes identification of outliers important for dry matter prediction analysis. The reason for possible outliers is different growth rate at different parts of the grasslands. The applied boxplot results are displayed for the 23 observations of individual grasslands datasets and the two fields combined dataset of 46 observations.

Figure 9 Vonderweg RGBVI outliers detection results. The outliers are identified for the first two flights cumulative values of MGRVI, first two flights mean of MGRVI, last two flights cumulative values for NGRDI, the last flight conducted one day before the mowing of grass on 30th of April, all three flights cumulative and mean for the MGRVI. Based on the results of boxplot for RGBVI values for the vonderweg grassland the outliers common for all the predictors were removed. The outliers specified to individual predictor were replaced with the mean values. Figure 10 Vonderweg MI outliers detection results display the detected outliers for the MI outliers for the same grassland. Boxplot detected outliers for only one predictor, which was the mean values for the last two flight of NDVI. The boxplot results for Vonderweg grassland identified more outliers for RGBVI dataset based predictors compare to MI dataset predictors. Barbosa et al. (2019) suggests RGBVI are more sensitive to variability in lightening conditions compare to MI, which can be the reason for more outliers for the RGBVI.

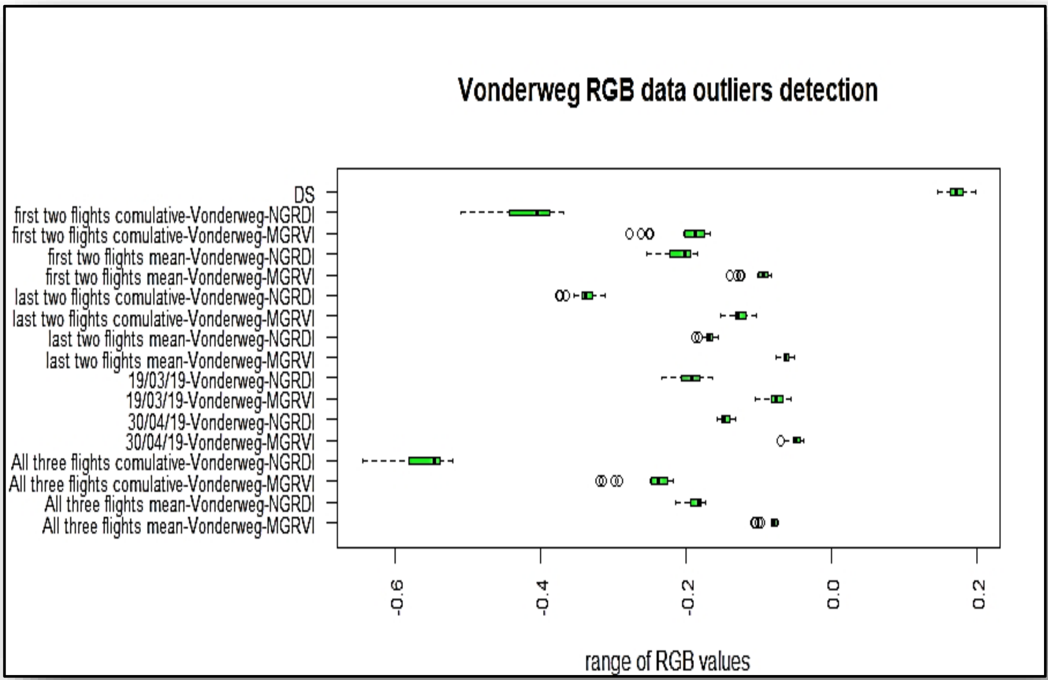

Figure 9 Vonderweg RGBVI outliers detection results

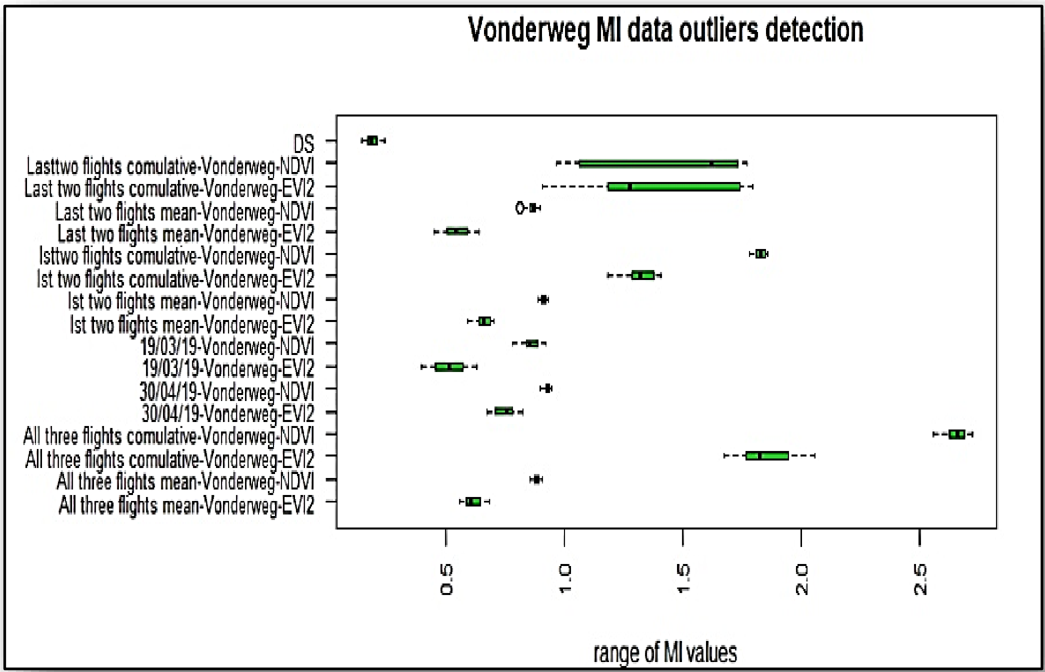

Figure 10 Vonderweg MI outliers detection results

The results for the Kieftenweg shows identification of outliers for both RGBVI and MI. The Kieftenweg outliers results like the Vonderweg detected for the low VI values. The reason for this common trend is the patch within the two grasslands within no manure treatment. The trend is the Figure 11 Kieftenweg RGBVI outliers detection results. The outliers were detected for the last two flights cumulative and mean values for NGRDI, the flight conducted on 19th of March based MGRVI values and the last flight before mowing of grass (i.e. 30th of April) based NGRDI values. The outliers were removed for the RGBVIs values before using the data for dry matter prediction in Kieftenweg grasslands. Figure 12 Kieftenweg MI outliers detection results for Kieftenweg. The results spot outliers for last two flight based cumulative NDVI, last two flights cumulative EVI2, first two flights mean values for NDVI and EVI2 and the last flight before mowing grass NDVI and EVI2 values.

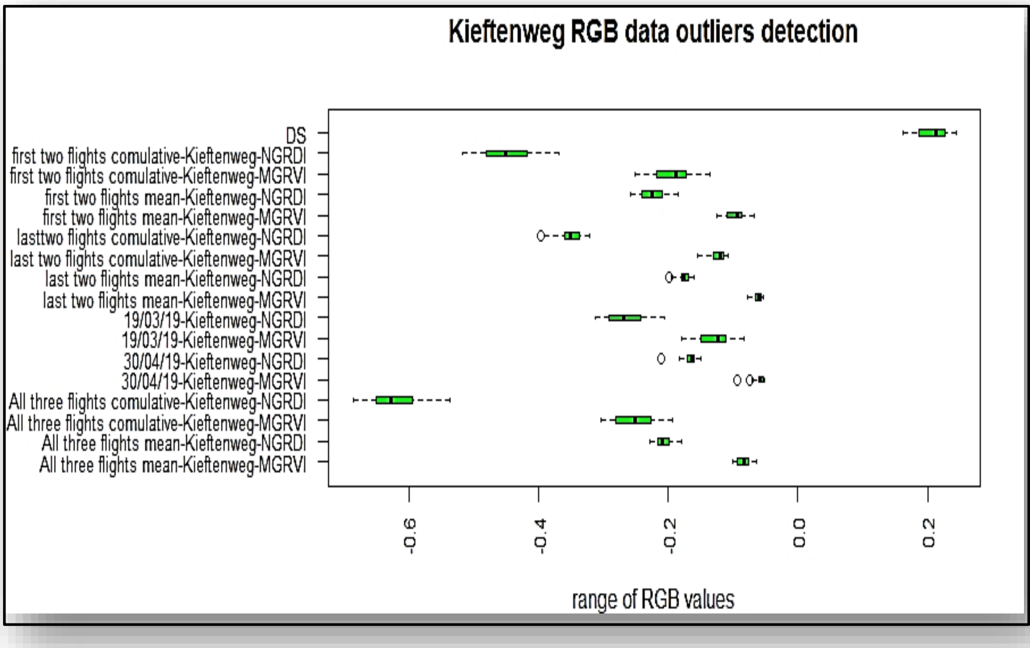

Figure 11 Kieftenweg RGBVI outliers detection results

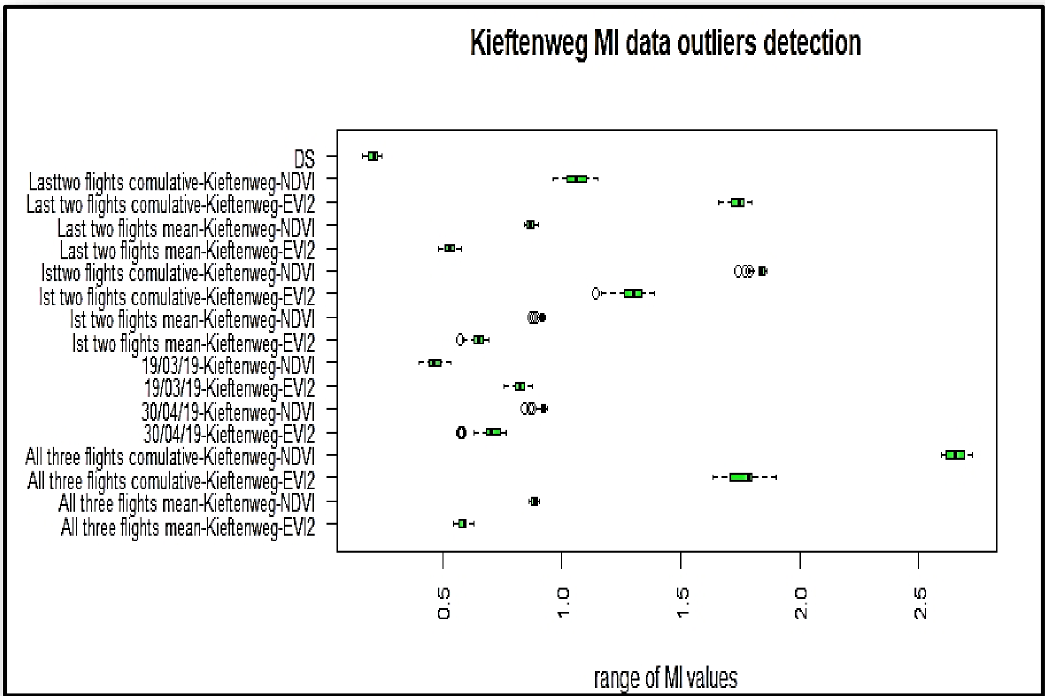

Figure 12 Kieftenweg MI outliers detection results

Figure 13 Two fields combined RGBVI outliers detection results for two fields combined are displayed in Figure 14. Using the same boxplot tool in R programming language the outliers are identified for the last two flights mean values for MGRVI and Ist two flights cumulative and mean values for NGRDI. Figure 14 two fields combined MI outliers detection results. The last two flights mean values for the NDVI was the only predictors with identified outliers. The outlier shows the spectral heterogeneous regions within the two fields for the two fields combined datasets (Hemissi & Riadh Farah, 2015). However, the results for two fields combined datasets outliers identification result shows less outliers compare to individual fields datasets, which shows the spectrally homogeneous regions within the two grasslands.

The identification and removal of outliers impacted the selected metrics of the two prediction models. The RMSE values decreased for the two predictions model. The L.R model metrics(i.e. RMSE, MAE, R-square) values were more effected from the removal of outliers compare to the R.F regression model. The reason is the R.F regression models are split into leaves. R.F is applied more locally compare to the L.R model, which is applied for the entire area. This means the initial splits for training the model may affect the model results, while the later splits get less affected from the outliers. Another reason is the randomness of the predictors selection for the training of R.F model for dry matter prediction. Moreover, the randomness of subset of the data selection to train the model also make the R.F model more robust to noise and overfitting.

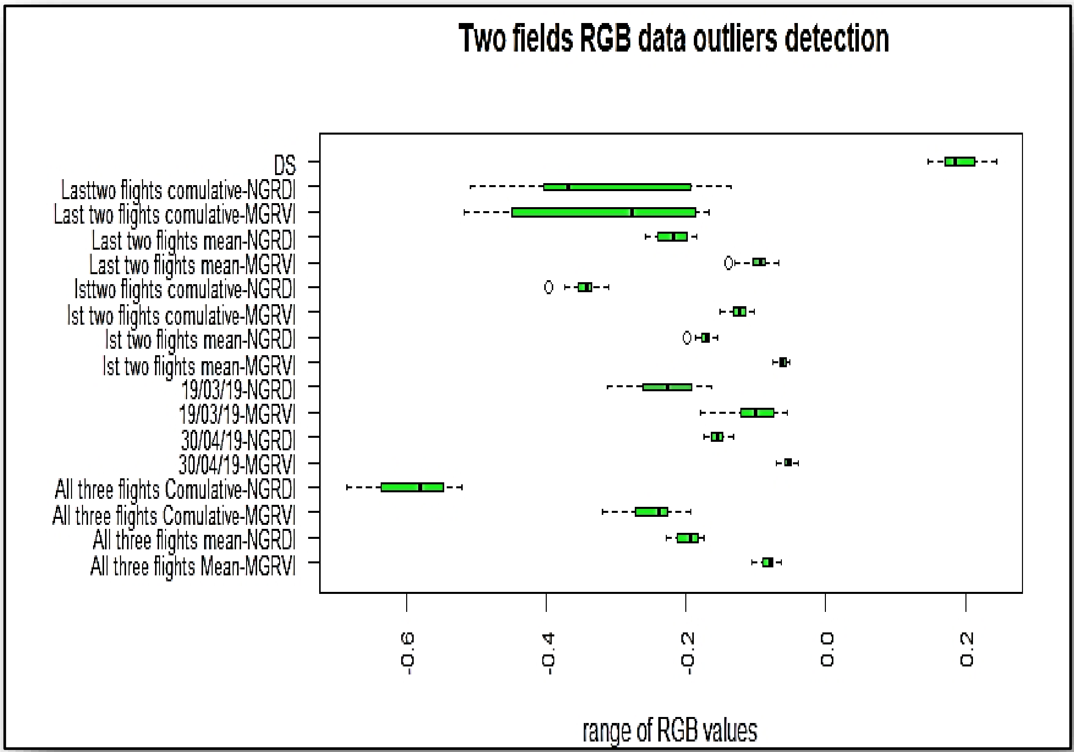

Figure 13 Two fields combined RGBVI outliers detection results

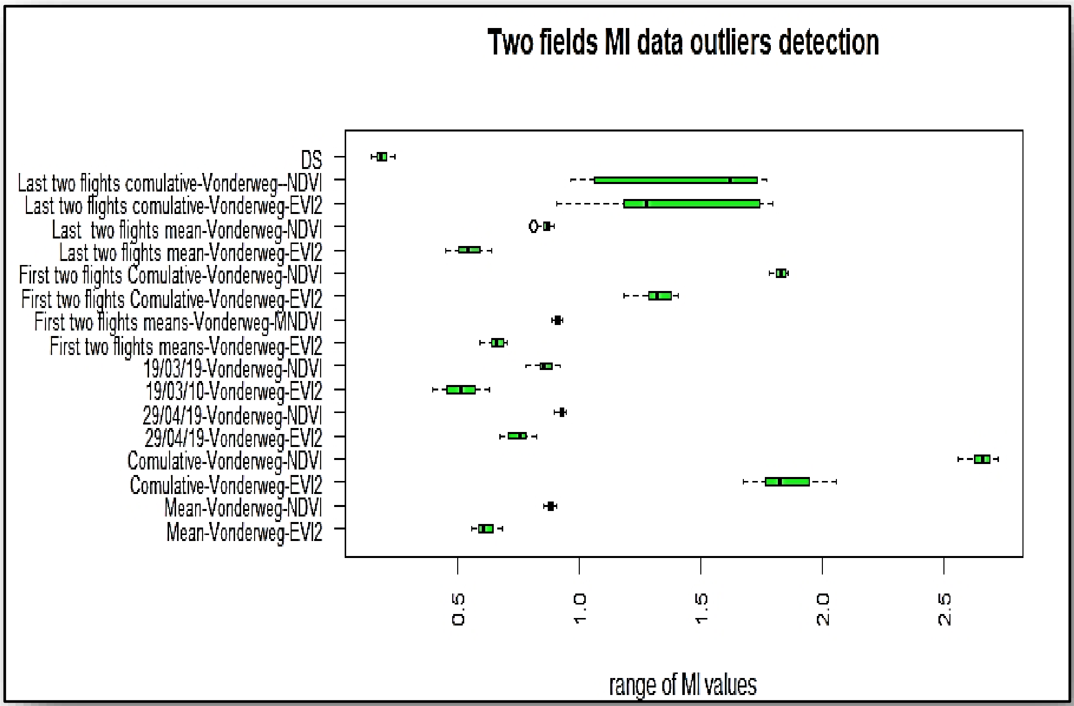

Figure 14 two fields combined MI outliers detection results

4.1.2. Correlation Matrix:

The correlation computed in Figure 15 Vonderweg correlation matrix RGBVI The correlation results used the 22 observations with treated outliers. The matrix shows positive correlation of 0.28 VI (i.e. MGRVI and NGRDI) calculated before the mowing of grass compare to the other used predictors correlation with dry matter. The dry matter (i.e. DS) in the figure shows a negative correlation with the first two flights mean and cumulative values of (-0.25). A positive correlation of low intensity also exist for the last two flight mean and cumulative VIs of about 0.15. Figure 16 Vonderweg correlation matrix MI dataset. The dataset contain 22 observations. The figures shows a positive correlation of 0.35 for MI dataset for Vonderweg. The dataset shows a negative correlation for the mean and cumulative values of the first two flights in the start of the season. The remaining variables used have low correlation values below 0.1 or greater than -0.1. The results shows a very weak correlation between the predictors (i.e. VIs) and the response variable (dry matter) for both RGBVI and MI. The Pearson correlation coefficient is a test of linear relationship between the variables, which seems weak in the case of Vonderweg. The reason can be the variability of observation values for Vonderweg.

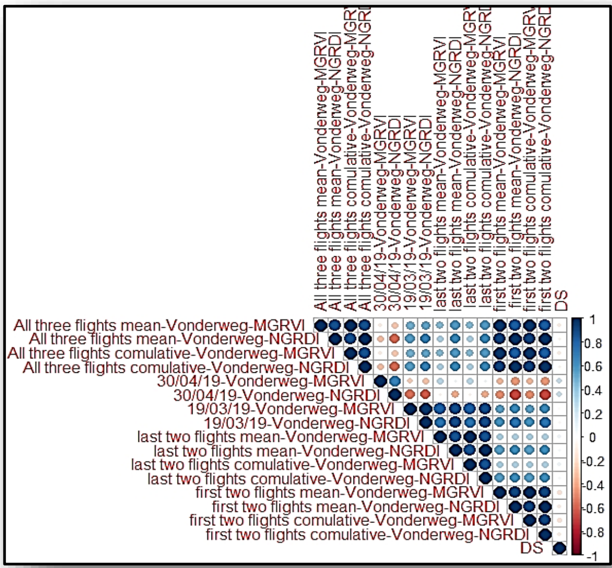

Figure 15 Vonderweg correlation matrix RGBVI

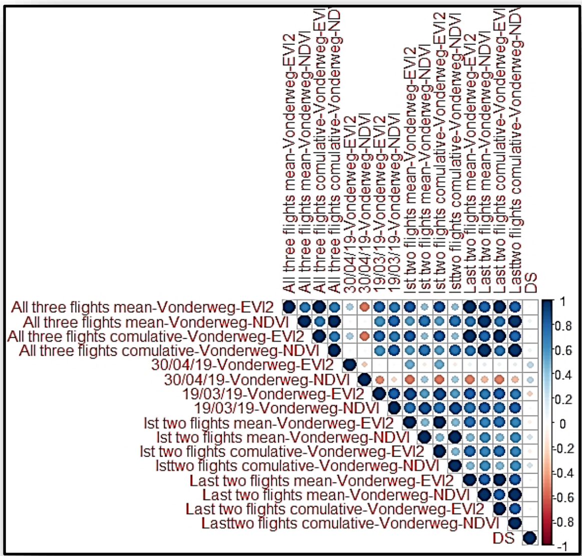

Figure 16 Vonderweg correlation matrix MI

Figure 17 Kieftenweg correlation matrix RGBVIKieftenweg. The correlation matrix shows the result for 19 observations after the removal of the outliers detected. The matrix shows a positive correlation of 0.6 for the MGRVI mean and cumulative values of the last two flights before mowing of grass. The matrix shows a positive correlation of 0.5 for the NGRDI mean and cumulative values of last two flight before mowing of grass. The MGRVI and NGRDI both have a positive correlation of 0.35 for the last flight conducted before mowing of grass. Figure 18 Kieftenweg correlation matrix MI dataset. The dataset uses 19 observations. The EVI2 shows a positive correlation of 0.4 for the last flight before mowing of grass. The three flights mean and cumulative values for the NDVI shows a positive correlation of 0.4. The last two flights mean and cumulative value of EVI2 shows a positive correlation of 0.25. The remaining variables used in the creation of the two matrices have positive correlation values equal to or below 0.1. The results for Kieftenweg shows more linear relationship compare to Vonderweg. The correlation values for Kieftenweg are more higher than the values for Vonderweg.

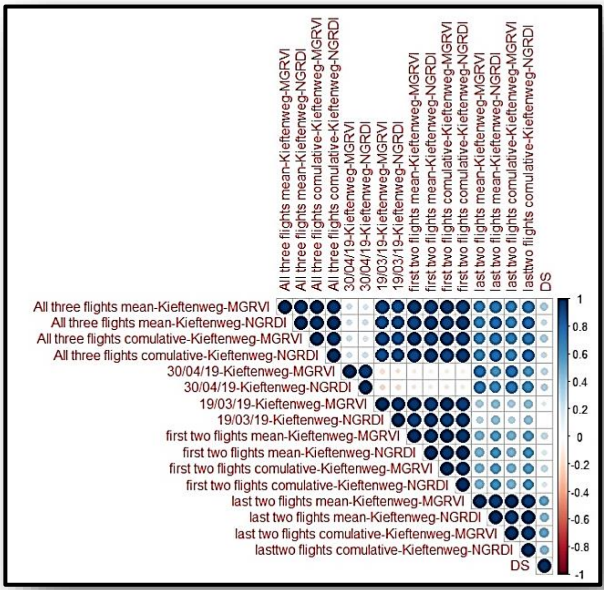

Figure 17 Kieftenweg correlation matrix RGBVI

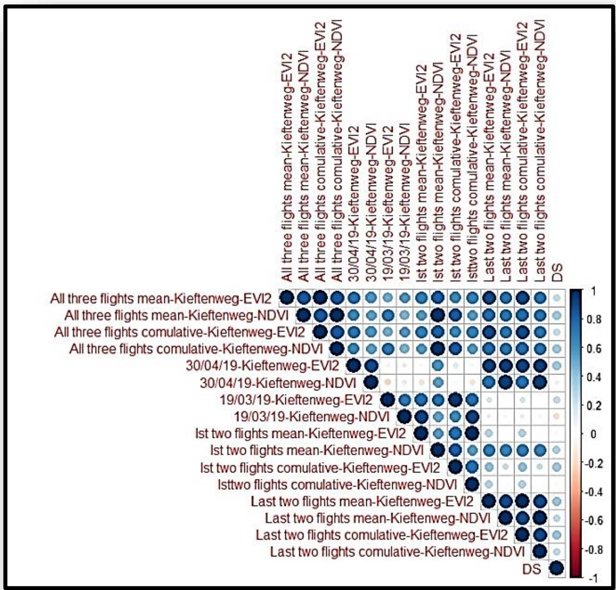

Figure 18 Kieftenweg correlation matrix MI

Figure 19 Two fields combined correlation matrix RGBVIThe dataset used for correlation matrix is consist of 41 observations. The NGRDI shows a correlation of -0.65 with the last two flight before mowing of grass. The NGRDI VI value calculated from flight conducted on 19th of March shows a correlation of -0.70. The MGRVI for flight conducted on the 19th of March shows a correlation of -0.65. The last two flight for MGRVI shows a correlation of -0.70. The NGRDI for last two flight cumulative value shows a correlation of 0.70. Figure 20 two fields combine correlation matrix MI. The EVI2 correlation for the last flight before mowing is -0.70. The correlation value for NDVI values calculated for flight before mowing is 0.6. The correlation value for the last two flight cumulative values of EVI2 is 0.75. The cumulative value of NDVI for last two flight is -0.70. The remaining predictors values are less than or equal to 0.30 or -30. Goodwin & Leech (2006) suggests correlation for observations more than

30 is more robust, which is the reason for combined dataset shows high correlation values and less affected from the dissimilar values within the 41 observation.

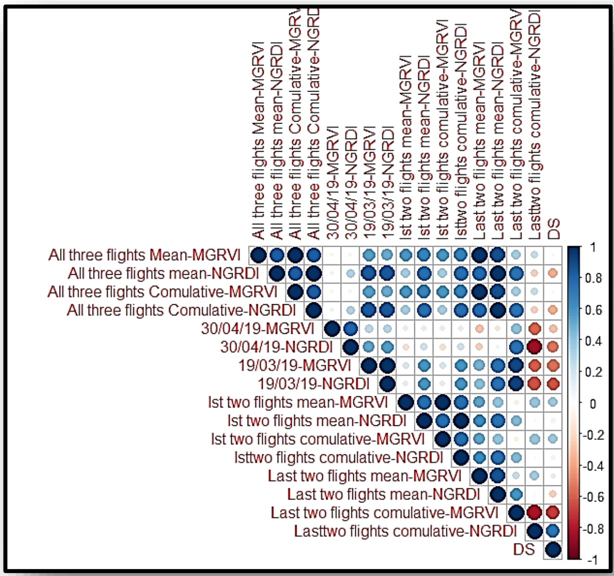

Figure 19 Two fields combined correlation matrix RGBVI

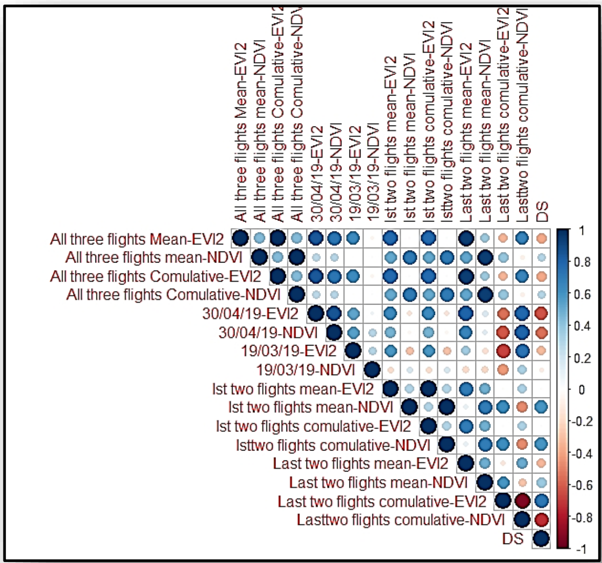

Figure 20 two fields combine correlation matrix MI

4.2. Linear vs non-Linear models using two types of VIs

The results of the two models were compared using the selected metrics (i.e. RMSE, R-square & MAE) for the two grassland. The L.R model dry matter predictions metrics results are approximately the same to R.F model for combined datasets of two grasslands. The R.F model outperform the L.R model for the datasets of two separate grasslands, the results are visualized in Table 5 Combined results for two models and two types of VIs. The R.F is a non-linear regression model, which explained the non-linear relationship better than the linear regression model for Vonderweg. The RF regression model is perform better in terms of the selected metrics for dry matter prediction using the small dataset of only 22 observations (Mutanga, Adam, & Cho, 2012).

Table 5 Combined results for two models and two types of VIs

Data	Regression Models	RMSE		R2		MAE	
		RGB	MI	RGB	MI	RGB	MI
Two fields combine	L.R	0.018	0.017	0.51	0.55	0.015	0.014
	R.F	0.020	0.015	0.41	0.61	0.016	0.013
Vonderweg field	L.R	0.021	0.017	0.14	0.016	0.016	0.015
	R.F	0.015	0.014	0.31	0.16	0.011	0.011
Kieftenweg field	L.R	0.025	0.024	0.16	0.13	0.021	0.024
	R.F	0.024	0.019	0.016	0.19	0.018	0.015

The predictions results for the dry matter using the two types of VIs are compared using the metrics values in Table 5 Combined results for two models and two types of VIs. The model predictions results for selected metrics using the dataset for two fields combined approximately identical to R.F. The difference in the result for the two models is very small. For instance, the RMSE values for the two fields combined is 0.018 and 0.017 for the two datasets (i.e. RGB and MI). Similarly the R.F model results for the combined two fields datasets is 0.020 and 0.015 (RGB & MI). The similar trend can be seen in the R-square metric as well. The R-square values for the L.R model for the two field combined datasets are 0.51 and 0.55. The random forest model results are 0.41 and 0.61 for the type of datasets used to train the model. The MAE metrics results shows nearly similar computation results for the two models as well. The MAE values for the two field combined datasets using L.R model are 0.015 and 0.014. The R.F model MAE metrics values are 0.016 and 0.013 for the two data sets. The reason for L.R performance similar to R.F can be a more linear relationship among the predictors. The number of training samples also increased, which also reduces the variation of dry matter across the two fields with similar manure provision plan. Initially, the LR model performance for the individual grassland and combined dataset without the exclusion of outliers for the two grasslands in terms of the prediction errors was high. The RMSE value was larger than the smallest value of dry matter ground observation. After the removal of the outliers the results were more comparable. The LR model prediction results are more affected from outliers. Unlike the LR model, the RF regression model is less affected from the outliers within the datasets. The RF model prediction results were identical for the dataset including the outliers and after the removal of outliers (Long & Servedio, 2008; Loureiro, Torgo, & Soares, 2005).

Huang & Boutros (2016) suggests the RF regression model is a better fit a highly varying non-linear limited dataset. The Pearson correlation test results displayed a weak linear relationship between the predictor and the response variable for vonderweg. Which is the reason for the non-linear RF model performing better in terms of the prediction metrics in Table 5. The Vonderweg grassland RMSE metric values for the two datasets using L.R are 0.021 and 0.017. The RMSE values for the R.F model are 0.015 and 0.014. The R.F model performs slightly better in terms of the RMSE values. However the comparing the two models based on the two datasets, R.F outperform the L.R model for both datasets RGB and MI. The RGB dataset for the Vonderweg perform better with r-square value of 0.31 to 0.16 of MI. The MAE values of the two models using the two different datasets shows very less variation. The Kieftenweg grassland RMSE metric results of the two models were quite identical. The comparison shows a linear relationship between the predictors to the target variable. However, the R.F model seems to perform better with the multispectral dataset based on the r-square value of 0.19. The L.R model performs better with the RGB dataset for the grassland with r-square value of 0.16. The MAE values differ for the two models. The MAE value for the R.F is less compare to the L.R model, which can be seen in Table 5.

4.3. Time series Analysis:

The regression models for the prediction of dry matter uses time-series datasets collected with UAV. The importance of the time-series data is analysed based on its impact on the error in the prediction of dry matter. The RF model uses RMSE metrics for prediction of dry matter in the two selected regression models. As previously discussed in section 4.2, the RF shows overall lowest value of RMSE. The graphs in this section are obtained using the R.F model for the lowest RMSE metric values. The predictor contributing the most are ranked based on the least values of the RMSE using datasets of RGBVI and MI for the two grasslands.

Figure 21 Two fields combined feature importance RBVI. The MGRVI values for the last flight conducted before mowing of grass is ranked with highest score of 94 percent. The last two flight commutative values for the NGRDI is ranked with second highest score of 90 percent. The last two flight commutative values for MGRVI is ranked with the third highest score of 79 percent. Figure 22 two fields combined MI based feature importance. The last two flight cumulative values for EVI2 is ranked the highest score of 95. The EVI2 values based on the last flight before mowing of grass (i.e. 30 of April) is scored the second highest with score of 39. The last two flight cumulative values for NDVI is scored the third highest with score 30.

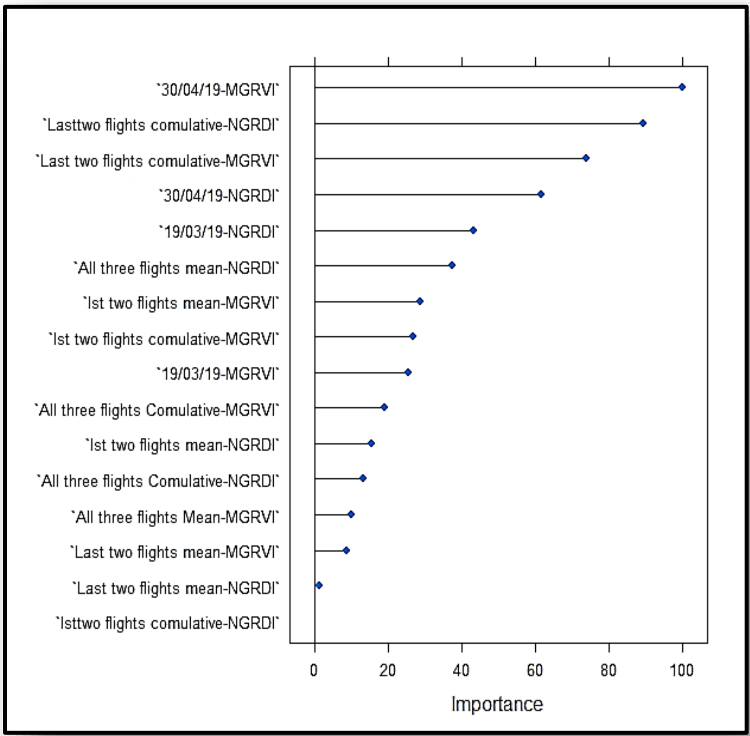

Figure 21 Two fields combined feature importance RBVI

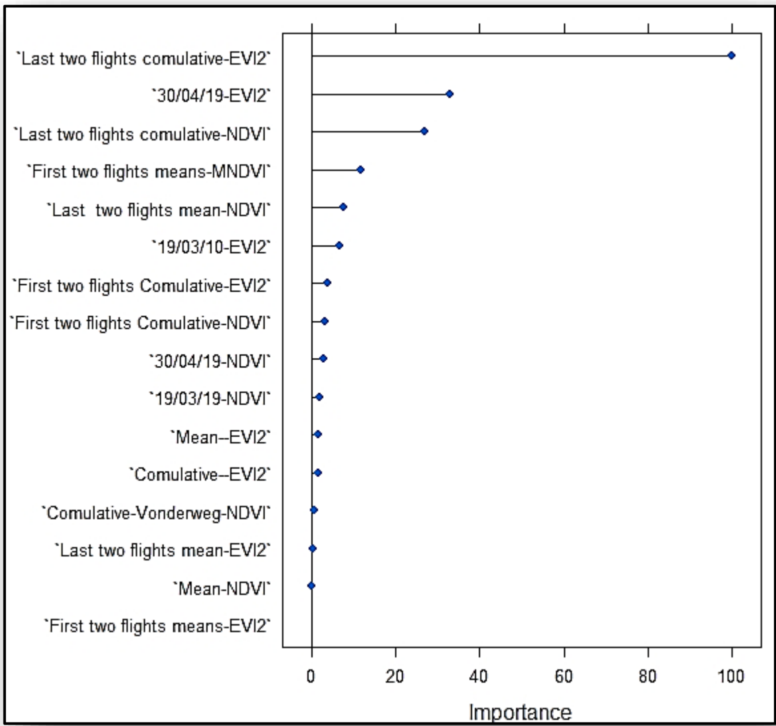

Figure 22 two fields combined MI based feature importance

Figure 23 Vonderweg feature importance RGBVI using the 22 observation dataset of RGBVI with 16 predictors. The last flight based calculated MGRVI values before mowing of grass is ranked the highest with score of 96. The second highest score of 59 is assigned to the three flight mean values for MGRVI. The third highest predictor ranked is NGRDI calculated for the last flight before mowing of grass with score of 55. Figure 24 Vonderweg feature importance MI dataset 22 observation with 16 predictors. The last two flight cumulative values for EVI2 is ranked the highest with score of 94. The last two flight cumulative value for NDVI is ranked the second highest with score of 70. The last flight conducted before mowing grass calculated EVI2 is ranked the third highest with sore of 30.

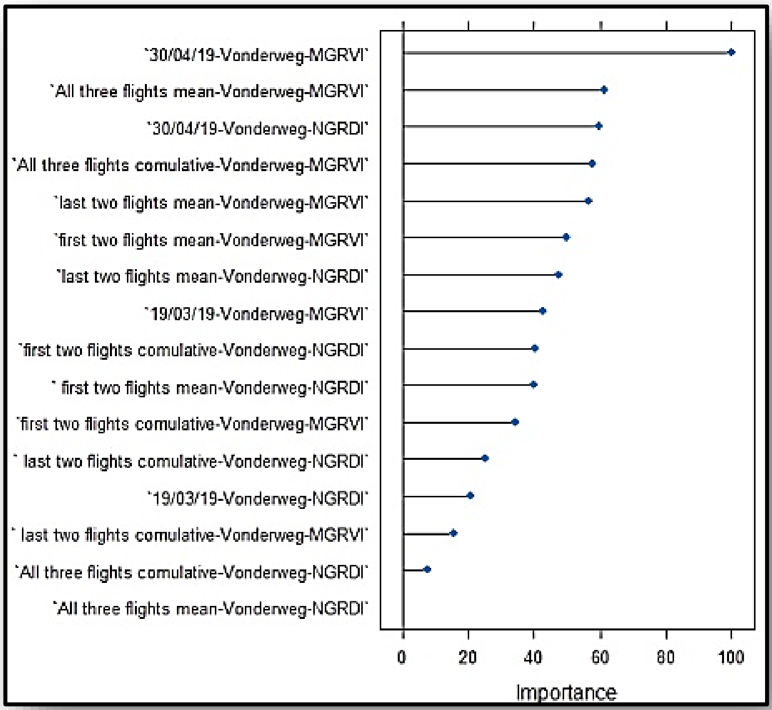

Figure 23 Vonderweg feature importance RGBVI

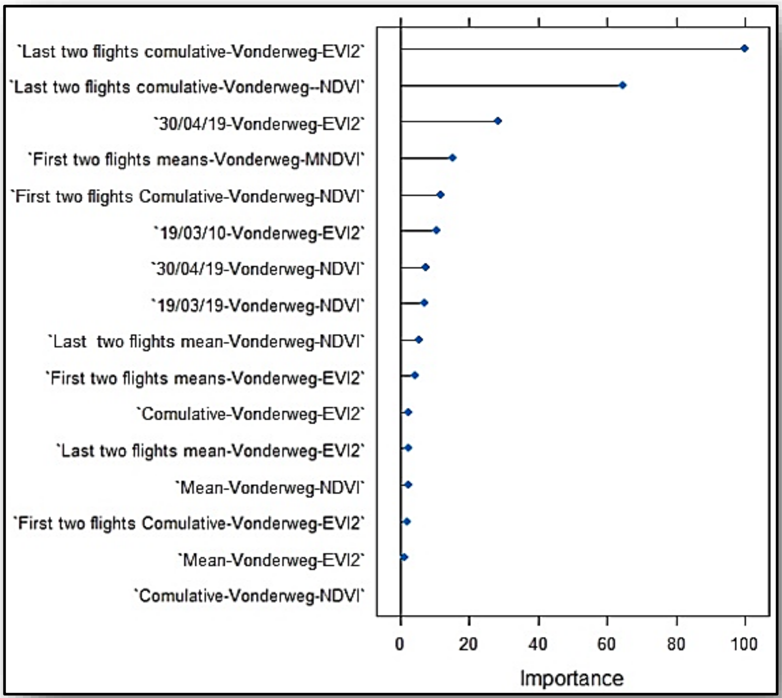

Figure 24 Vonderweg feature importance MI

Figure 25 Kieftenweg feature importance RGBVIsame 16 predictors but with 19 observations in RGBVI dataset. The last two flight cumulative values for the MGRVI predictor is ranked highest with score of 97. The second highest predictor is NGRDI calculated for the last flight before mowing of grass with score of 42 The third highest ranked predictor is MGRVI mean for last two flight with score of 40. Figure 26 Kieftenweg feature importance MI dataset with 19 observations and 16 predictors. The EVI2 calculated for last flight before mowing is ranked the highest with score of 97. The second highest score of 30 is assigned to NDVI for the last flight before mowing. The third highest score of 21 is assigned to all three flight mean for NDVI.

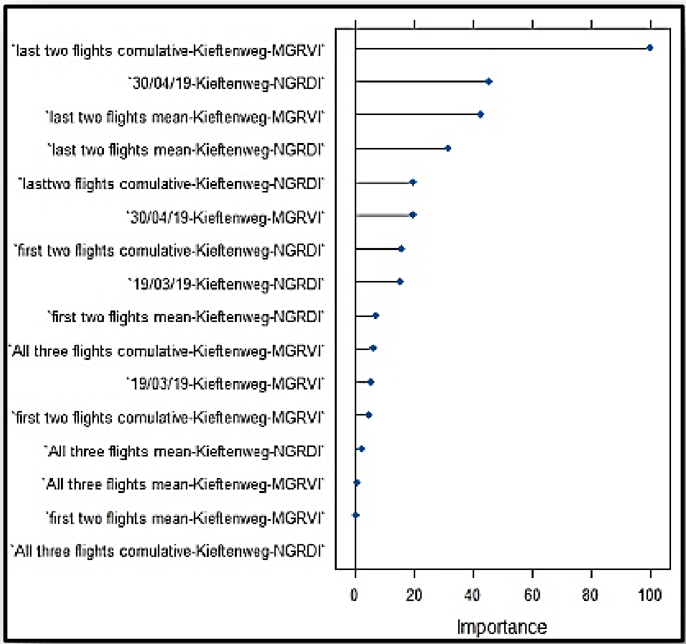

Figure 25 Kieftenweg feature importance RGBVI

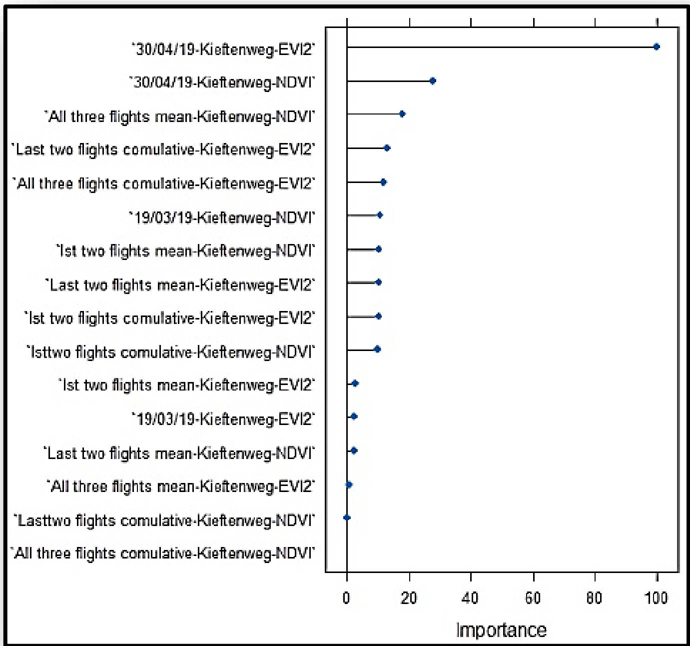

Figure 26 Kieftenweg feature importance MI

4.4. Dry matter prediction maps

The created prediction maps use the random forest model using RGBVI for Vonderweg. The prediction map for Kieftenweg uses the LR model with the RGBVI dataset. The two fields Kieftenweg and Vonderweg prediction maps are also created using RF model for the two fields combined RGBVI dataset. The Kieftenweg prediction map is created using LR model. The maps display the dry matter prediction results for pixels around the ground observations were collected. The ground observation measurements and spatial location are also displayed in the maps. The red circles shows the surrounding pixels around the ground observation. The predicted dry matter values can be observe using legend colour scale bar. The predictions results for the surrounding pixels display the dry matter spatial distribution and the results are generalized for the whole fields.

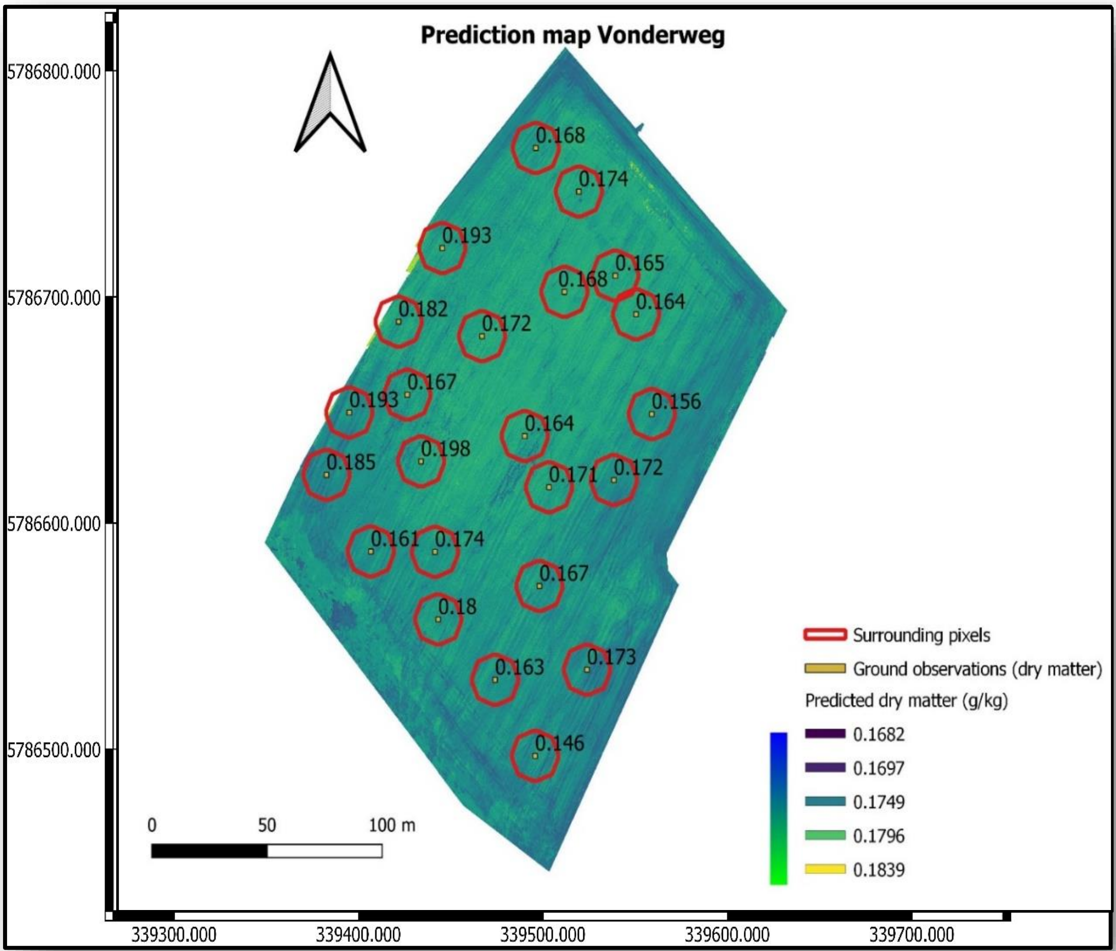

Figure 27 Vonderweg prediction map for dry matter spatial distribution using individual grassland RGBVI dataset.

Figure 27 Vonderweg prediction map for dry matter spatial distribution using individual grassland RGBVI dataset. This map displays the dry matter spatial distribution within the range of 0.1682 and 0.1839. There are 8 out of 23 ground observations outside the range of the limits specified within the legend of the map. More specifically, the surrounding pixels within the radius of 10 meters cannot shows high dry matter values between the range of 0.1839 to 0.193. The same is the case for dry matter low values ranging from 0.146 to 0.1682.

Figure 28 Kieftenweg prediction map for dry matter spatial distribution using single grassland RGBVI dataset This map predicted dry matter within the range of 0.195 to 0.216. Only 8 ground observations are identified within this range. There were 9 ground observation within range of 0.216 to 0.245, which couldn't be displayed with the surrounding pixels circle of radius 10 meter. There were 6 ground observation within the range of 0.195 to 0.162, which couldn't be identified using the dry matter prediction model.

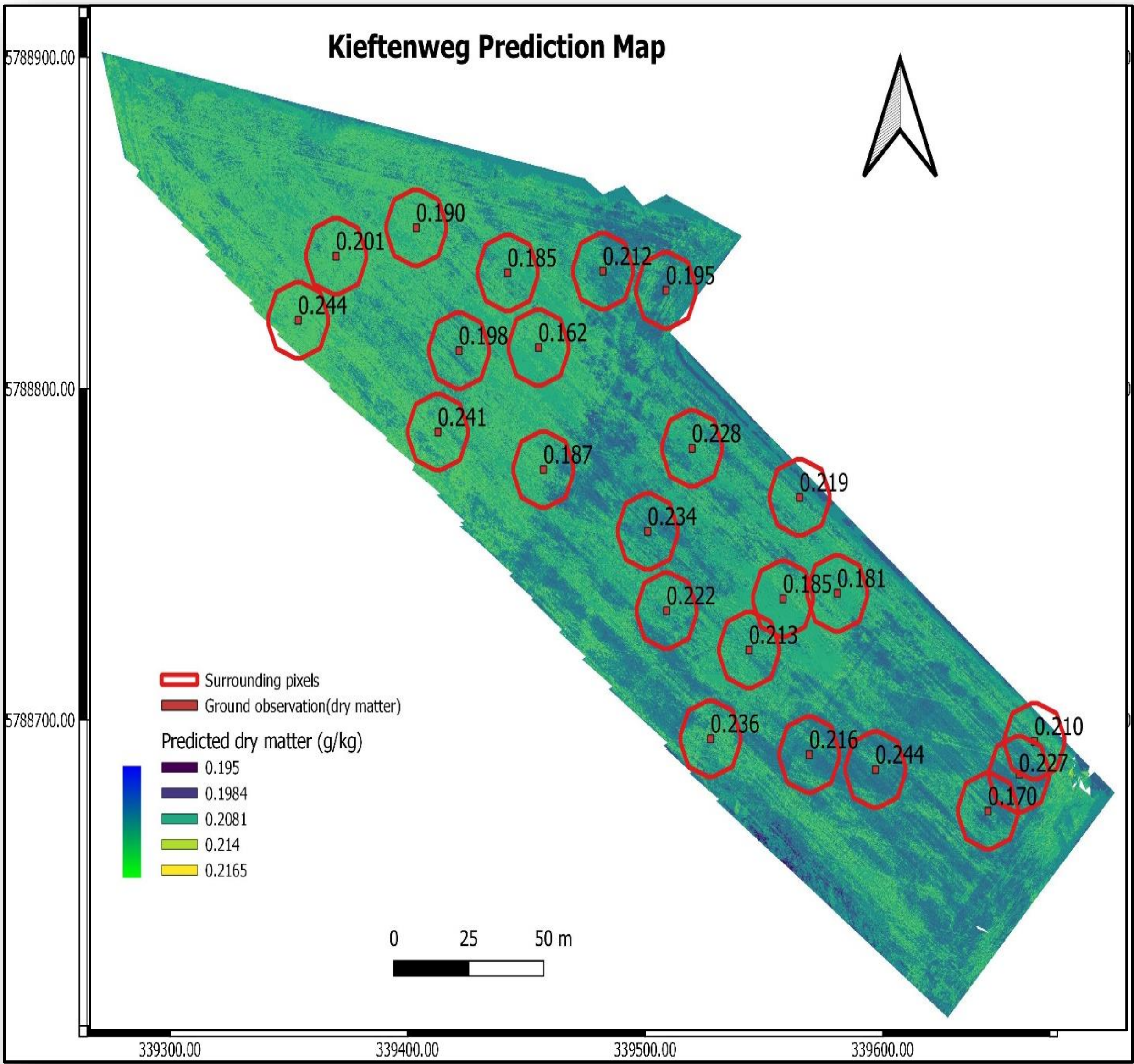

Figure 28 Kieftenweg prediction map for dry matter spatial distribution using single grassland RGBVI dataset

Figure 29 Vonderweg prediction map for dry matter spatial distribution using two grassland RGBVI dataset of 41 observations and 16 predictors. This map predicts 7 dry matter ground observations within the range of 0.1742 to 0.1945. There are 12 ground observations within the range of 0.146 to 0.1742, which the models couldn't predict. There are 4 ground observations within the range of 0.1945 to 0.198, which were also not within the predicted dry matter range specified within the 10 meters circle of surrounding pixels.

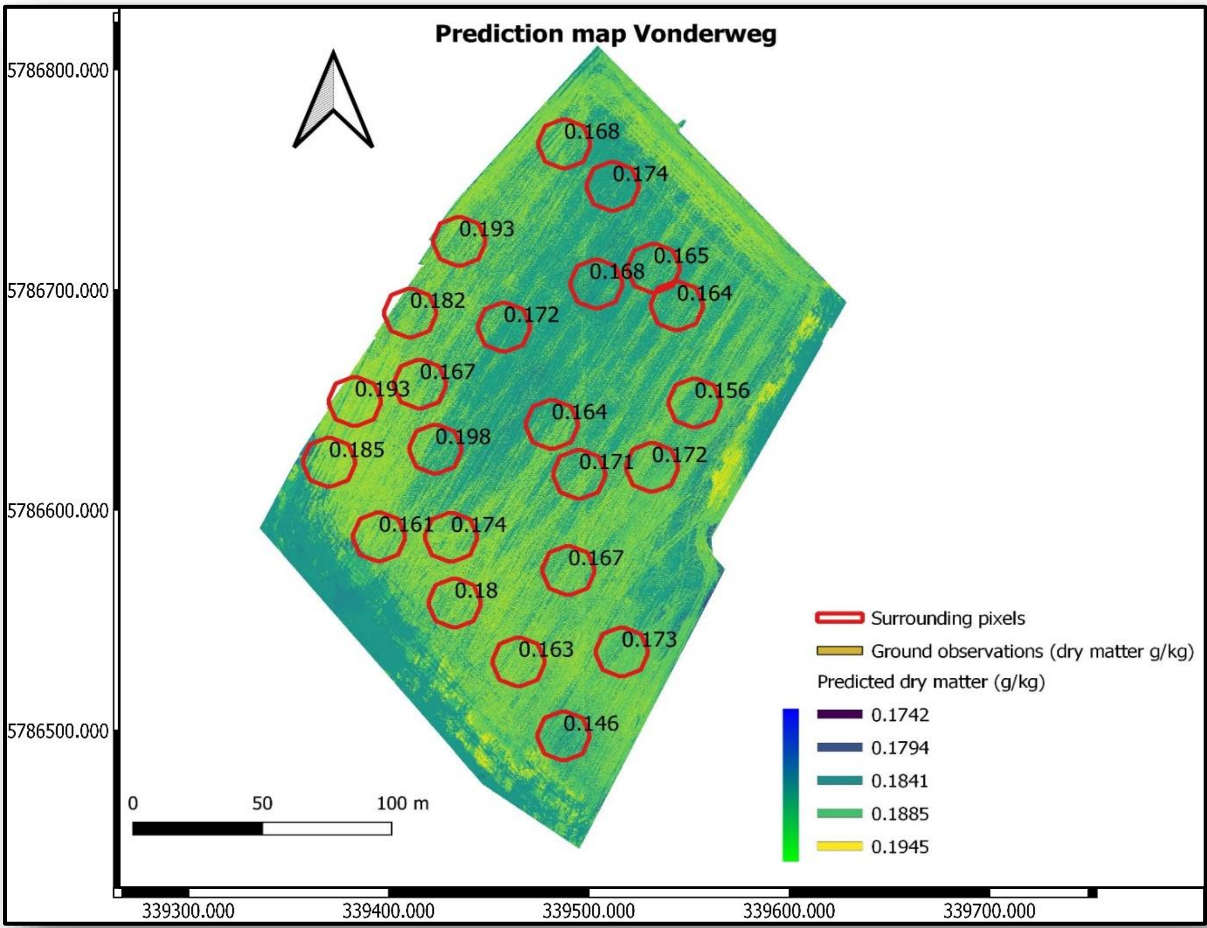

Figure 29 Vonderweg prediction map for dry matter spatial distribution using two grassland RGBVI dataset

Figure 30 Kieftenweg prediction map for dry matter spatial distribution using two grassland RGBVI dataset. This map predict 8 dry matter observations within the range of 0.1699 to 0.2043. The 10 meters radius circle displaying surrounding pixels couldn't predict the high value 12 ground observations within the range of 0.2043 to 0.244. This map also couldn't predict only 1 dry matter ground observation below 0.1699.

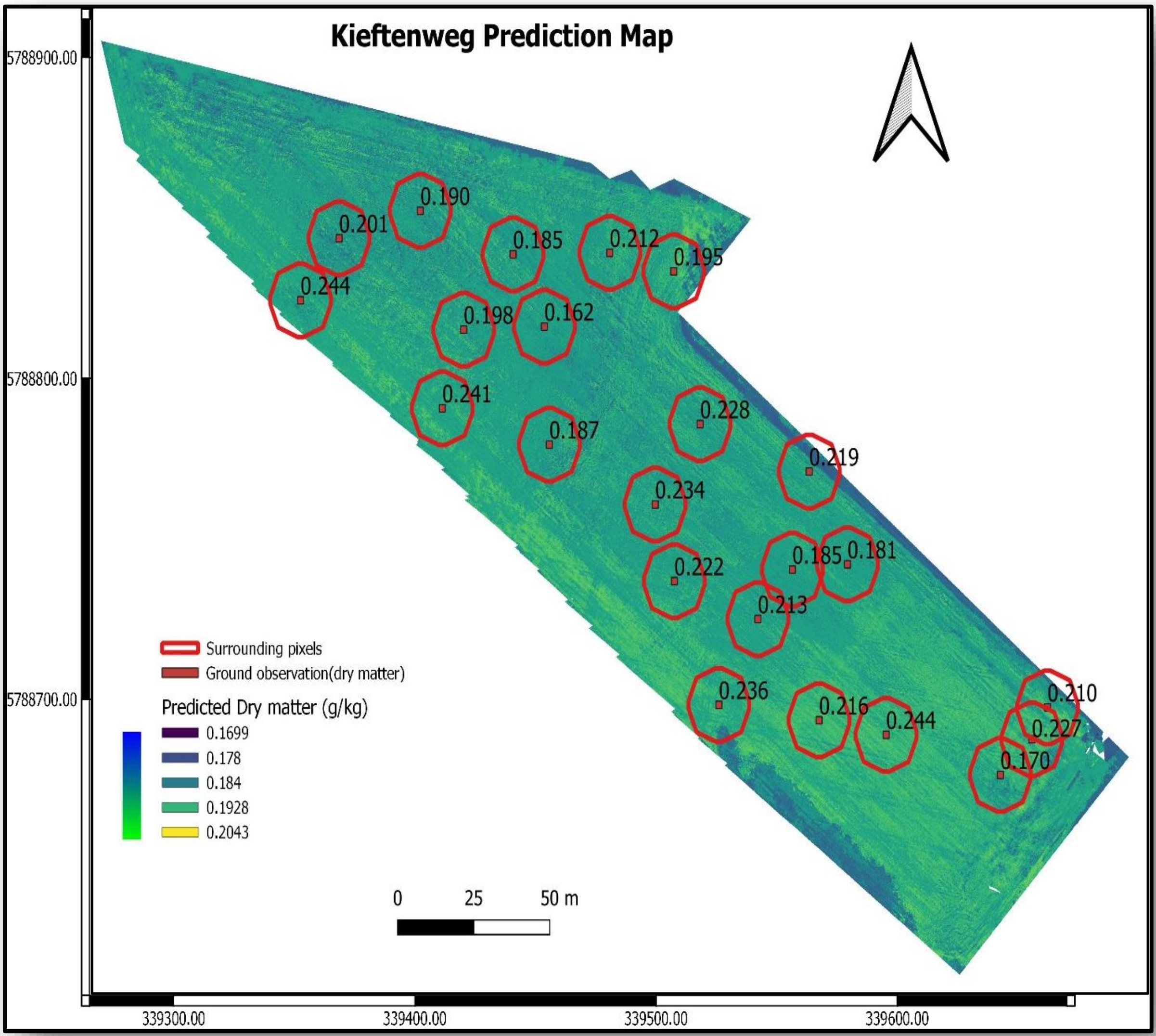

Figure 30 Kieftenweg prediction map for dry matter spatial distribution using two grassland RGBVI dataset

4.5. Discussion

The overall discussion section is structured based on the results of the exploratory data analysis, the comparison results of the two models for two types of VIs, time-series analysis and prediction maps.

The exploratory data analysis detected outliers for the two types of VI's (i.e. RGBVI & MI). The linear regression model was more effected from the outliers compare to the RF regression. However, the performance for the two model for the prediction of dry matter was assessed without the presence of any outliers in the datasets for the two regression models. One other aspect of the outliers for two type of VIs was observed the less number of outliers in the MI dataset compare to the RGBVI dataset. There were no outliers detected for MI dataset except for the mean of last two flights of calculated NDVI in Vonderweg. However, the RGBVI dataset displayed outliers within 7 predictors values. The reason for the different outliers detection can be the fluctuation of growth rate change during the winter season(ref).

Another reason for outliers within the grasslands can be the different percentage of manure provision within the Vonderweg grassland, which can cause non-uniform growth of grass within the field Vonderweg.

The models performance can also be assessed using the correlation matrix based on the predictors correlation with dry matter results. The correlation matrix for Vonderweg showed stronger positive correlation results of last flight before mowing of grass(i.e. 30 of April) compare to the other predictors. The reason is ground observations were collected one day after the last flight before mowing of the grass(i.e. 30th of April). The ground observation of dry matter and the last flight of UAV almost concedes with one day gap. However, the correlation matrix results for Kieftenweg showed stronger correlation results for the mean and cumulative values of the last two flight for both types of VIs (i.e. RGBVI & MI) compare to the other predictors. Using Table 2 UAV flight details comparison shows the gap between the dates of last two flights for the Kieftenweg grassland is smaller then the flight gap for Vonderweg. This means the last two flights conducted on UAV's to calculate VIs are more close to the date for which ground observations samples were collected for Kieftenweg. Kieftenweg grassland correlation results have high person correlation co-efficient values compare to the vonderweg. The correlation matrix results for the two grasslands combined shows stronger negative correlation results for the last. The EVI2 calculated before mowing of grass predictor shows very strong correlation results with dry matter, the reason is the EVI2 is specially used at times when the NDVI get saturated. The vegetation is very dense at the end of the season before mowing of grass. The linear relationship between the predictors and the dry matter is more pronounced is the reason for high correlation matrix values for the fields combined datasets. The RGBVI dataset correlation results also shows high correlation values with increase in the number of datasets values. The relationship for correlation are consider more reliable for increase samples.

The models comparison for Vonderweg shows a very non-linear relationship of the predictors with dry matter. The correlation matrix results is also one of the way to prove the non-linear relationship of the predictors with the dry matter. Which explains the Random forest model outperforming the linear regression model results using the RMSE, r-square and MAE values in Table 5 Combined results for two models and two types of VIs. The reason for RF model performing better can also be the less available ground observations with high variability, which requires flexibility of the model to adapt to the variation in the dataset. Using RF model the RGBVI dataset results perform better for the Vonderweg grassland compare to the MI dataset. The RMSE results are almost the same 0.015 for the RGBVI and 0.014 for the MI dataset. The R-square values for the RGBVI dataset are two times the results for MI. The MAE values are both equal to 0.011. Kieftenweg in comparison to Vonderweg the LR model performs almost similar to the random forest. The correlation matrix results also displayed a very linear relationship of the predictors with the dry matter content in grass. Another reason can also be the high dry matter values of the grassland compare to the dry matter values for Vonderweg. The reason for the high dry matter values can be explained with the management practices within the two grassland. Vonderweg was used continuously as a grassland for two years compare to Kieftenweg, which was used as a grassland for nine years without any crop rotation.

The models results are generalized to two fields with same manure provision plan and increasing the observation of training samples to 41 in number, which optimized the results of the two models in terms of the selected metrics (r-square values, RMSE & MAE) for dry matter predictions. Though the results are not very different for two types of VIs used for dry matter prediction but the MI performs slightly better than the RGBVI for two fields combined dataset. The optimized performance for MI comes with more cost of equipment.

Furthermore, UAV flights in different instants of time are assessed for its usefulness to the prediction model. Increasing the dimensionality of the data parameters increases the complexity of the model in terms of computation time. However, using feature importance can select the most relevant features for prediction. The results for the MI dataset of Vonderweg grassland using the RF model shows the model assigned the highest two score to predictors using multiple flights information compare to other predictors. As explained earlier, the VI values fluctuates in time based on the reason, which may involve variation in the water stress and sunlight. The Kieftenweg also shows the last two flights cumulative MGRVI predictor scored highest for prediction of dry matter. In the combined fields with collective observation also used last two flight cumulative value based calculated EVI2 predictor highest for dry matter prediction using the MI dataset. These information about the growing phase can be very useful insight to know the variation of dry matter values at the end of the season.

The prediction maps for the two fields using the RF model trained with individual field dataset and combined two fields datasets shows a specific trend of prediction for the two fields. The RF model trained with only the individual field dataset shows the model cannot predict the very high and low values of dry matter as show in Figure 27 Vonderweg prediction map for dry matter spatial distribution using individual grassland RGBVI dataset. Figure 28 Kieftenweg prediction map for dry matter spatial distribution using single grassland RGBVI dataset. The possible reason for this specific trend can be the removal of outliers in the process of identification of outliers. The soil types of the two fields is slightly different as well. The soil texture of Vonderweg is more sandy compare to the soil texture of Kieftenweg, which is loamy and sandy with a ratio of 40 to 60. Unlike the sandy type of soil the loamy part of the soil can hold water and nutrients necessary for grass growth, which results into more dry matter contents (Günal, Erdem, & Çelik, 2018). The prediction map of Vonderweg using the two fields combined dataset for training the RF model was able to predict the high values of dry matter contents, which it failed to predict for its training with individual grassland dataset Figure 29 Vonderweg prediction map for dry matter spatial distribution using two grassland RGBVI dataset. The same results were repeated for Kieftenweg but for the lower dry matter values spatial distribution. The RF model trained with two fields combined dataset was able to predict the low dry matter content values in Kieftenweg, where it could only predict the high dry matter values when trained with individual grassland dataset Figure 30 Kieftenweg prediction map for dry matter spatial distribution using two grassland RGBVI dataset. The reason of this trend is the different trend of dry matter values distribution in the two grassland. Vonderweg grassland dry matter values are smaller compare to the Kieftenweg grassland dry matter distribution values.

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The main objective of this MSc thesis was to compare the cost effective RGBVI to MI dataset for dry matter prediction in grass using linear and non-linear regression models. The RGBVI datasets performed better for individual grasslands as compare to observations combined for two grasslands. Vonderweg based on the selected regression model metrics values performed better with the RGBVI dataset. However, the RGBVI dataset have an inflated r-square value for the RF regression model used in Kieftenweg grassland but the results for the LR model is almost similar to the RF in terms of r-square. The non-linear model better explain the dry matter spatial distribution using the individual grassland observations for Vonderweg. Using the Pearson correlation test the Kieftenweg predictors displayed a more linear nature compare to the Vonderweg, which is the reason the linear regression model predict dry matter better in Kieftenweg . However, the linear regression model perform almost similar to non-linear regression model for two fields combined dataset based on selected metrics (r-square, RMSE, MAE). This research conclude that the combination of both linear and non-linear model are required to better explain the dry matter spatial distribution in grass. The linear regression model based on the metrics values for RGBVI is a better fit for Kieftenweg grassland to analyse the dry matter spatial distribution. The vonderweg and combined two fields dataset for RGBVI were using RF model were a better fit for dry matter spatial distribution. The dry matter predictions map helps in assessing the models results for surrounding pixels based on the range of predictions values. The models were able to explained a certain range of values of dry matter in the predictions map. The time series analysis give an insight to the growing conditions of the grass. The variation in the VI's computed values for the multiple flights of UAV at different instants of time optimized the model predictions based on the feature importance results.

5.2. Review to research questions.

Research question 1: Which of the two linear and nonlinear regression models is better for predicting the dry matter in the grass with RGBVI?

The dry matter prediction requires ground samples for training of regression model. The model can generalize the results better if there are enough ground observations. Again, the homogeneity of the ground samples is another factor. However, the RF model is a better choice for prediction if the homogeneity of the ground observations are not known to the farmers. The non-linear model of regression perform better for the vonderweg grassland. The grassland used continuously as a grassland without crop rotation showed a more non-linear approach. The management of the grassland is also important to consider for choosing the right method for dry matter prediction maps. The linear regression model perform better for Kieftenweg, which has been used as a grassland for nine years without crop rotation. The linear and non linear model perform almost similar for the two fields combined dataset. The generalization of the model is more easy based on the number of ground samples.

Research question 2: How is the performance for the two data sets (i.e. RGBVI and MI) analysed via the prediction error?

The RGBVI is a cheaper option to assess dry matter spatial distribution. The RGBVI using the two linear and non linear regression models produce prediction results with less difference results than MI results based on the metrics used in this research. This makes RGBVI dataset for individual grasslands with very little ground observation samples better results than MI. The results of the two fields combined datasets of MI are marginally better in terms of the selected metrics than RGBVI.

Research question 3: What is the impact of time-series remote sensing data on dry matter prediction in grass?
The feature importance results shows that mean and cumulative values of last two flights close to the mowing of grass were ranked very high for the Kieftenweg grassland, which means the models results were impacted from the previous flights based computed VI's. The time-series flights of UAV were also useful for predictions for Vonderweg and two fields combined dry matter predictions but they were ranked the second highest. Multiple flights during the growing season is important for dry matte prediction. This means the farmers should consider multiple flights of UAV within the different growing phases of grass.

5.3. Future research work

- The ground observation involved for validation of the results were taken before the mowing of grass but It is recommended to use ground observation in the growing phase of grass as well. The dry matter within the growing season variation can be observed and based on the dry matter spatial distribution the manure distribution can be planned and the growth problems will be dealt earlier.

- This research uses ground observation for dry matter prediction using dataset for only one year but future research should consider multiple years dataset. This could help in the generalization of model results.

- This research uses the feature selection method assigning equal importance weight to features but feature selection methods with unequal weight assignment based on importance to prediction error can optimized the performance further.

- Compare to other researches using canopy height data for dry matter prediction shows promising results. It will interesting to see future RGBVI based regression models inclusion of the Grass height information for dry matter.

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