Yield assessment at field level using satellite measurements and semi-empirical crop modelling

– A case study in Gutland area, Germany

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by

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Abstract

Crop models seek to quantify relationships between weather, crop growth and effects of managements to allow yield prediction, diagnosis, management decision and environmental assessment. Remote sensing provide alternative methods of measuring crop variables such as Leaf Area Index (LAI) and canopy cover which when used together with meteorological data improve crop models' accuracy. Winter rape is essential for oil seed extraction which supports a number of other industries and families in European Union (EU) countries such as Germany. Most EU countries experience near overcast weather conditions which makes acquisition of active remote sensing data problematic due to cloud cover. The year 2003 was generally warmer and cloud free in EU hence this study focussed yield assessment for winter rape using the 2003 growing season. The study assesses if a combination of SPOT data and Monteith's model allows an accuracy improvement compared to an empirical model in estimating crop yield within fields of winter rape in Gutland, Germany. This was done with a special focus on the optimisation of LUE within the model. Three fields of winter rape were measured for yield and global solar radiation. This data was used together with fAPAR and climate efficiency to optimise LUE and then compare accuracy levels of Monteith's model and empirical model. In empirical modelling, measured yield was related to ANDVI using regression analysis. Field 1 data was used for calibration while fields 2 and 3 data was used for validation. Results show that Montheith's model with pixel optimised LUE values does improve yield prediction accuracy and the accuracy levels are higher than using empirical model, or than Montheith's model with a constant from literature or than Monteith's model with a constant field optimised LUE value. Average RMSE were 0.64, 1.18, 0.66 and 0.41 ton/ha for empirical modelling, semi-empirical with LUE from literature, semi-empirical with field-optimised LUE and semi-empirical with pixel optimised LUE respectively. Average relative RMSE were 28, 36, 28 and 13 percent of average measured yield for the respective models. Pixel optimised LUE values were investigated for consistency with crop condition classification from an aerial photograph for the same winter rape growing season. Future work should consider validating pixel-optimised LUE values of winter rape using measured values.

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List of Abbreviations

ASAR	Advanced Synthetic Aperture Radar
ANDVI	Accumulated Normalised Differences Vegetation Index
CERES	Crop Environment Resource Synthesis
ENVISAT	ENVIronment SATellite
LACIE	Large Area Crop Inventory Experiment
LUE	Light use efficiency
MARS	Monitoring Agriculture with Remote Sensing
MERIS	Medium Resolution Imaging Spectrometer
NDVI	Normalised Differences Vegetation Index
VIs	Vegetation Indices

1. Introduction

1.1. Background and Significance

1.1.1 Crop yield models

Crop yield models are formulated to analyse crop growth using biological and physiological data of the crops and interaction of the plant and the environment (Dorigo, et al., 2006). They seek to quantify relationships between weather, crop growth and effects of management (Challinor, et al., 2004). Such models are essential for yield prediction, diagnosis, management decision and environmental assessment (Whisler, et al., 1986; Horie, et al., 1995). Crop state variables are defined as those variables whose quantities can be measured such as biomass, chlorophyll content and LAI (Kropff, 1993).

Crop yield models can be grouped into three broad groups, that is, empirical, semi-empirical and mechanistic models (Moulin, et al., 1998). Empirical models directly relate variables such as canopy cover, chlorophyll content and carbon with the yields while semi-empirical methods combine measured data with empirically derived values to estimate yield. Empirical models have a number of limitations which include the exclusion of radiation data, surface temperature and other variables that affect crop growth. The Monteith's model (sometimes referred to as light use efficiency model) is an example of a semi-empirical model. The model assumes biomass accumulation to be a continuous process that is correlated to the amount of photosynthetically active radiation (PAR) absorbed or intercepted by vegetation (Fensholt, et al., 2006). The Monteith's model has light use efficiency (LUE) coefficient as one of the important variable. Mechanistic models utilise soil, climate and management data to simulate the time profile of main crop state variables such as leaf area index, energy, carbon, water and nutrients at crop-soil-atmosphere interfaces (Moulin, et al., 1998).

Although mechanistic models depict relationships that are close to reality, their variable data is difficult to collect and validate (Monteith, 1996; Passioura, 1996). Some variables may be less well known and others are unknown because they vary with space and time (e.g. leaf biomass) (Gastellu-Etchegorry, et al., 2003). Empirical models, therefore, remain still attractive and practical to use (Inoue and Olioso, 2006). Crop yield models have focussed on production and yield over the years with both satisfactory and unsatisfactory results (Bouman, et al., 1996; Landau, et al., 1998). Crop modelling contributes towards the global monitoring of net primary production. This adds its relevance to the goal of understanding global carbon cycle and its effects on food and fibre production (Running, et al., 1999).

1.1.2 Remote sensing applications in crop modelling

The applications of remote sensing in agriculture can be divided into two broad groups, that is, classification (De Wit and Clevers, 2004; Lloyd, et al., 2004)of crops and deriving biophysical variables that determine agricultural production variables (Moreau and Le Toan, 2003). Remote sensing has been used in classification of agricultural landscape due to its ability to detect features such as colour, architecture and composition (Jago, et al., 1999; Turner, et al., 1999). In estimating biophysical variables from remote sensing, the focus has been on quantifying crop biomass (Aparicio, et al., 2000), leaf area index (Turner, et al., 1999), estimating evapotranspiration and chlorophyll (Zarco-Tejada, et al., 2003). Such important crop state variables can be estimated using hand-held devices (Maas, 1988) or satellite data through vegetation indices, linear mixture models or radiative transfer models(Maas, 2000; Weiss, et al., 2001).

Examples of crop modelling programmes that incorporate remote sensing are Large Area Crop Inventory Experiment (LACIE) in the USA (Erickson, 1984) and the Monitoring Agriculture with Remote Sensing (MARS) in the European Union (Meyer-Roux, 1989). Crop Environment Resource Synthesis (CERES) model is another mechanistic model that allows the estimation of crop state and yield for crops such as wheat and winter rape and on large areas (Savin, et al., 1995). The model uses leaf area index retrieved from ENVIronment SATellite (ENVISAT) Advanced Synthetic Aperture Radar (ASAR) and Medium Resolution Imaging Spectrometer (MERIS) image data for accuracy improvement of yield predictions (Dente, et al., 2008).

The use of remote sensing in crop modelling has a number of advantages that include being less laborious and time-consuming compared to traditional field measurements (Jongschaap and Booij, 2004). In addition, remote sensing makes it easier to downscale or upscale crop models since variables that influence crop growth and yields tend to vary in space and time (Moulin, et al., 1998). Downscaling refers to the use of large scale to determine statistical characteristics at smaller scale

(Wood, 1998) while upscaling is the opposite. Remote sensing provides spatial information and crop models provide point information over time and a combination of the two may result in higher accuracy estimation (Delécolle, et al., 1992). The accurate prediction of temporal-spatial dynamic of the crop-soil system allow management activities to avoid economic losses and reduce risks of environmental pollution (Jongschaap, 2006). However, they are a number of disadvantages in application of remote sensing in crop modelling. Errors in crop models that assimilate remotely sensed variables can occur due to processes not well understood, influence from conditions outside model boundaries or situations not included (Jongschaap, 2006).

1.2. Research Problem

Light use efficiency (LUE) is defined as the ratio of dry matter produced to absorbed photosynthetically active radiation (APAR) (Shibles and Weber, 1966). It is usually measured in grams of dry matter per mejajoule (g DM MJ^{-1}) (Gallo, et al., 1993). Different researchers used different LUE values depending on the biomes, crop types, stages of succession (Leblon, et al., 1991) and species (Gower, et al., 1999). LUE can also be affected by environmental variations (Turner, et al., 2003) and stress (Sinclair and Horie, 1989) due to lack of moisture, nitrogen and other nutrient components. Water stress, for example, was found to have an effect on LUE of barley (Jamieson, et al., 1995). LUE values do vary even in plots of the same vegetation type for example C_3 crops in adjoining fields can have different LUE values (Gower, et al., 1999). In cases like this, assigning a uniform LUE to coarse grid cells introduces an error on the final predicted yield results. However, a constant LUE value over the whole season is widely used (Monteith, et al., 1983; Baret, et al., 1989).

Attempts were also made to remotely sense LUE. Several studies have shown relationship between the photochemical reflectance index (PRI) derived from hyperspectral data and LUE (Gamon, et al., 1992; Peñuelas, et al., 1994; Inoue and Peñuelas, 2006). Deriving LUE from relationship with PRI requires appropriate hyperspectral data and has to take into account that the relationship between PRI and LUE is affected by soil water content (Inoue and Peñuelas, 2006) and species type (Hilker, et al., 2007).

Although, Monteith's model has been applied regionally (Goetz, et al., 1999) and globally (Ruimy, et al., 1994), it still runs short of proper validation which can be attributed to the with-in field heterogeneity of LUE (Behrenfeld, et al., 2001.). The need for with-in field and/or between-field spatial information is essential in efficient agricultural systems such as precision agriculture that promotes efficient use of agrochemicals, water and energy (Inoue, 2003). The objectives below were attained using remotely-sensed spectral indices, measured radiation, fAPAR and measured yields to calibrate the light use efficiency and subsequently test if there is a significant difference between simulated and measured yields. Europe experienced its warmest temperature in 2003 (Gómez and Souissi, 2008). Clear skies made it possible to acquire satellite imagery during the growing season of winter rape of 2003.

Both spatial and temporal resolutions are of primary importance to crop modelling (Delecolle, 1988), especially in small parcels of land. Hence this study utilises SPOT-4 High-Resolution Visible Infra-Red (HRVIR) and SPOT-5 HRVIR imagery to derive spectral indices which are in turn used to optimise the LUE at field and pixel level for yield prediction using semi-empirical modelling. It analysed yield prediction under four scenarios: i) using the empirical relationship between yield and sum of NDVI for 5 months (this will be regarded as base line), ii) using Monteith's model with a constant LUE from literature, iii) using Monteith's model with a field optimised LUE and iv) Monteith's model with pixel optimised LUE. The sum of NDVI is herein referred to as ANDVI (Accumulated Normalised Difference Vegetation Index).

1.3. Research objectives

General objective

- The study assesses if a combination of remote sensing data and Monteith's model allows more accurate estimation than an empirical model of crop yield within fields of winter rape. There is a special focus on the optimisation of LUE within the model.

Specific objectives

- Compare accuracy in yield prediction of the semi-empirical Monteith's model to an empirical model based on ANDVI,
- Assess the performance of Monteith's model in three different modes of LUE optimisation: constant from literature, constant field optimised and pixel optimised.

1.4. Research questions

- Does Monteith's model improve accuracy level of winter rape yield estimation compared to empirical modelling?
- Does the use of pixel-adjusted LUE give better yield estimates than use of the field optimised LUE in Monteith's model?

1.5. Hypotheses

- There is a significant positive relationship between yield and ANDVI
- There are significant relationships between measured yield of winter rape and modelled yields using Monteith's model in the three different LUE optimisatisation modes.
- Accuracies are expected to increase from Monteiths models with LUE from literature< field optimised LUE< pixel optimised LUE.
- There is a significant difference between LUE values from areas of good growing conditions (growing condition to be determined from aerial photography) and ones from poor growing conditions ($\Theta>0$), where Θ = good crop condition LUE minus poor crop condition LUE.

2.

Methods

3.1 Study area

To test the validity of the above objectives and hypothesis, data was collected from the Gutland area of south west of Germany with coordinates 49°8`N, 6°5`E. The mean annual temperature of Gutland ranges from 7°C to 9°C and annual precipitation is about 800mm (The Weather Channel Interactive, 2008). Crop production is practiced in two major seasons, that is, winter and summer seasons. Main crops grown in this area are wheat, maize, rape, barley and forage crops and the agricultural plots have an average area of 100x100m^2 (Lohnertz, 2006). The crops under consideration are winter wheat and rape.

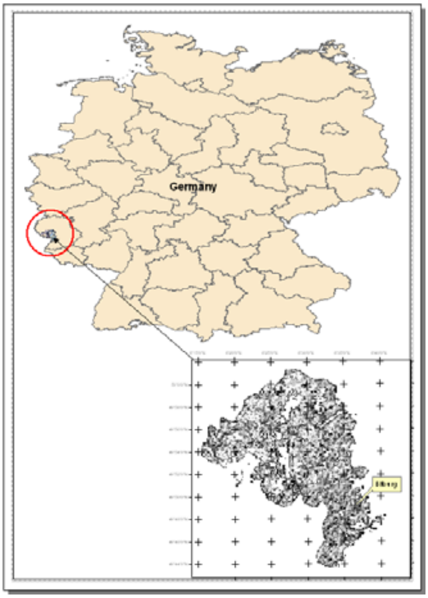


Figure 3.1 Map of Gutland area in Germany.

3.2 Data available and Data to collect

This study makes use of ground measurements, meteorological data and satellite image data for the growing season of 2003.

3.2.1 Field Data

Ground measurement data for yield was collected using Global Positioning System (GPS) on board automatic harvesters, as part of the EU Interreg IIIb NEW project WARELA (Water Retention by Land Use). A total of measured points were collected in fields 1, 2 and 3. Random samples were considered out of all these points since most points were falling in the same pixel of remote sensing data and to eliminate the effect of spatial autocorrelation. Required samples were determined using the formula below (Equation 1). In the end, 198, 102 and 134 randomly samples were selected for field 1, 2 and 3 respectively. Field 1 data was used for calibrating the empirical and semi-empirical models. Field 2 and field 3 were used for model validation.

$$n_{req} = \frac{t^2 * CV\%^2}{AE\%^2}$$ (Equation 1) (Husch, et al., 2002)

Where

n_{req} – number of required samples
t- t value from the t distribution table
CV – coefficient of variation
AE – allowable error (in this case it 10 % was chosen)

Yield data was collected using the applied principle of volumetric measurement. The volume of the flow of grain is determined and converted to mass using a value for specific weight which is density (kg/dm^3). The data was measured using the system Claas Quantimeter and this was done at the end of the 2003 winter rape growing season. The machine works by intercepting a light barrier on a certain amount of grain on a paddle for a certain period of time. The longer the dark phase, the higher the amount of grain on the paddle.

The calibration function on the volume of grain is derived from the height measurement. A standard calibration function was applied which often results in an error of less than 10 percent (Deutsche-Landwirtschafts-Gesellschaft, 2001). Since grain mass also depends on its moisture, the determined yield values were corrected to standard moisture using a moisture sensor that is continuously working in the system. The accuracy of the position with differential GPS was between 1 and 5 metres.

3.2.2 Remote Sensing Data

SPOT 4 and 5 satellite images, with spatial resolution of 10 m and 20 m respectively, were radiometrically and geometrically corrected (Lohnertz, 2006). NDVI values were then calculated for the months of April, May, June and August. Frequent satellite observations for crop modelling are usually affected by climatic conditions (Inoue, 2003). The particularly dry, cloud-free periods of 2003 (Rebetez, et al., 2006) allowed the acquisition of the these monthly images. The images were all taken in the morning between 10:30 Hrs and 11:08 Hrs. SPOT-HRV images were used because of the small sizes of land parcels in the region (about 100*100m^2) demand high spatial resolution sensors (Lohnertz, 2006).

3.2.3 Meteorological data

Solar global radiation data of the climate station "Trier-Petrisberg" was obtained from the German National Meteorological Service. The meteorological data was then checked for missing and suspicious value. Solar radiation values were used as input to the Monteith's Model.

3.2.4 Phenological Data

The growing season and phonological data crops grown in the area was provided by the German National Meteorological Service (DWD, 2006. The crops under consideration in this study were winter rape. Crop phenology is defined as the rate and order of appearance plant physiology as a cause of environmental factors. Temperature is the major environmental factor that affects crop phenology (Russell, et al., 1989). The phenological crop calendar provided explained the growing period as characterised by the different growth stages of the crops (Table 2.1).

Table 2.1: Phenological data for winter rape in Gutland, Germany, in 2003

	J	F	M	A	M	J	J	A	S	O	N	D
Stage				Leaf expansion and tillering	Begin Flowering	End flowering	Harvesting					
Date				13	02	05	15					
Julian Day				104	123	157	197					

3.3 Crop yield modelling

3.3.1 Processing of yield data

The first procedure was the identification and removal of extreme values from the data. Extreme values can be a result of errors in measurement, georeferencing and data processing (Shearer, et al., 1997; Blackmore and Moore, 1999; Arslan and Colvin, 2002). Descriptive statistics was used to produce box plots that showed the distribution of yield data and thereafter identify outliers which were then removed. Thus outliers were treated as extreme values and therefore removed. In summary, Table 2.1 shows a summary of the data utilised in this study.

Table 2.2: Characteristics of model parameters

Variable	**Source**	**Temporal Characteristic**	**Spatial Characteristic**
Radiation (Rg)	Measured at Trier	varies	constant
Climatic efficiency (ε_c)	Literature (Varlet-Grancher, et al., 1982)	Constant	Constant
fAPAR	predicted from NDVI profiles	Varies	Varies
LUE Mode 1	Literature (Bastiaanssen and Ali, 2003)	Constant	Constant
LUE Mode 2	Field-adjusted	Constant	Constant
LUE Mode 3	Pixel-adjusted	Varies	Varies
Harvest index	Literature (Greef, et al., 1993)	n/a	n/a

3.3.2 Empirical modelling

Yield was calculated using the statistical relationship between ANDVI and ground measured yield. This was done by first calculate ANDVI map, that is, sum of the NDVI maps of the four months (April, May, June and August) of 2003. Point data with measured yield was then used to extract ANDVI values for the respective points. Regression analysis was used to calculate the model parameters for the empirical model of yield from ANDVI. The resulting regression (empirical) model was tested for significance using the F-test. The model was validated by using measured yield data from fields 2 and 3. Root mean square error values for the predicted yield compared to measured yield were then used to compute the accuracy of the model in the two validation fields.

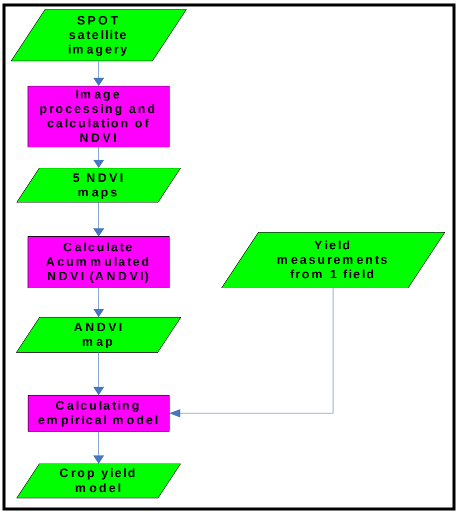


Figure 3.2: Empirical modelling processes and products

3.3.3 Semi-empirical modelling

The Monteith's model was used to estimate yields and LUE in some instances and then compared to the measured yield to assess the performance of the method. Monteith's efficiency model (Kumar and Monteith, 1981) uses measured data of global radiation and reflectance measurements for derivation of fAPAR to model dry matter production. The following steps processing were performed to estimate yield in the different LUE modes.

3.3.3.1 Fraction of Photosynthetically Active Radiation (fAPAR)

In this study fAPAR was derived from multi-temporal satellite reflectance measurements. fAPAR is defined as the amount of photosynthetically active radiation that is actually absorbed by the crop (Justes, et al., 2000). It can also be accounted by the difference between photosynthetically active radiation (PAR) that reaches the canopy and PAR transmitted through the canopy (Dorigo, et al., 2006). Variations of fAPAR can be due to solar irradiance, chlorophyll content (Dawson and Curran, 1998), leaf–sun geometry (Chen and Leblanc, 1997), extreme temperatures (Mendham and Salisbury, 1995) and developmental stage of crop (Justes, et al., 2000). Estimation of fAPAR was done by interpolating NDVI values to daily time steps and conversion into fAPAR using an empirical relationship.

a) Interpolation of NDVI

The NDVI values for the study were interpolated to daily time steps. Spline interpolation uses a specific polynomial between each pair of discrete parameter values. The coefficients of the polynomial are calculated in such a way that the polynomial function is continuous through the second derivatives (Gastellu-Etchegorry, et al., 2003).

b) Conversion to FAPAR

Often a linear relationship between NDVI and fAPAR is observed. Interpolated NDVI values were converted into fAPAR values using the following empirical relationship:

ε_i=1.164*NDVI-0.143 (Equation 2) (Myneni and Williams, 1994)

This relationship is widely used to estimate fAPAR in both crops (Lobell, et al., 2003; Mo, et al., 2005) and forests (Maselli, et al., 2009) and crops.

3.3.3.2 Global solar radiation

Data on shortwave radiation is often restricted to few discrete observations. There are also some optical models which infer PAR from top of the atmosphere solar irradiance. But this study used daily global solar radiation data measured at the nearby Trier-Petrisberg Meteorological Office.

3.3.3.3 Climatic efficiency

Climatic efficiency describes the rate at which energy reaches the canopy of the plants. It varies mainly with atmospheric conditions (Blackburn and Proctor, 1983), solar elevation, time and geographic location. In this study, 0.48 % was adopted as the climatic efficiency parameter (Varlet-Grancher, et al., 1982) since its generally accepted (Moulin, et al., 1998).

3.3.3.4 Harvest index

Harvest index refers to the proportion of the dry matter of harvested parts to the total dry matter produced (Moulin, et al., 1998) or the ratio of grain mass to above-ground mass (Patel, et al., 2006). It is used to convert dry matter produced during the season into yield. It is measured as a percentage and interpreted as the percentage of above-ground biomass which is rape seed (Rathke, et al., 2005). This study adopted a value of 25 percent (i.e. 0.25) for winter rape (Greef, et al., 1993).

3.3.3.5 LUE

a) Monteith's model with a constant LUE from literature

In the first instance a constant LUE term from literature was adopted and applied on the model to estimate yields for the calibration and validation datasets. Winter rape is usually estimated using similar LUE terms as wheat and these range from around 1.94 g DM MJ^{-1} (Zhang, et al., 2008) to 3.22 g DM MJ (Garcia, et al., 1988). High LUE values are usually obtained during the vegetative stages while low values are found during rest of the growing season of C_3 crops such as winter rape and wheat (Zhang, et al., 2008). Average LUE values for wheat and winter wheat for whole season usually range between 2.5 g DM MJ^{-1} (Bastiaanssen and Ali, 2003) and 2.9 g DM MJ^{-1} (Bradford, et al., 2005). In the first scenario of constant LUE, 2.5 g DM MJ^{-1} (Bastiaanssen and Ali, 2003) was adopted as the LUE from literature and applied to the Monteith's model.

b) Monteith's model with a constant field optimised LUE

In this instance, field based optimisation of LUE was conducted using a look up table procedure. Optimisation was done using a look-up-table created using various thresholds of a certain range given by literature. The range adopted in the optimisation is from 2 g DM MJ^{-1} (Gallaghar and Biscoe, 1978; Zhang, et al., 2008) and 3.22 g DM MJ (Garcia, et al., 1988) as the minimum and maximum values, respectively. The procedure is repeated using the loop function in programming until a minimum local Root Mean Square Error (RMSE) is found (Challinor, et al., 2004). This method uses real time calibration. The final LUE value is obtained when the residual error is minimum (Inoue, et al., 1998). One of the major advantages of optimisation is that it eliminates the need for field measurements which are often expensive (Catania and Paladino, 2009).

The procedure is automated and applied to all data points in field 1. An average of all the LUE values in the field was then calculated and adopted as the field-optimised LUE value. The field-optimised LUE value was then validated using independent data from fields 2 and 3. The steps followed in this procedure are summarised in Figure 3.3 below.

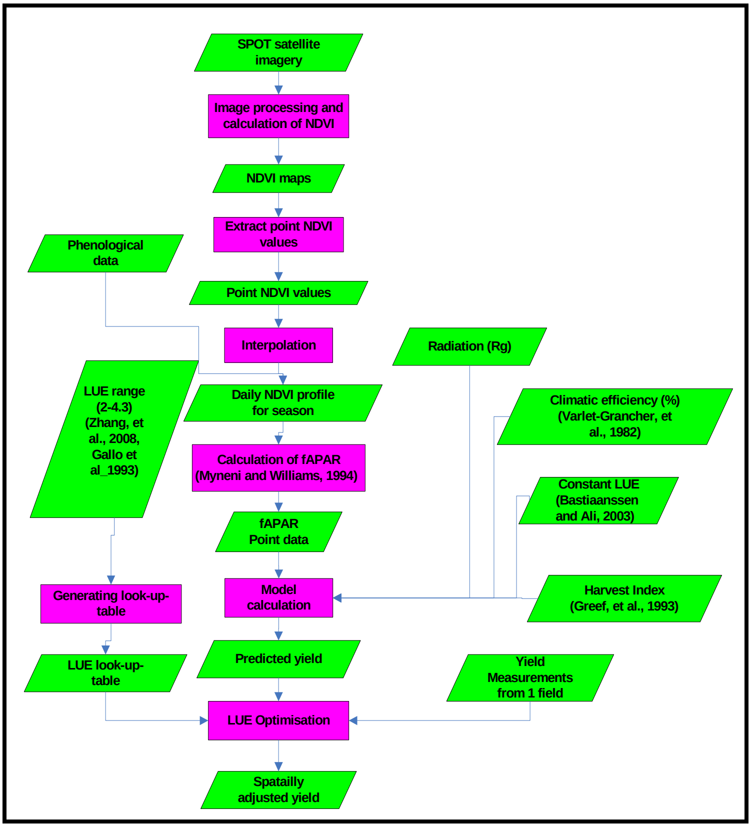


Figure 3.3: Monteith's model (with field-optimised LUE) processes (in purple) and products (in green).

Predicted yield from fields 2 and 3 were then compared with measured yield to test the validity of the field-optimised LUE value.

c. Monteith's model with a pixel optimised LUE

Pixel optimisation follows similar same procedures as in field optimisation (above) up to the calculation of the LUE values for the individual pixel. Pixel-based optimisation was done for LUE values for all the fields (that is fields 1, 2 and 3). Thus all fields' data were used in the calibration of the model. Therefore LUE was allowed to vary within a defined range. The allowed range in LUE was established on representative values taken from literature, 2.0-3.3 g DM MJ^{-1} (Gallaghar and Biscoe, 1978; Garcia, et al., 1988; Zhang, et al., 2008). LUE estimation was done for the whole season per pixel within each field to capture spatial variation of LUE. Constant LUE values were therefore applied over the season; daily or hourly LUE variations were not considered. The rationale of pixel optimisation is that LUE can vary within a mono-species field for and this can be due to factors such as nutrient supply, water supply (Garcia, et al., 1988). The study also assumes that the dry summer of 2003 (Gómez and Souissi, 2008) could have made soil moisture a limiting factor in certain parts of the agricultural fields compared to the rest of the fields.

3.3.4 Validation of models

Validation of the methodology was carried out on independent data in fields 2 and 3 with The validation of the empirical model, semi-empirical with literature and field optimised LUE values was done using measurements data from fields 2 and 3. Pixel optimised LUE values could not be validated since we do not have measured LUE values but they were checked for consistency with mid-infrared reflectance from Landsat Band 5 and growth condition classification from an aerial photograph of the same season. The justification for this is that mid-infrared reflectance ability to reflect soil moisture conditions within the fields. It was assumed that LUE differed with different soil moisture conditions.

To test the validity of the LUE values, the aerial photograph was classified into '*good*' and '*poor*' growth condition. This was performed using moving filter on reflectance values of the aerial photograph. Aerial photographs, like satellite images can provide essential information for precision agriculture (Wood, et al., 2003). A *3 x 3* standard deviation filter was used on the aerial photograph to be able to classify the points according to crop condition as shown by comparing standard deviation of a pixel containing a point with its surrounding pixels. Standard deviation of less than 15 was classified as *'poor'* while the rest was classified as *'good'* crop condition. Both methods were used to compliment each other since measured LUE values were not available.

Pixel-optimised LUE values were then separated according to crop condition as classified from the standard deviation filter applied to aerial photograph. The two groups of LUE data, one from points with ‘good’ and one from points with ‘poor’ crop condition were then subjected to a normality test and subsequently to Wilcoxon signed rank test to compare the means of the two groups. The null hypothesis for the test was that there is no significant difference between LUE values from areas of good crop condition and ones from poor crop condition ($\Theta > 0$), where Θ = good crop condition LUE - poor crop condition LUE.

The performance of the different models was assessed using root mean square error (RMSE), relative RMSE and coefficient of determination (R^2). R^2 is defined as the total variance in the dependent variable that is explained by independent variable(s) (Miles and Shevlin, 2001). On the other hand, RMSE measures dispersion of the observations from the true values (Longley, et al., 2005). When comparing two models, smaller RMSE depicts higher accuracy compared to the one with higher RMSE (Watson and Teelucksingh, 2002). Relative RMSE was also calculated and used in the final assessment of the methods. Relative RMSE is RMSE divided by the measured mean. Both RMSE and relative RMSE are expressed as percentages of the measured yield (Timmermans, et al., 2009).

4 Results

Table 4.1: Summary statistics for yield (in 1000 kg/ha) and ANDVI (unitless) for each of the 3 fields

	N	Min	Max	Sum	Mean	Std Error	Std. Deviation	Variance
Field 1 yield	198	0.6	3.4	430.10	2.17	0.05	0.65	0.42
Field 1 ANDVI	198	1.64	2.40	411.82	2.12	0.015	0.20	0.04
Field 2 Yield	102	1.13	2.97	212.07	2.08	0.04	0.44	0.20
Field 2 ANDVI	102	1.94	2.42	225.88	2.22	0.01	0.11	0.01
Field 3 YIELD	134	0.50	3.94	351.37	2.62	0.08	0.85	0.72
Field 3 ANDVI	134	1.83	2.27	277.50	2.07	0.01	0.09	0.01

Table 4.1 shows the summary for the data of field 1, 2 and 3. Variance of measured yield for field 3 is the highest whilst it is lowest in field 2.

4.1 Relationship between measured yield and ANDVI

Data from field 1 was used to calibrate the empirical model for winter rape by relating measured yield to ANDVI. The correlation coefficient for field 1 shows a moderate relation ($r = 0.722$) between measured yield and ANDVI (Figure 4.1). The prediction model of the relationship was calculated using the regression model to produce an empirical relationship between yield and ANDVI. The null hypothesis for the relationship was that there was no significant relationship between yield and ANDVI. This was tested using the Fischer (F) test. The results show that there was a significant ($p < 0.05$) relationship between measured yield and ANDVI in field 1. Regression analysis resulted in the following empirical relationship between yield and ANDVI.

$$Yield = 2.304\ ANDVI - 2.620 \quad \text{(Equation 3)}$$

The model has R^2 (coefficient of determination) of 0.522% meaning that 52% of yield variability is explained by ANDVI.

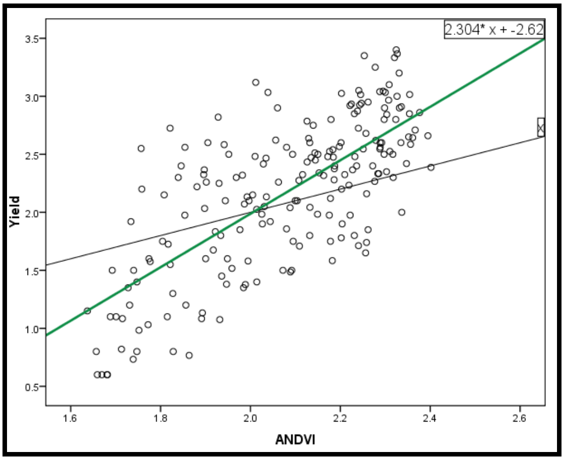


Figure 4.1: The empirical relationship between Yield and ANDVI from field 1.

The model was validated using measured yield from the other two fields (field 2 and field 3) by predicting yields and then comparing to measured yields. The F-test measures the significance of the relationship within the regression analysis. The null hypothesis for the test was that there was no significant relationship between measured and predicted yield. The relationships between measured yield and predicted yield in the two fields are illustrated by graphs (Figure 4.2) below:

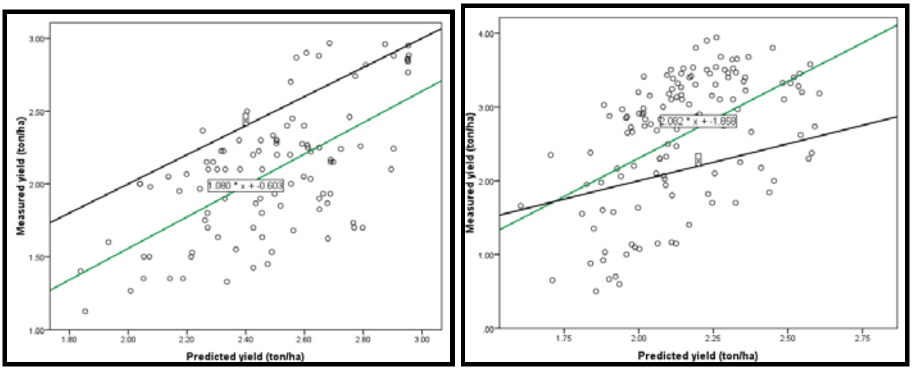


Figure 4.2 Comparison of measure d yi eld and predicted yield for the tw o validation fields (field 2 and field 3), ((-), 1:1 line and (-) regression line).

Field 2 and field 3 showed positive relationships between measured and predicted yields (r=0.641 and r=0.509 respectively). The Root Mean Square Error (RMSE) for the field 2 is 0.527 ton/ha while for field 3 it is 0.915 ton/ha. Since RMSE for field 2 is lower than the one for field 3 it is therefore illustrated that the empirical model is valid and it estimates winter rape estimates better in field 2 than in field 3.

The empirical model managed to predict yield to accuracy levels stated above. Semi-empirical models may overcome certain limitations and provide models which predict yield with higher accuracy levels.

4.2 Semi-empirical model with a constant LUE from literature

A number of variables were calculated and measured in order to model winter rape yield using the Monteith's model and these include: global solar radiation, fAPAR and climate efficiency. LUE was neither measured nor calculated but was obtained from literature (Bastiaanssen and Ali, 2003). The study assumes that all points in the fields received uniform daily global solar radiation values. Figure 4.3 shows the daily radiation values for the winter rape growing season of 2003 at climate station Trier-Petrisberg.

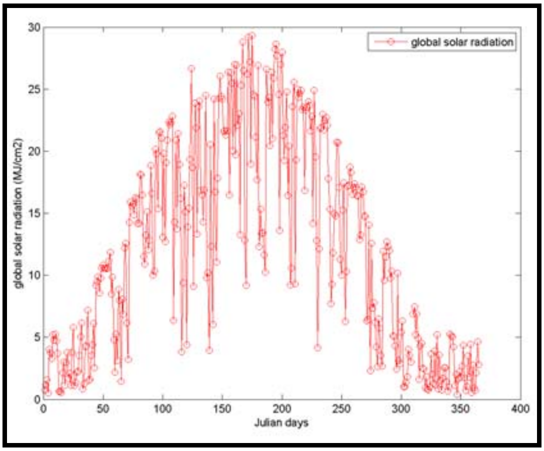


Figure 4.3 Daily global radiation for 2003.

NDVI values for the study points were extracted and interpolated to show the daily NDVI values for the whole winter rape growing season in Gutland. Figure 4.4

illustrate the interpolated NDVI values for a typical point in field 1 (a point where a large yield was predicted).

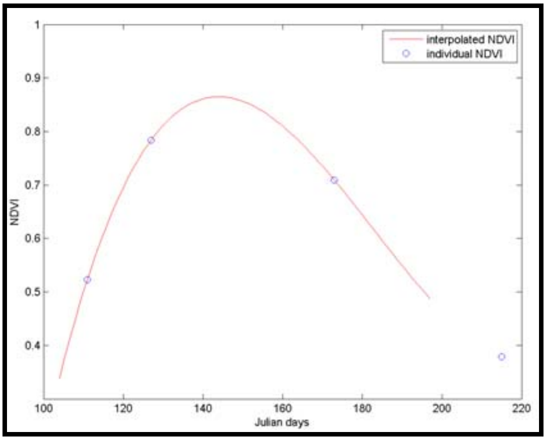


Figure 4.4: Individual and interpolated NDVI values for one sampling point in Field 1.

From the diagram above, NDVI is therefore is at its highest around Julian day of 140. According to the phenological data, this period is characterised by flowering stage in winter rape growth. Winter rape flowering stage starts and ends on the 124th and 153rd Julian day respectively.

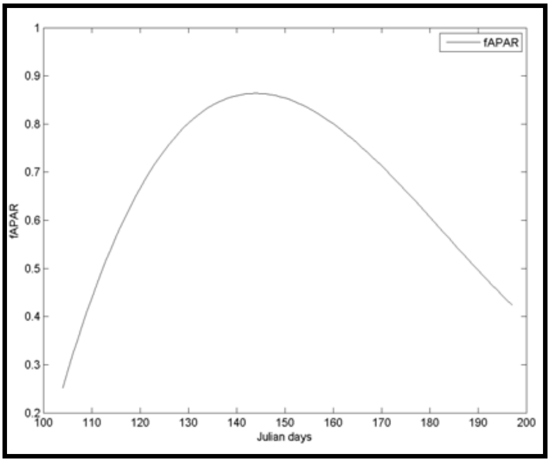


Figure 4.5: Fraction of Photosynthetically Active Radiation (fAPAR) calculated from NDVI for same sampling point in Field 1 as in Figure 4.4.

Figure 4.5 above shows empirically- derived fAPAR values for a sampling point within Field 1 for the whole winter rape growing season. The selected point is from one of the most productive spots within the field. The distribution of the values of fAPAR show a similar trend to the one of NDVI (in Figure 4.5 above) since fAPAR was calculated from empirical model that had NDVI as the input variable.

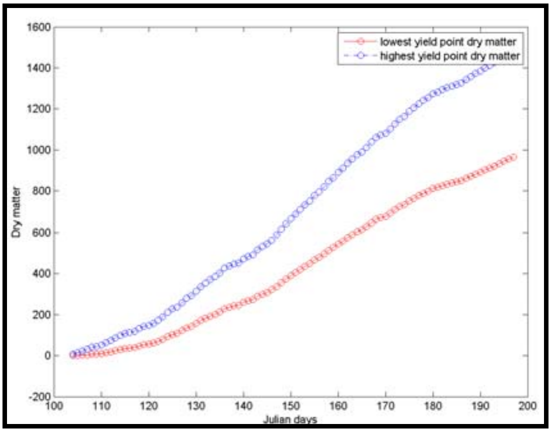


Figure 4.6: Accumulated daily dry matter production (kg/m^2) for two sampling points, one with lowest and the other with highest yields in Field 1

Figure 4.6 shows the increase in accumulated biomass at two points (one most productive and the other least productive). Accumulated dry matter (Figure 4.6) for the sampling points was then calculated as a product of LUE (from literature), climatic efficiency (from literature), global solar radiation (measurements) and fAPAR (derived from NDVI). The accumulated dry matter at maximum was 1484.5 g MJ while at minimum it was 964.24 g MJ^{-1}. Predicted yield and its relationship with measured from this method is illustrated in the Figure 4.7 below.

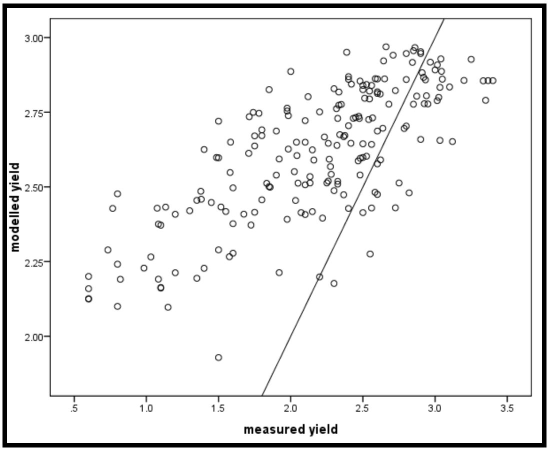


Figure 4.7: Relationship between predicted and measured yield in field 1 (line represents y=x).

There is a linear relationship between predicted and measured yields. R^2 for the relationship was 0.55 and RMSE was 0.68 ton/ha. An F-test was tested and it showed that the relationship was significant ($p<0.05$).

The constant LUE value was also applied in the two validation data sets and F- test used to test for the significance of the relationship. Figure 4.8 shows the comparison of modelled and measured yield for the fields 1 and 2.

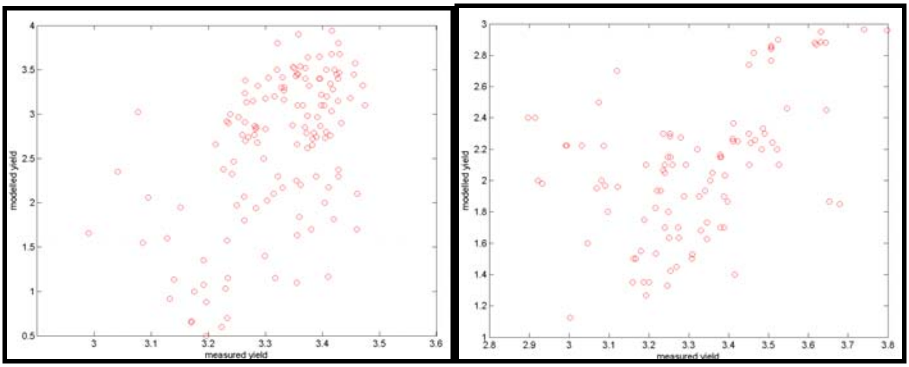
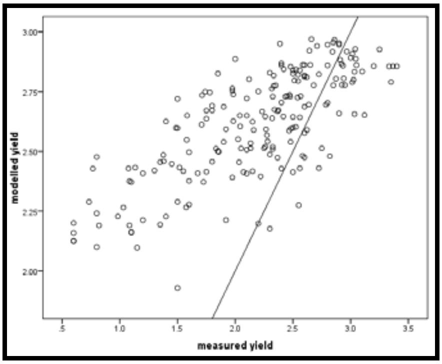


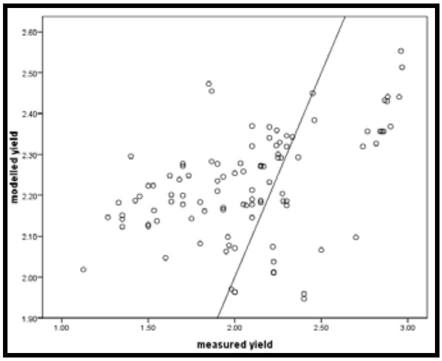
Figure 4.8: Comparison of modelled and measured yield for the fields 1 and 2

4.3 Semi-empirical model with a field optimised LUE

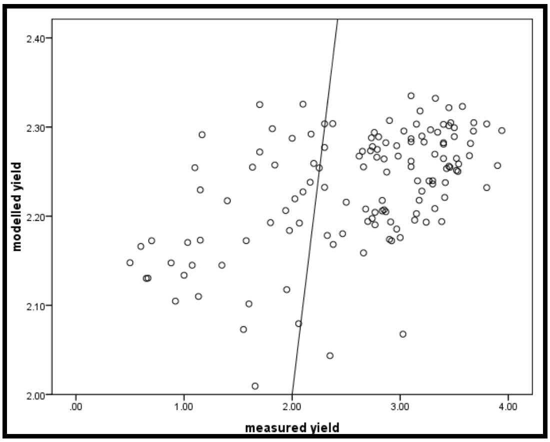
Field optimisation in field 1 gave an average LUE value of 2.0 g/MJ for the whole field. The value was used to estimate yield in field 2 and field 3 and their respective coefficient of determination (R^2) and RMSE were computed for the relationship between predicted yield and measured yield. This can also be illustrated by the following graphing comparing modelled yield and measured yield in the three fields. In the plots below (Figure 4.9), modelled yield is plotted against measured yield using the LUE value from the first field.



a)`



b)



c)

Figure 4.9: Comparison of modelled yield and measured yield using the LUE value optimised using field 1 data a) 1, b) 2 and c) 3.

The relationship was tested for significance using F test and the results show that in all the fields there was a significant relationship between modelled yield and measured yield ($p<0.05$). Figure 4.10 represents a graph summarising accuracy and performance of the modelled yield when compared to measured yields for the three fields.

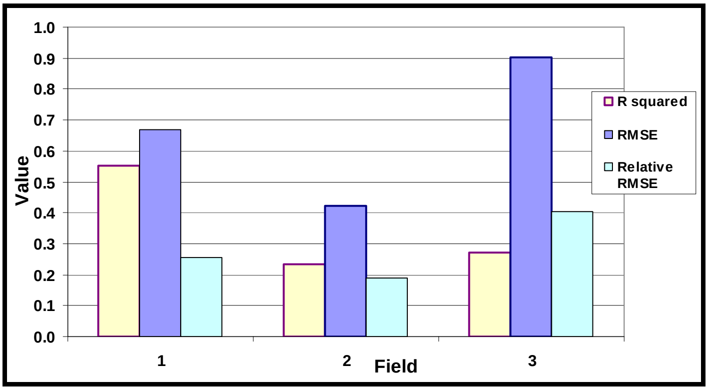


Figure 4.10: Coefficient of determination (R^2), RMSE, and Relative RMSE for fields 1, 2 and 3 after applying field optimised LUE.

The fields have different accuracies and Figure 4.10 illustrates the relative importance of the method in estimating LUE. R^2 for the field 1, field 2 and field 3 is 0.55, 0.23 and 0.27 respectively meaning they do predict measured yield at 55%, 23% and 27% predictability. The RMSE for fields 1, 2 and 3 is 0.68, 0.42, and 0.90 t/ha respectively. Thus accuracy levels were highest in field 2, then field 1 and lastly field 3. The difference in accuracy levels maybe spatial difference due to other crop conditions not explained in the Monteith's model such as different management regimes and soil characteristics.

Although the model managed to predict the yield to relative RMSE values of 20% - 40% of measured mean, the explanation power of modelled data on measured yield was very low in the two validation datasets as shown by the low values of R^2. Thus using field optimised LUE values (constant LUE over the entire field) as shown in the figure 4.8 results in limited predictive ability. Therefore a fixed LUE value can not account for the local variation in yield that is present within a field hence giving room for further optimisation, that is, pixel based optimisation.

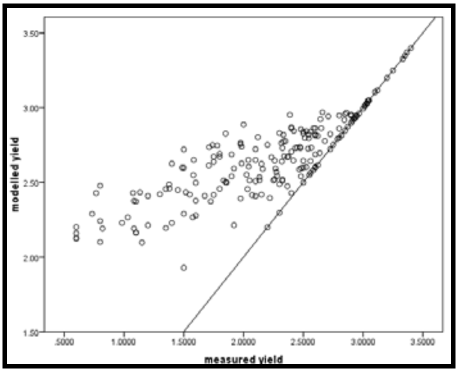
4.4 Semi-empirical modelling with pixel optimised LUE

The above section shows that a constant LUE value applied over an entire field can not account for the local variation that is present within a field. After the optimisation process, season average LUE values for each pixel were obtained and their variation differs as shown in Table 4.2 below.

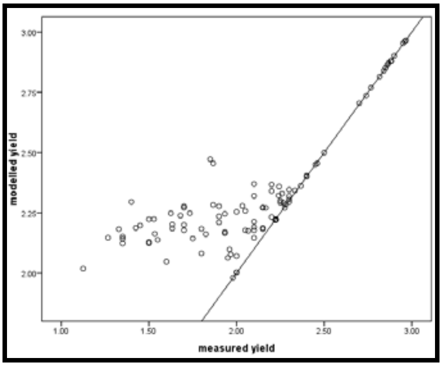
The distribution of LUE (g DM MJ^{-1}) values in the three fields.

	Minimum	Maximum	Mean	Std. Deviation
field1	2	3	2.27	.290
field2	2.000	2.900	2.19030	.264463
field3	2.000	3.220	2.60383	.475378

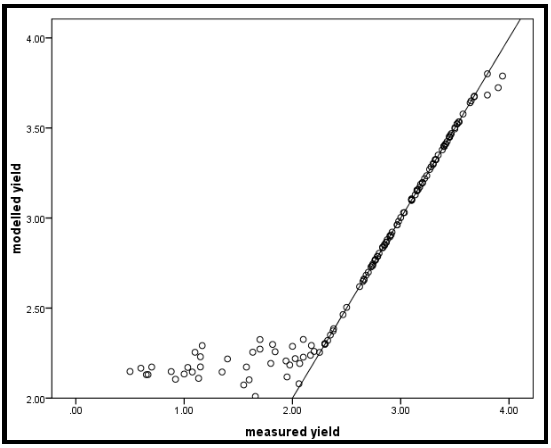
The optimised minimum LUE value in all the fields was 2 g DM MJ^{-1} (in all fields) and the maximum was 3.22 g DM MJ^{-1} (in field 3). Mean LUE values were 2.137 g DM MJ^{-1}, 2.059 g DM MJ^{-1} and 2.527 g DM MJ^{-1} for fields 1, 2 and 3 respectively. However, LUE variability in field 3 was larger than in the rest of the fields. The standard deviation values of LUE for fields 1, 2 and 3 were 0.444, 0.396 and 0.646 respectively. These values illustrate variability in the three fields as shown below (Figure 4.12).



a)



b)



c)

Figure 4.12: The relationship between modelled yield and measured yield for a) Field 1, b) Field 2 and c) Field 3

The above results show a stronger relationship between the predicted and measured yield in all the fields. The coefficients of determination (r^2) for the relationship were between modelled and measured yield were 0.8333, 0.6686 and 0.9547 for field 1, 2 and 3 respectively. Measured yields therefore are therefore explained by predicted yield by about 83.3 %, 66.86 % and 95.47 % for the respective fields. RMSE values for the prediction of yields in fields 1, 2 and 3 were 0.408 g DM MJ^{-1}, 0.371 g DM MJ^{-1} and 0.231 g DM MJ^{-1} respectively. Although the predictive power and accuracy levels were high, the method over estimate yields in points with low measured yield.

4.5 Validation of pixel optimised LUE values

The LUE values obtained after pixel based optimisations were validated by testing for the significant relationship between them and the mid-infrared (band 5) reflectance from Landsat ETM images for the 3rd of August in 2003. Hence, regression analysis was used to test for the significance of the relationship and the following results were obtained from the test of the three fields. The null hypothesis for the test was that there is no significant relationship between LUE values and Mid-infrared reflectance.

Table 4.2: Summary table showing regression results with the P-value (F test) results

	R	R Square	Adjusted R Square	Std. Error of Estimate	P (Sig.)
Field 1	0.209	0.044	0.039	0.435	0.003
Field 2	0.016	0.000	-0.027	0.297	0.925
Field 3	0.085	0.007	0.000	0.646012	0.332

The above results show only a significant relationship between LUE and reflectance in the mid-infrared band in field 1 only ($p<0.05$). The correlation coefficient representing the strength of the relationship depicts a weak relationship although it is significant. However, results for other fields show that the relationship is not significant ($p>0.05$).

The values were also tested for consistency and agreement with data from aerial photograph for the study area. This procedure, using aerial photography, shows a moderate agreement between the LUE values and crop growth condition within the area. Data from field 1 was used in this procedure. A visual interpretation of the aerial photograph draped with pixel-optimised LUE show that most of the low LUE values were found in areas of poor growth condition as illustrated in the aerial photography in Figure 4.13 below.

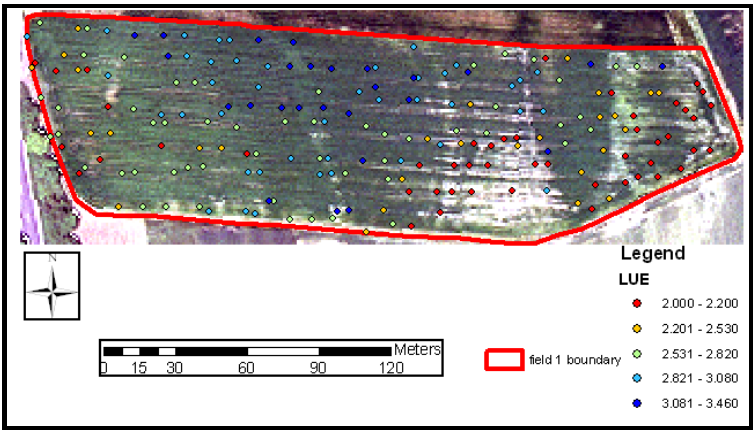


Figure 4.13: Pixel-optimised LUE and (a) original aerial photograph

The classification procedure using a moving standard deviation filter resulted in the following classified map for field 1 (Figure 4.14). The resultant classified map is shown with an overlay point map of the pixel-optimised LUE values.

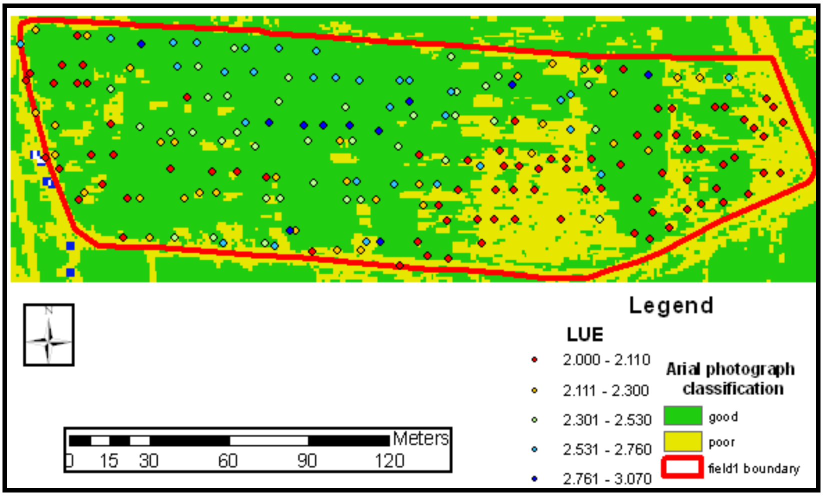


Figure 4.14: Pixel-optimised LUE and classified map showing growth condition in field 1.

Pixel LUE values from the two different classes (good and poor crop condition) were then compared using the Wilcoxon signed rank test. The test was performed as a one tailed test with H_1 being $\mu_1=\mu_2$. This non-parametric test was used since the LUE values were not normally distributed. The test gave the following output (Table 4.3)

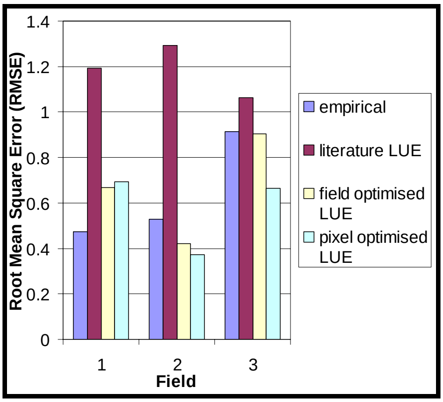
Table 4.3: Wilcoxon signed ranks test results.

	Good - Poor
Z	-3.641[a]
Wilcoxon Signed Ranks Test Asymp. Sig. (2-tailed)	.000

The above results from the test show a p value of 0.000 which is less than 0.025. We therefore reject H_0 and conclude that there is evidence that the mean LUE values from points that falls in areas classified as having 'good' crop condition (from the aerial photograph) is greater than that of LUE values from 'poor' crop condition areas. In this case the pixel optimised LUE values shows consistence with information extracted from the aerial photograph. LUE depicts the efficiency of conversion of light energy into fixed carbohydrate (Sims, et al., 2006) which ,in this case, is shown by winter rape greenness. There is a significant relationship correlation between greenness and LUE (Gower, et al., 1999; Sims, et al., 2006).

4.6 Comparison of the four models

The four modelling procedures were assessed for accuracy levels using the RMSE values. Figure 4.14 shows RMSE values for the three fields of winter rape.



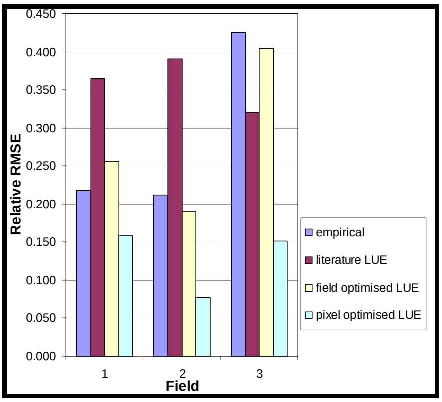


Figure 4.15: RMSE and Relative RMSE values (tons/ha) of the 4 models in the three fields

As illustrated above, lowest RMSE values were obtained in all the fields when the LUE was optimised at pixel level while highest were in semi-empirical modelling using LUE value from the literature. Average RMSE values were 0.64, 1.18, 0.61 and 0.41 ton/ha for empirical modelling, semi-empirical modelling with LUE from literature, semi-empirical modelling with field-optimised LUE and semi-empirical modelling with pixel optimised LUE, respectively. Average relative RMSE were 0.28, 0.36, 0.28 and 0.13 ton/ha for the respective models. This means that accuracy levels were highest in a semi-empirical model with a pixel optimised LUE while lowest in one using LUE from literature. Empirical model and Monteith's model with a field optimised LUE estimate winter rape with almost similar accuracy levels. The least accurate yield estimates were from the Monteith's model with a constant LUE value from the literature.

5: Discussion

Semi-empirical modelling using the Monteith's model also managed to significantly model winter rape yield in all the three modes. Optimisation of the LUE in the improved the performance of the Monteith's model in the modelling of winter rape yield compared to empirical model or Monteith's model with constant LUE. Of the two optimisation procedure performed, pixel optimisation produced yield estimates with higher accuracy levels compared to the field optimisation. The method and study managed to show the importance of spatial LUE optimisation in yield assessment. Contrary to some studies (Monteith, 1977; Baret, et al., 1989), LUE is shown here to vary spatially within fields. Although the derived spatial pattern of LUE values could not be validated directly, it shows good agreement with growth conditions as interpreted visually from an aerial photo of the same season. Although the predictive power and accuracy levels were high, the method over estimate yield in points with low measured yield.

This study demonstrate the possibility of improve yield modelling and assessment using the remote sensing data and semi-empirical modelling through LUE optimisation using the look-up table method. This is made possible using sensors with high spatial resolution such as SPOT, which was used in this study. However, further studies of the method may be conducted to incorporate within season variations as well. LUE depends on a number of factors some of which change along the season, optimisation LUE spatially and over time presents an opportunity of improving yield assessment and understanding winter rape's physiological processes. The pixel optimisation method may also be subjected to further tests with independent measured data for validation.

The study aimed at assessing winter rape yield through an analysis of the effect of spatial optimised LUE on the performance of the Monteith's model. The model also determined the empirical relationship between winter rape yield and ANDVI which was then used as a baseline to assess the performance of the semi-empirical model. The study confirms that there is a significant relationship between measured rape yield and ANDVI. The sum of NDVI did not perform badly either in empirically estimate yield of winter rape and this can be explained by the high correlation between amount of PAR absorbed by crop canopy and reflectance in the visible and near infrared portions of the electromagnetic spectrum (Baret, et al., 1989).

The importance and contribution of other physiological factors that are not represented by ANDVI may be the cause of the lower accuracy compared to Monteith's model with pixel-optimised LUE. The performance of the empirical model compared to the Monteith's model with constant LUE values from literature and from field-optimisation highlights their continued importance in yield assessment. This agree with the conclusion of other studies that empirical models are still helpful in yield assessment despite recent advances in mechanistic and semi-empirical models (Inoue and Olioso, 2006). However, the empirical model is valid for estimating winter rape yield data for this region only.

Given the wider range included in the optimisation method, results show that adopting a single constant LUE value from literature may affect yield assessment in winter rape. LUE variability of winter rape within the three fields further supports the idea of pixel optimisation of the variability to improve accuracy levels. Standard deviation values of LUE for fields 1, 2 and 3 were 0.444, 0.396 and 0.646 respectively. While use of a constant LUE value from literature had higher accuracy than use of a field optimised LUE value, the two modes may have almost similar accuracy levels if all the fields have similar variability as field 3. This is shown by the standard deviation values (above) and mean LUE values which were 2.137 g DM MJ^{-1}, 2.059 g DM MJ^{-1} and 2.527 g DM MJ^{-1} for fields 1, 2 and 3 respectively.

Conclusion

In light of the above finding, this study concludes that optimisation of LUE to give LUE values at pixel levels increases the accuracy levels in the yield assessment of winter rape. Interpolation of NDVI values, estimation of fAPAR and the look-up-table method of optimisation were useful in estimating LUE values at both field and pixel levels. The look-up-table method used in this study has shown the potential to optimised crop model variables, such as light use in this instance, to show variability within mono-crop fields. On the other hand, empirical model for the relationship between winter rape yield and ANDVI estimates winter rape yield to certain yield levels which can be as good as semi-empirical model using constant LUE values. Although the predictive power and accuracy levels were high, the method over estimate yields in points with low measured yield. This could have been due to low plant population or other factors not captured by the Monteith's model.

In light of the research findings, the study therefore recommends the use of look-up-table in LUE. The study also suggest use of more images (if available) to improve ANDVI and interpolated fAPAR values for empirical and semi-empirical models respectively. We also recommend use of spatially optimised LUE values in yield assessment for winter rape and other related crops. Although the study managed to answer all the questions set aside in the introduction, there is room for further development of the optimisation procedure and improvement in validation. The study also suggest further extension of the model using measured LUE values to confirm pixel optimised LUE values. All in all a combination of remote sensing data and semi- empirical modelling can be used to improve accuracy levels of yield prediction using optimisation procedures which tend to simulate values of LUE within pixels. This therefore account for the within field variability of LUE in a monocrop field, which in this case was winter rape.

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