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Research paper

Assessing on-farm productivity of Miscanthus crops by combining soil mapping, yield modelling and remote sensing

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ABSTRACT

Biomass from agricultural land is a key component of any sustainable bioenergy strategy, and 2nd generation, ligno-cellulosic feedstocks are part of the UK government policy to meet the target of reduced CO_2 emission. Pre-harvest estimates of the biomass supply potential are usually based on experimental evidence and little is known about the yield gap between biologically obtainable and actual achievable on-farm biomass yields. We propose a systematic integration of mapped information fit for estimating obtainable yields using an empirical model, observed on-farm yields and remote sensing. Thereby, one can identify the sources of yield variation and supply uncertainty. Spatially explicit Miscanthus potential yields are compared with delivered on-farm yields from established crops $\geq$5 years after planting, surveyed among participants in the Energy Crop Scheme. Actual on-farm yield averaged at 8.94 Mg ha^{-1} and it varied greatly (coefficient of variation 34%), largely irrespective of soil type. The average yield gap on clay soils was much larger than that on sandy or loamy soils (37% vs 10%). Miscanthus is noticeably slower to establish on clay soils as shown by fitting a logistic Gompertz equation to yield time series. However, gaps in crop cover as identified by density counts, visual inspection (Google Earth) and remote sensing (Landsat-5) correlated with observed on-farm yields suggesting patchiness as causal for reduced yields. The analysis shows ways to improve the agronomy for these new crops to increase economic returns within the supply chain and the environmental benefits (reduced GHG emission, greater carbon sequestration) and reduce the land demand of bio-energy production.

1. Introduction

Bioenergy from agricultural crops has come under severe criticism when sourced from 1st generation, starch/sugar providing feedstocks due to environmental concerns [1] and impacts on food security [2]. In contrast, 2nd generation, ligno-cellulosic feedstocks are more acceptable due to their superior greenhouse gas (GHG) benefit due to low fertiliser and management inputs [3]. For large parts of the United Kingdom, a previous comparative study on GHG emissions [4] was based on feedstock estimated and up-scaled with empirical yield models for two major agricultural biomass crops: Miscanthus and short-rotation coppice [5,6]. These feedstocks were rated according to their potential regional performances [7] based on experimental observations, but there was no information with regard to the actual on-farm performance or yield gap.

On-farm yield prediction is vital for the successful implementation of a sustainable energy supply chain based on biomass crops. Bottom-up verification of model-based supply estimates is essential to assess the wider impact on food and energy security, land use change, and GHG emission. In England, farmers have been encouraged to grow short rotation coppice and Miscanthus as biomass within the Energy Crops Scheme (ECS). Planting of Miscanthus has increased between 2006 and 2011 from 6 to 8 thousand ha[1] [8]. According to expert knowledge one could produce an estimated total of 80–120 thousand tonnes of oven dry matter (odmt which corresponds to “Mg”) per annum. Potential yield maps [9] [2] were based on long-term temperature and radiation only and

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[1] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/141626/defra-stats-foodfarm-landuselivestock-nonfoodcrops-latestrelease-130125.pdf.

[2] http://webarchive.nationalarchives.gov.uk/20140605090108/http:/www.naturalengland.org.uk/ourwork/farming/funding/ecs/sitings/default.aspx.

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categorised land into three different yield classes (low/medium/high), suggesting an economic threshold of 12 Mg ha^{-1} in a well-established crop. In fact, the average Miscanthus yield was 12.8 Mg ha^{-1} in experimental observations [6] and the simulated, obtainable average yield was 12.5 Mg ha^{-1} if grown on agricultural land in England [10]. However, the national average of delivered on-farm oven dry matter biomass yield is about 9 Mg ha^{-1}. This would correspond to a yield gap of close to 30%. Questions arise about the reasons for this gap, whether soils differ in terms of yield realisation and variation, and whether a diagnostic tool can be developed to overcome the sub-optimal performance of these new crops. Considering the economic threshold of between 12.5 [9,11] and 9 Mg ha^{-1} for Miscanthus [10] many farmers would be well below the break-even point and, therefore, it is crucial to identify avenues to improve productivity.

No studies have been conducted to assess the extent to which farmers successfully grow these new crops, although this has been identified as a future research need in particular in relation to marginal lands [12]. It is not clear, whether there is a yield difference due to the effect of soil type in terms of water availability or texture class, and how achievable on-farm yields compare with model-based estimates of biologically obtainable production (i.e. accounting for bio-physical constraints). It would be valuable to examine whether available remote sensing (RS) data enable us to quantify patchiness which has been shown to impact on yield and economic feasibility [13], and trade-offs between two major ecosystem services, yield related soil carbon sequestration [13] and biodiversity [14].

The aim of this study was to compare model-derived productivity potentials, based on soil water availability and long-term climate data, with sustainable (i.e. achievable and consistently delivered) on-farm Miscanthus yields. The latter are defined as the reported average annual field or on-farm yields of well-established crops, i.e. ≥5 years after planting. In a second step we investigated how observed yields related to the variability of the crops by using geo-referenced optical satellite data to derive the Normalized Difference Vegetation Index (NDVI) per field from Miscanthus growing farms. Finally, this led us to discuss the potential of developing a decision support tool for farmers to improve crop cultivation (e.g. decide on gap remediation or total replanting), and for policy makers to monitor and improve the effectiveness of support mechanisms.

2. Materials and methods

This study takes a bottom-up approach and uses on-farm yield surveys at the field and farm scale to verify the outputs (yield maps) of productivity models established on the basis of experimental, plot-scale observations (Fig. 1). Google Earth was used in photo-interpretation for quality control and to verify the field locations given in the ECS database. Geolocation of fields was essential to create field- and crop-specific masks to overlay information layers, in particular the spatially explicit potential yield map and the satellite image-derived NDVI (see also Fig. 6). For a subset of fields, ground observations on crop density, height and leaf area (morphometric data) were also taken.

2.1. On-farm survey

With the support of Natural England (NE) we conducted an anonymized field survey among farmers within the ECS. Three consecutive questionnaires were sent out in 2009, 2011 and 2013 to (1) establish a database of corresponding field locations with UK grid geographic references (Ordnance Survey map), soil type and hydrology, and soil texture class; (2) record data on land use history and management (Miscanthus planting date, fertiliser use, harvest dates); and (3) collate time series of biomass yield to estimate actual deliverable on-farm yield potentials.

From the coordinates (UK Ordnance Grid) or the postcode provided by some farmers, fields or farm sites were located using UK Streetmap software. Screenshots of the field sites using Google Earth time line and Ordnance survey maps (1:25,000) were instrumental to verify field locations initially starting from the coordinates recorded by NE in the ECS database.

The questionnaires were circulated to farmers to identify individual field or farm characteristics. Questionnaire 1 was centrally distributed by NE and designed to record site details in terms of soil water availability and fertility to understand site selection criteria and local yield formation. As feedback from farmers on questions regarding soil, climate and site hydrology was rare the simplified Questionnaire 2 was distributed by NE as well as being sent directly to farmers who had provided their addresses. Questionnaire 3 was further complemented with feedback reports to communicate results and prepare for personal interviews with background

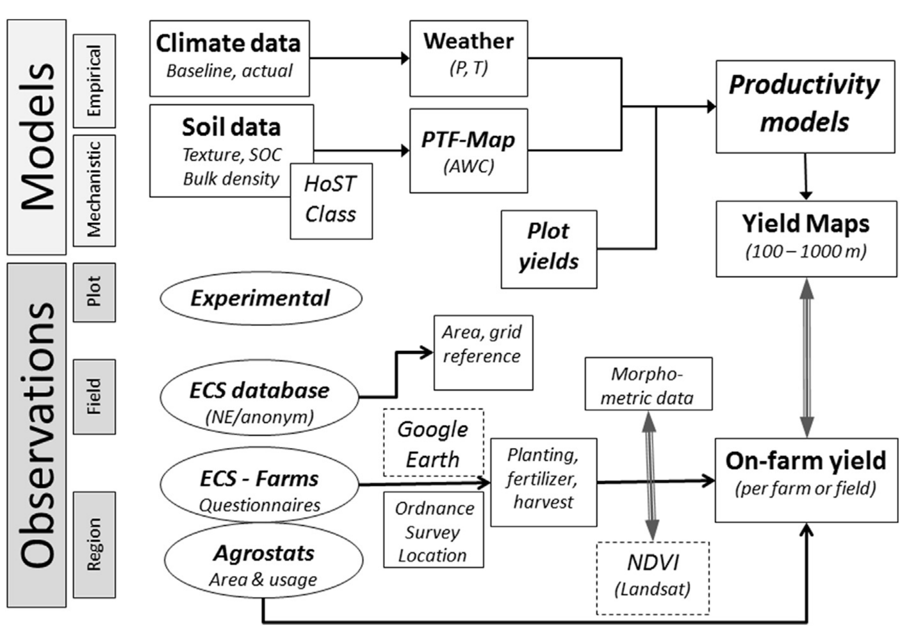

Fig. 1. Data integration for on-farm yield evaluation, estimation and improvement.

information. Its main purpose was to develop and verify a comprehensive yield database. Some farmers conveniently recorded yields as number of total bales per year across the whole farm, but some also distinguished field-specific yields. Conversion of bale number to weight was based on the assumption that each bale (size $0.9 \times 1.2 \times 2$ m) consisted of 600 kg at 25% moisture content (i.e. an equivalence of 450 kg oven dry matter per bale).

2.2. Model-estimated obtainable yields

Crop productivity depends strongly on variety, agronomy and environment but for commercial farms a single Miscanthus genotype is grown. The best yield achievable using current variety and recommended agronomic practices under any physical and biotic conditions is defined as obtainable yield. Obtainable Miscanthus yields were estimated using an empirical model (Y_{EM}) based on soil available water capacity (SAWC) and long-term monthly climate data (precipitation, temperature, radiation) for each field [6,10].

This empirical yield model is based on a multiple regression of experimental yields from 14 experiments across 10 different sites in the UK, with SAWC ranging from <100 mm–>300 mm within the rooting depth and observed local weather records [6]. A yield map had been generated using long-term weather data (1950–2000) [15] at a 1 km by 1 km grid scale across the UK and SAWC was estimated using the method described earlier [10]. In short, soil hydrological site properties combined water retention properties (derived from soil physical properties) [16] with depth to groundwater and water from underlying porous rock (i.e. hydrology of soil type (HoST) classes [17]). For the on-farm yield evaluation all relevant soil data were downscaled from NATMAP1000 to a 100×100 m^2 grid by combining the soil survey data and NATMAP vector maps [18] and selecting the respective soil properties and yield potential of the dominant soil series and association.

2.3. Calculating the empirical on-farm yield plateau

An empirical on-farm yield plateau (i.e. the likely peak or achievable yield of a given plantation), Y_{OF}, was estimated using the time series of site-specific commercially harvested oven dry matter yield reported in the survey. Unlike arable or fodder crops, maximum and peak productivity of a Miscanthus crop can take three to five years after planting [19,20]. In the case of long and complete time series (10–15 years) such as the plot size experiments at Rothamsted Research, a double exponential model [21] was found most appropriate to describe the first phase rise and the final phase decline of obtainable biomass yields (Y) over years after planting (X) as observed in many other experimental data [22]:

$$Y = Y_0 \exp\left(\mu_{min}(X-1) + \frac{\mu_0 - \mu_{min}}{\nu}(1 - \exp(-\nu \cdot (X-1))\right) \quad (1)$$

where Y_0 is the potential biomass yield at the end of first establishing year, X the number of years after planting, μ_0 and μ_{min} are the initial and final annual net relative increase rate of biomass yield, respectively, and ν is the parameter determining the rate of change from μ_0 to μ_{min}.

In the survey database, most farmers had annual biomass yields for fewer than seven years after planting. For practical and economic reasons only a small number of fields were harvested after the first year (ca. 9% of the recorded fields), this increased during the second and third year of growth to 50 and 90% of the recorded fields, respectively. A total of 79 fields represented about 1000 ha with annual yields for four or more years after planting, and only half of these extended beyond six years after planting. Therefore, Equation (1) was simplified to the Gompertz equation (Equation (2)) in order to estimate the maximum potential biomass yield at a pre-determined harvesting year ($X = 5$) beyond which biomass yield increased very little to reach an asymptote (i.e. the on-farm yield peak or plateau, Y_{OF}):

$$Y = Y_0 \exp(\mu(1 - \exp(-\nu \cdot (X-1)) \quad (2)$$

Equation (2) has only three parameters; as in Equation (1), Y_0 is the potential biomass yield at the end of first year, μ equals μ_0/ν since no decline of biomass yield was assumed (i.e. μ_{min} was at zero in Equation (1)) and ν is rate of change relative increase of biomass yield.

Preliminary analyses showed that biomass yield reached more than 97% of the on-farm plateau yield on the 5th year after planting in all soil texture classes. Therefore, the 5th year after planting was used to estimate on-farm plateau biomass yield, Y_{OF}. This same pre-defined year was also used to calculate the average actual observed on-farm plateau of biomass yield using available yields from fields harvested on the 5th year after planting. This average on-farm biomass yield plateau was later used to calculate yield gaps. Curve-based yield plateaus and biomass yield by the end of the first year (Y_0) were estimated for each soil texture category (heavy, middle and light; H/M/L) using the Gompertz model (Equation (2)).

2.4. Normalised difference vegetation index (NDVI)

Normalised Difference Vegetation Index (NDVI) was derived from Landsat-5 TM scenes (183×172.8 km) provided by the European Space Agency (ESA) [23] in the Universal Transverse Mercator (UTM) coordinate system with a 30 m pixel spacing. Scenes were selected for dates during the late growing season (September 2011) for comparison to the harvest data. Landsat-5 TM Level 1 System Corrected data had undergone pre-flight and in-flight radiometric calibration [24] and was geometrically accurate within 1 sigma [23,25]. The nearest neighbour (NN) resampling algorithm preserves the maximum original radiance values, and makes it free from distortions from the sensor, satellite or Earth [26,27]. The satellite imagery was pre-processed in ERDAS Imagine 10 to remove undesirable image characteristics, correct for geometric distortions and calculate NDVI.

2.4.1. Atmospheric and topographic correction

Dark Object Subtraction (DOS) is a radiative transfer approach applied to remove atmospheric distortions (within ERDAS Imagine software). This method corrects for the effect of atmospheric scattering (the dominant atmospheric affect for Landsat TM data) based on the darkest pixel in the image to produce apparent surface reflectance [28]. This was accomplished in four steps by: (1) selecting a clear water body as a dark object with low digital number (DN) values as previously suggested by Gordon [29]; (2) selecting a representative pixel from each reflective band from its DN frequency histogram where there was a sudden increase in the number of pixels; (3) implementing the conditional statement to subtract the per-band haze DN value from the respective spectral band of the whole scene; and (4) preventing the value of zero [30].

A 10 m spatial resolution Land Form Profile Digital Terrain Model (DTM) acquired from the Ordnance Survey [31] showed that terrain slopes varied from 2 to 15%. However, with the exception of a few fields in the 2011 crop survey, none of the fields in 2009 and 2013 crop survey exceeded the critical threshold of 7% slope. Only slopes of 7% or higher would be significant enough to impact on the crops' spectral signatures [32].

2.4.2. Calculating radiance and reflectance

Spectral radiance values (L_λ) at the sensor's aperture were calculated using Equation (3) from the total potential energy reaching the sensor (Q_{cal}) normalised for solar irradiance using ratio of spectral radiance scaling factors $LMAX_\lambda$ and $LMIN_\lambda$ (range 0–1; NASA, 2011) over the maximum and minimum energy ($Q_{cal\ max}/Q_{cal\ min}$) measured in each band pixel (values of DN range from 1 to 255 for 8 unsigned Level-1 Product Generation System products).

$$L_\lambda = (LMAX_\lambda - LMIN_\lambda)/(Q_{cal\ max} - Q_{cal\ min}) \times (Q_{cal} - Q_{cal\ min}) + LMIN_\lambda \quad (3)$$

Respective solar spectral irradiances $ESUN_\lambda$ 1533 and 1039 W/($m^2 \times \mu m$) for spectral band 3 (red) and 4 (near-infrared, NIR), respectively, were obtained from NASA (2011) to calculate the spectral reflectances, ρ_λ using Equation (4).

$$\rho_\lambda = \left(\pi \times L_\lambda \times d^2\right) \Big/ (\mathrm{ESUN}_\lambda \times \cos\theta_s) \quad (4)$$

where π is a mathematical constant (3.14159), L_λ is the solar spectral radiances for band 3 or 4, respectively, d^2 the distance on the Julian day, $ESUN_\lambda$ is 1533 (for Landsat-5 TM band 3) or 1039 (for Landsat-5 TM band 4) and $\cos\theta_s$ is the solar zenith.

2.4.3. Calculating the NDVI

The NDVI depends on the orientation of the surface with respect to the observer. As all selected sites were below 7% the NDVI was simply calculated using Equation (5) within ERDAS Imagine from spectral reflectance for band 3 and 4; ratios of red and NIR spectral bands determine the presence of vegetation [33]. Output numbers must be in float single data type.

$$\mathrm{NDVI} = (\rho_{NIR} - \rho_{RED})/(\rho_{NIR} + \rho_{RED}) \quad (5)$$

where ρ_{RED} and ρ_{NIR} are reflectance in band 3 and band 4, respectively

2.5. Building a GIS data base for field sites

A GIS database was created in ArcGIS (version 10) to overlay soil and obtainable yield data (both at a 100 m × 100 m grid resolution), derived from the empirical Miscanthus model which uses soil and long-term climatic inputs, and the NDVI for verified field locations. The analysis of variance was done with Genstat [34] for samples grouped according to soil texture group, which covered clayey (heavy-H), loamy (medium-M) and sandy (light-L) soil textures.

Box and whisker plots, using the Tukey method [35], were used to display the quartiles and outliers of NDVI from combined fields and within individual fields on various farms (SigmaPlot 13.0 software). When frequency histograms for NDVI and ground-based data deviated from the normal distribution non-parametric correlation (Spearman's ranking) was used, which was more appropriate to handle data with outliers. Landsat image-derived NDVI were extracted from subplots to relate pixel properties to ground-based estimates, e.g. LAI, plant density, using a linear regression model [36].

3. Results

3.1. Survey results – structure of the sample

In 2009, farmers growing a collective 573 ha of Miscanthus responded to the first survey sent out by NE; in 2011, the response to direct contacts was >90% which in conjunction with additional contact through NE resulted in retrieval of information for a further 669 ha. Knowledge Transfer activities and farm visits within the NERC-funded Microclimates project increased the area with background information to >2100 ha. Of the approximate 2100 ha, 940 ha provided biomass yield data from crops planted >4 years ago, which could be analysed to estimate a yield plateau by fitting Equation (2) (see 3.2). The data set covered a similar number of sites with yield data in 2011, which could be examined in relation to the NDVI. Over all of the area, the average field size was about 6.7 ha.

The questionnaire characterised the topographic, pedological, management, land use history and other site properties (Fig. 2). In the 2011 crop survey samples, almost 70% of area was flat to slightly sloped (<5%) but 10% was above the suggested slope threshold of 15%, considered unsuitable for crop cultivation [10]. About half of the crop was grown on medium textured soils (Table 1), which

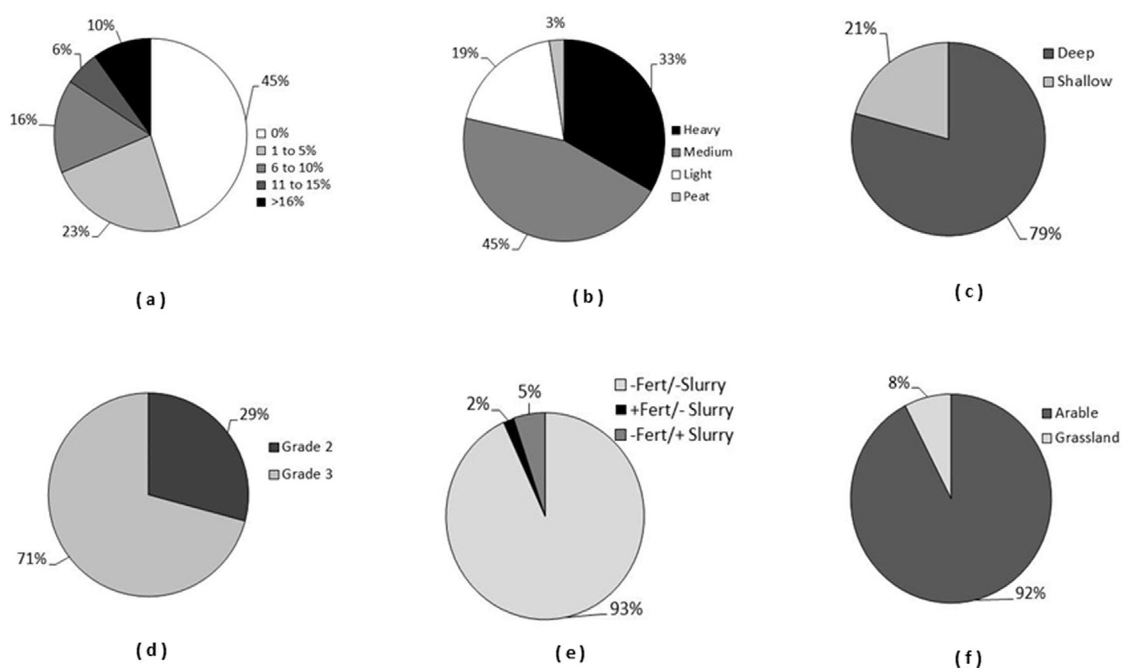

Fig. 2. Qualitative information provided in questionnaires for 77 Miscanthus fields, field characterisation according to slope (a), soil texture (b), profile depth (c), grade according to Agricultural Land Classification (d), fertilizer/slurry application (e), and prior land use (f).

usually have deep profiles and plenty of plant available water. With few exceptions, the farmers' classification of soil textures (H/M/L) agreed with the information on the soil map. In contrast to earlier scenarios [10] ~30% of the area was classified as good agricultural land (Grade 2) and no Grade 4 land was used. Less than 10% of the area surveyed in 2011 had grassland as the previous land use, and very few farmers (<10%) applied any nitrogen (N) or organic fertilizer to their Miscanthus crops.

3.2. Actual on-farm yield (Y_{OF}) plateaus

A total of 66 observations were available for estimating achievable on-farm plateau yields (Y_{OF}) harvested five years after planting. On average, Y_{OF} was 8.94 Mg ha^{-1} over all soils and varied between 7.85 and 9.51 Mg ha^{-1} depending on the soil texture group (Table 1). There was considerable variation within each soil texture group and the calculated coefficient of variation (CV) ranged from 23% to over 41% in medium and light/heavy textured soils, respectively.

The achievable on-farm yield plateau (Y_{OF}) was also estimated by fitting the three parameter Gompertz equation (Equation (2)). It was first fitted to all combined data points among all soil texture classes (Fig. 3a) and then separately to three subsets pooled according to distinctive soil texture groups (Fig. 3b). The estimated parameters are given in Table 2. The estimated biomass yield harvested in the first year was 2.36 Mg ha^{-1} over all soils but it varied appreciably from one soil texture group to another. There were few fields with 1st year harvests, which caused great uncertainty in these estimates, particularly in the loamy textured (M) soil group.

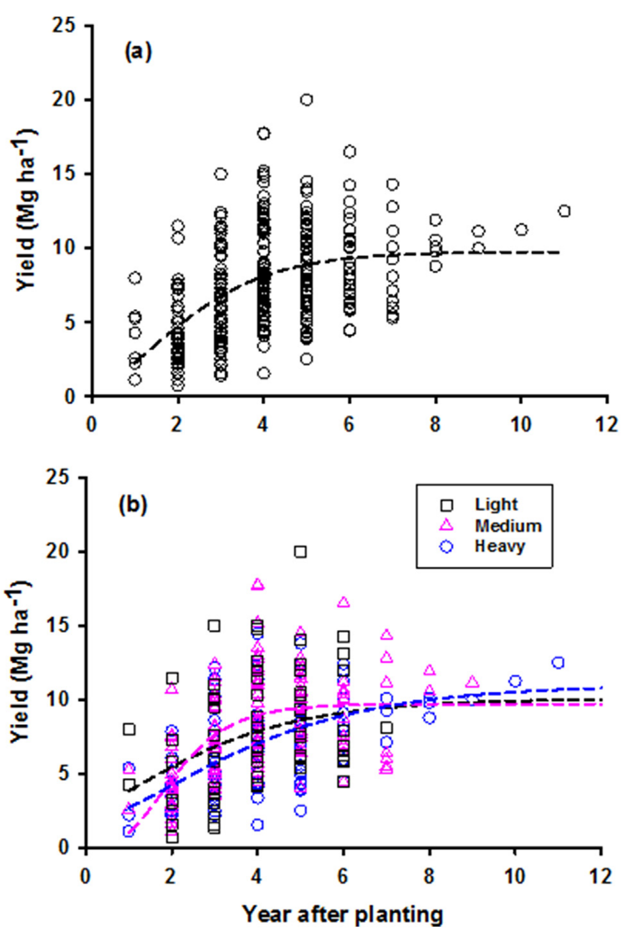

Fig. 3. Fitted curves for progression in annual biomass yield of UK Miscanthus crops after planting, based on fields from all soils (a) and on fields grouped according to light, medium and heavy soil texture (b).

The Gompertz equation-based estimate of achievable on-farm biomass yield plateau (i.e. in the 5th year harvest) was 8.90 Mg ha^{-1} over all soils while it varied between 8.13, 9.46 and 8.62 Mg ha^{-1} on H/M/L soils, respectively (Table 2). These estimates compared well with the corresponding achievable on-farm biomass potential yields calculated using observed yields on the 5th year after planting (see Table 1). The added benefit of this analysis was that it clearly showed that a longer timespan was required to reach the yield plateau in heavy clay soils (Fig. 3B).

3.3. Predictability of on-farm Miscanthus productivity – yield gap

The yield map was generated using the empirical relationship between peak yields of established crops (i.e. ≥5 years after planting) from experimental sites and biophysical control variables (precipitation, temperature and soil available water capacity) [6,10]. This yield represents the bio-physically obtainable biomass yield of the genotypes grown at the time. The downscaled vector map allowed readings at the hectare resolution, and a total of 100 map entries could be compared to 66 surveyed on-farm yield records (see Table 1). Site-specific biological yield potentials estimated using the empirical model (Y_{EM}) ranged from <5 to >15 Mg ha^{-1} with an average of 11 Mg ha^{-1}. The area-weighted observed average yield (8.94 Mg ha^{-1}) remains 18.7% below the site-specific average Y_{EM} (see Table 1) and 28.5% below the predicted national average (12.5 Mg ha^{-1}) [10].

The biggest yield gap, exceeding 35%, between the actual achievable on-farm yield (Y_{OF}) and the biologically obtainable yield estimated using the empirical model (Y_{EM}), was found for heavy clay soils. On-farm delivered yields on medium and light textured soils came closer to their biologically obtainable yields, with the yield gaps averaging about 10% (Table 1). The achievable on-farm plateau yields (Y_{OF}) estimated for >5 year old plantings using Equation (2) were very similar to those actual reported on-farm yields calculated using survey yields harvested from mature crops (i.e. on the 5th year after planting; see Tables 1 and 2). Therefore, the yield gaps between the Y_{EM} and on-farm plateau yields estimated using the Gompertz equation were also similar to those between the Y_{EM} and the actual on-farm yields.

3.4. NDVI – a measure for patchiness of Miscanthus fields?

A total of about 100 fields that covered ca. 700 ha were subjected to spatial analysis using the Landsat image-derived NDVI, which

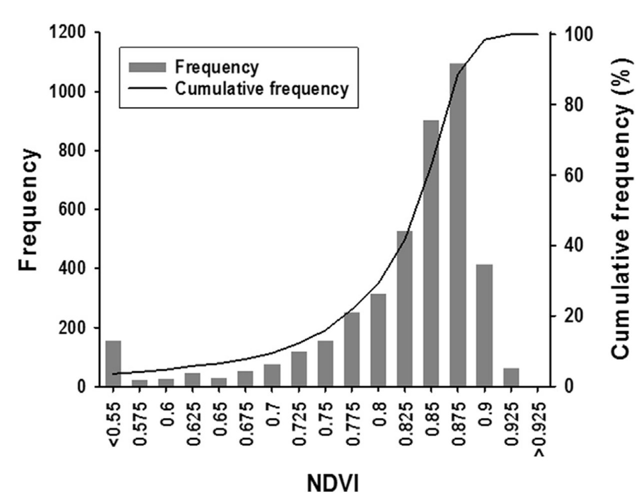

Fig. 4. Frequency distribution of the normalised difference vegetation index (NDVI) across 98 Miscanthus fields sampled and covered by the Landsat-5 TM images for 2011 cropping season (50 separate field or farm observations).

was related to field-specific yield measurements. A total of 23 farms were included in the analysis. For 36 individual fields (about 300 ha) on 11 of the 23 farms, field-specific yields could be compared to the corresponding field specific NDVI while for the other 12 farms, field-specific NDVI were aggregated to a farm average to be compared with yields reported at the farm scale. The NDVI ranged from 0.227 to 0.939 and its right skewed distribution (Fig. 4)indicates that the median was higher than the mean (0.836 vs. 0.805). About 200 values were smaller than 0.6, which corresponds to less than 5% of the total readings and of which 66 readings were associated with a recently established field (averaged at 0.553; see Fig. 6). Some of the low readings could be associated with shaded borders or other non-radiative bodies on the border, but could also be due to poor establishment in some of the fields, which was visible even on Google Earth images.

Considering this value of 0.553 as a reference threshold, the box and whisker plot (Fig. 5) reveals more NDVI outliers below this value where only farm-level aggregated (Fig. 5a) rather than field-specific yields were recorded (Fig. 5b). These pixels could represent areas with low stand density, where NDVI differed from the overall mean of field or farm beyond the inner and outer fences of their interquartile range. There were five samples in the farm-specific set (Fig. 5a) that show many outliers (Farm Nos. 4, 5, 7, 9 and 13), in particular the multiple field set of Farm No. 13. The suspected patchiness could be verified in all cases using Google Earth images. This box and whisker plot also identifies entire farms or fields

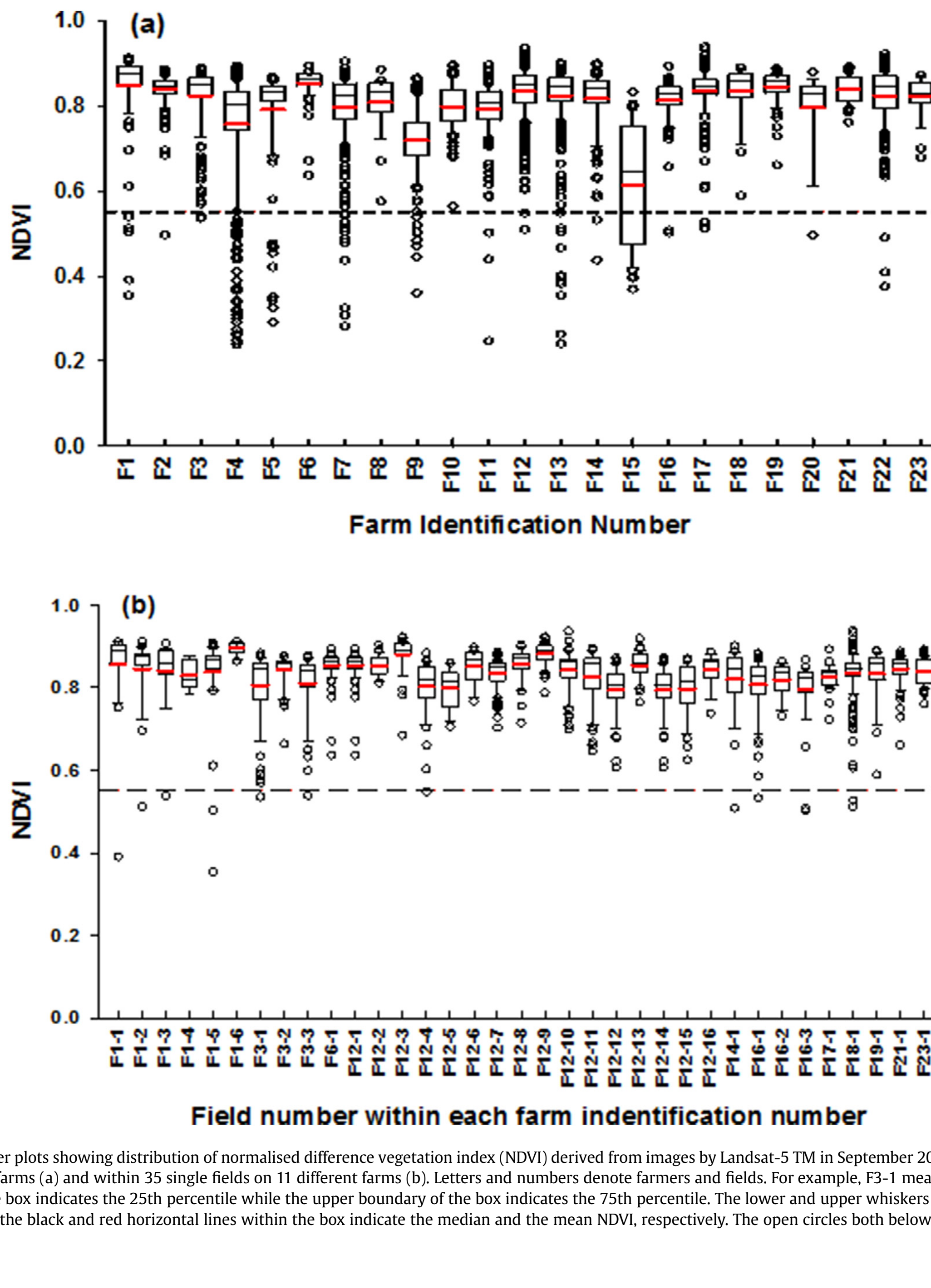

Fig. 5. Box and whisker plots showing distribution of normalised difference vegetation index (NDVI) derived from images by Landsat-5 TM in September 2011 within farm-grouped fields on 23 different farms (a) and within 35 single fields on 11 different farms (b). Letters and numbers denote farmers and fields. For example, F3-1 means field 1 on farm 3. The lower boundary of the box indicates the 25th percentile while the upper boundary of the box indicates the 75th percentile. The lower and upper whiskers indicate the 5th and the 95th percentile while the black and red horizontal lines within the box indicate the median and the mean NDVI, respectively. The open circles both below and above the whiskers are outliers.

which underperformed in terms of the mean (for example Farm No. 15) and revealed that patchiness further reduced the farm-specific NDVI (see Farm Nos. 7, 9 and 11). In the case of field-specific yield monitoring there were fewer outliers in total and hardly any below the NDVI threshold (Fig. 5b). Most of the outliers in these samples were observed in between the inner and outer interquartile range and above the threshold.

3.5. Relationship between NDVI and biomass yield

NDVI derived from reflectance in the NIR and red spectrum has been used as a proxy for canopy leaf area index (LAI) and fraction of absorbed photosynthetically active radiation (fAPAR) and, consequently, can be an indirect measure of biomass productivity. As expected, the NDVI was a good overall indicator of increasing Miscanthus yield in mature stands, both at the farm level (Fig. 6) and in between different data sets across different farms, regions and soil properties (Fig. 7). At the farm scale, 4th year yield was about 25% below 5th year yields (Fig. 6) which was much more than the difference in NDVI (ca. −4%) derived for this set of fields. The newly planted crop on the same farm, for which a yield of about 2.4 Mg ha^{-1} could be expected, had already a substantial NDVI, which, however, was lower than other poorly performing Miscanthus crops (e.g. farms No 4 and 15). There are two implications from this example: (a) the difference in yield (biomass density) exceeds greatly that in NDVI (canopy density), and (b) there is a background reflectance which should be attributed to the undergrowth in spite of initial spray of herbicides.

There was one field from which the harvested yield was from the first year crop and therefore was not compatible with crops of more than four years after planting in other fields. Therefore, first, it was excluded in the simple linear regression analysis between biomass yield and NDVI. When a simple linear relation was fitted to data points among all soil texture groups, NDVI accounted for 32.4% ($n = 42$) of variation in the observed on-farm yield (see Table 3). When the simple linear relation was fitted to data points of separate soil texture classes, the respective best line is shown in Fig. 7a and the parameter estimates are shown in Table 3. Due to the narrow range in image-derived NDVI values, little variation in the biomass yield (~10%) can be explained by the NDVI in the heavy soil texture group (Table 3). However, the NDVI reflects more than 50% of the yield variation for both light and medium soils (Fig. 7 and Table 3). When the biomass yield from the first year crop was included, an exponential relation was better fitted to the data under all soils than the simple linear relation (Fig. 7b). With the fitted exponential curve, NDVI explained 54.2% of the yield variation.

Table 1
Summary survey data with mean actual on-farm plateau Miscanthus yields (Y_{OF}) in 5th year after planting (YaP) with standard error (SE) and coefficient of variation (CV) grouped according to soil texture group – light (L), medium (M) an heavy (H) in comparison to the long-term biologically obtainable potential yield map using an empirical model (Y_{EM}) and the calculated yield gap (YGap). n is the respective number of sampled fields.

Soil group	Area [ha]	n [5th YaP]	Y_{OF} (SE) [Mg ha^{-1}]	CV [%]	Y_{EM} [Mg ha^{-1}]	n [Y_{EM}]	YGap [%]
L	242	15	9.51 (1.02)	41.4	10.4	25	8.6
M	471	29	9.48 (0.41)	23.3	10.7	48	11.5
H	227	22	7.85 (0.70)	41.9	12.4	27	36.7
All	940	66	8.94(0.38)	34.1	11.0	100	18.7

Table 2
Parameter values and standard errors of the Gompertz model (Equation (2)) to estimate achievable on-farm plateau yields (Y_{OF}) for crops in the 5th year after planting on light(L), medium(M) and heavy(H) soil. Y_0 is the estimated yield harvested by the end of the first year, n is the number of data points.

Soil Group	Y_0 Mg ha^{-1}	μ	ν	p-value	Y_{OF} Mg ha^{-1}	n
L	3.86 (1.93)	0.962 (0.38)	0.453 (0.49)	<0.01	8.62	71
M	1.03 (0.89)	2.245 (0.84)	1.115 (0.32)	<0.01	9.46	147
H	2.71 (0.80)	1.400 (0.24)	0.383 (0.14)	<0.01	8.13	108
ALL	2.36 (0.68)	1.421 (0.26)	0.679 (0.16)	<0.01	8.90	327

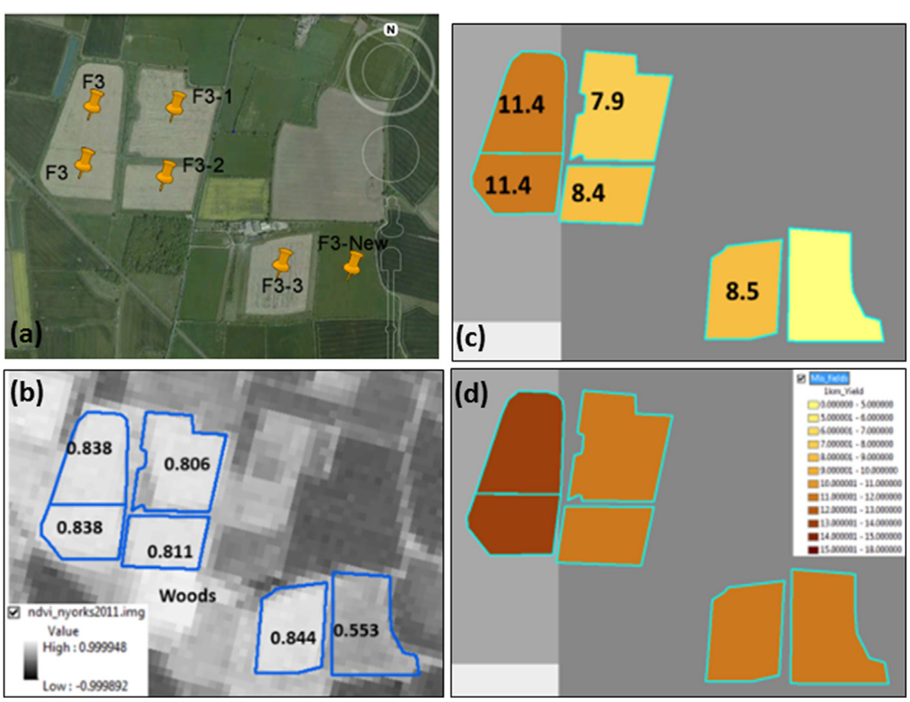

Fig. 6. Field map of Google Earth identified Miscanthus fields (a) and NDVI derived from Landsat-5 TM in 2011 (b), management effects (year of planting: brown – 2006; orange – 2007; yellow - newly planted) on average field yield (c), and yield map (d).

4. Discussion

This work set out to obtain a comprehensive view of the actual on-farm productivity of Miscanthus as a novel crop in the UK to see how it compares to the model-derived biologically obtainable biomass yield (i.e. yield gap analysis), and to find out whether there are diagnostic tools and ways to identify measures to close the yield gap.

4.1. How representative is our survey?

Surveyed on-farm Miscanthus yields reported here are not comprehensive but are still highly representative, being based on about 1000 ha of mature crops and representing about 20% of the whole Miscanthus crop area registered under the ECS until 2007 at the time. The present database is therefore an important resource to study biomass yield of Miscanthus in the UK and relevant to other regions where it is or will be grown for bioenergy. It can easily be expanded if the public funding were linked to clear reporting obligations at the source or user end. All data were provided on a voluntary basis and might bear some uncertainty due to reporting and conversion methods. For example, a biomass yield of 8 Mg ha^{-1} reported on a light soil for the first year after planting seems rather unrealistic. The harvested and delivered yields were extremely variable (2.4–20 Mg ha^{-1}). Although the overall average of about 9 Mg ha^{-1} stayed well below the predicted biophysically obtainable yield, as reported in the national yield map (see Table 1), it matches well the National Statistics. Compared to the biomass provided to the energy companies [8,9] the average on-farm peak yield plateau (Table 1) estimated from our database seems fairly representative. According to the latest statistics, biomass from Miscanthus used in power stations in the UK increased from 40 to 47 thousand tonnes [37] between 2010 and 2012, and was produced from a varying area of variable age crops. Assuming a fuel usage of about two thirds of the total production, and considering only mature stands, average Miscanthus yields from an increasing area (6400–7500 ha) would be ca. 9.5 Mg ha^{-1}, which is very close to the average reported here.

Although full establishments of Miscanthus crops can take as long as 7 years [22] depending on planting quality and density, the achievable on-farm biomass yield plateau (Y_{OF}) estimated using the Gompertz equation (Equation (2); X = 5 years) was in good agreement with the observed achievable on-farm biomass yield in the survey (see Tables 1 and 2). Miscanthus yields can be limited by a host of biotic and abiotic factors including agronomic practices. Firstly, poor and/or delayed establishment led to a variable shoot density; e.g. on fields of Farm No 11, shoot density ranged from 14 to 60 m^{-2} (Barker, unpublished results). The lower end of the range is well below the critical value of 39 m^{-2} above which peak yield is independent of shoot density [38]. Secondly, farmers had applied either limited or no N fertilizer (Fig. 2), which could explain declining yields over time, even on experimental plots [22,39]. It was further likely that both limited agronomic research and growing experience with this new crop and the low cost and minimum risk strategy of its introduction through the ECS led to this variable and low yield reality. The in-depth analysis and classification of yields showed that crops can fail or flourish on any soil texture class but failure is more likely on heavy soils (Fig. 7).

4.2. Yield maps and yield gaps

The yield maps generated by Lovett et al. [10] provided a long-term snapshot of biologically obtainable yield potential, derived from experimentally determined yields at the plot scale and their pedo-climatic inputs, largely explained by soil water availability [6]. Down-scaled to field-specific and farm-specific yields, it was assumed that the soil map of England and Wales of 1970s is still valid and precise both at the 1 km × 1 km grid (NATMAP1000) and its down-scaling using the vector-based field map (i.e. at hectare scale). The texture-based grouping of soils into light, medium and heavy soil categories by the farmers was correct for an overall 55% when compared to the NATMAP database, and more than 75% correctly classified for the heavy soil. The qualitative classification into light and medium textured soils was often interchangeably used by some farmers. We therefore, think that these pedo-climatic yield maps based on detailed soil information and soil hydrology [10] provided a good estimate of biological potential productivity of commercial Miscanthus. However, the probabilistic nature of the soil map (distribution of series within associations) introduces some uncertainty.

The individual farm- and field-specific yield plateaus varied greatly in comparison to the predicted yields (−71%–+262%), which indicates some limitation of the soil maps. Overall, the yield gap of quasi mature Miscanthus crops (i.e. 5 years after planting) averaged at 18.7% when compared to the mapped obtainable yields, whilst it was larger for heavy soils (>35%). The reasons for lower on-farm yields are many and well researched for arable crops [40,41] and well recognised in new biomass crops [12]. Our data however, are the first to compare actual, achievable yields to biologically obtainable potential yields. The reasons for the yield gap can be a lack of nutrients [39,42] and also crop establishment [13]. Miscanthus stands can have a large number of gaps, which may be beneficial for biodiversity [14] but severely reduce the actual achievable yields and consequently carbon sequestration in the soil [13]. Lesur-Dumoulin [38] found that yields on young commercial Miscanthus fields were about 20% lower than plot yields. Their analysis showed that shoot density <39 m^{-2} was the most limiting factor for yield formation, strongly related to weed cover occupying the gaps as a complementary indicator. There was no information on yield losses of Miscanthus crops while they were machine-harvested in the field. The uncertainty about such losses is large even under experimental conditions [43–45] and this may be an important factor for assessing yield gaps. Harvest losses in the supply chain for combustion are assumed to be 30% of the standing biomass at the field scale [46], however, no on-farm data exist.

4.3. What is the potential benefit of remote sensing?

It is clear from this analysis that on-farm productivity for mature stands (≥5 years after planting) can be assessed from NDVI; however, its precision for biomass estimation could be improved by linking information from images to an underlying understanding of growth dynamics. The analysis of two subsamples of Miscanthus fields created by different operators showed a similar range of NDVI (sample 1, 0.227 to 0.913; sample 2, 0.240 to 0.939) over a similar range of yields. Landsat-5 TM data for the 2011 cropping season of interest were scarce, and availability and image quality with <10% cloud cover over the whole scene is a well-recognised limitation [47].

Although RS images from *unmanned aerial vehicle* (UAV) can be better suited in providing supplementary data for assessment of crop canopy health and development, satellite-derived data from new Earth Observation data could improve productivity and management of the crop, and increase the efficiency of the supply chain. New satellites provide high spatial, temporal, spectral and radiometric resolutions, e.g. Sentinel-1 and -2, SPOT5, QuickBird GeoEye, WorldView-1 and World-View-2. This would help to overcome the problems of frequent cloud cover in the higher latitudes, under the maritime climatic conditions in the UK. Landsat-5 scenes from which to derive in-season growth estimates were scarce. Images taken earlier in the season would allow groundcover to be added into process-based model analysis. Patchiness, shoot density and

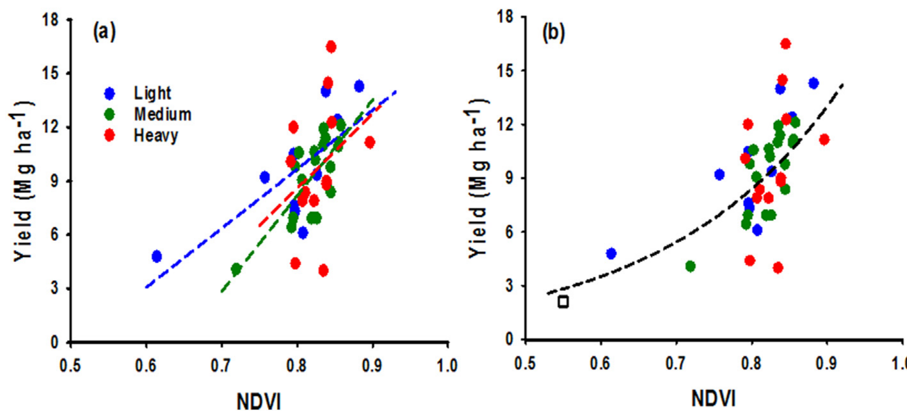

Fig. 7. Field-specific Miscanthus biomass yield in simple linear relation to field-specific NDVI grouped according to soil texture group without the yield from the first year establishing crop (a), but in an exponential relation to field-specific NDVI with the yield from the first crop (open square) (b) in which Yield = $0.1687\exp^{4.8712*NDVI}$, $R^2 = 0.542$, n = 43.

Table 3
Relationship between mean NDVI and mean observed Miscanthus yield at single field scale under light (L), medium (M), heavy (H) and all combined soil groups (ALL). Yield = a *NDVI − b, p-value is the significant probability level, R^2 is proportion of variance in yield accounted for by NDVI, n is the total number of data pairs.

Soil	Slope (a)	Intercept (b)	R^2	p-value	n	Mean yield [Mg ha^{-1}]
L	33.03 (10.43)	16.75(8.34)	0.556	<0.02	10	9.56
M[a]	53.53 (10.95)	34.64(8.78)	0.584	<0.01	19	9.19
H	41.54 (35.48)	24.63(29.40)	0.111	>0.25	13	9.76
ALL	36.64 (8.37)	20.45(6.85)	0.324	<0.01	42	9.46

[a] One data point was omitted because the yield was from the first year establishing crop (see Fig. 7).

canopy height could be important adjustment factors for field scale predictions. More work is needed with improved products to define field-specific benchmark crop cover measured by NDVI as its variation can help growers to gauge how well the Miscanthus crops are being performing during the establishment phase. A well-established crop is the key to reach the peak yield early and to maintain both high and stable yield during the whole plantation lifetime. It is clear from the evidence on a specific farm (Fig. 6) that growth dynamics affected 4th year yields, most probably via lower crop height. New RS data from systems, such as synthetic-aperture radar (SAR) from Sentinel-1, need to be tested to see if they can provide information on canopy height to supplement optical data. Light detection and ranging (LiDAR) imagery data can be an important source in assessing variations in canopy height most relevant for biomass estimates in forestry [48,49] but also for managing agricultural crops [50]. As they are now being made freely available for England and Wales (UK Environment Agency[3]), LiDAR data could be used to improve management of novel crops like Miscanthus.

4.4. Strategic planting of perennial crops

Our analysis showed that heavy soils can be potentially the most productive (with yields of >16 Mg ha^{-1}) but also the most variable in terms of stand density, most likely related to the soil being either too wet or too dry for planting. Limited contact in a dry, cloddy seedbed would expose the rhizomes to hazardous establishment conditions. However, too wet soils due to waterlogging can also cause large bare patches. The question is how to use the field-specific information on soil cover and its related patchiness to aid the decision-makers on termination or amelioration measures. Clay soils, that are difficult to work on an annual basis, should be the most likely to be selected for perennials. Annual sowing and harvest are likely to hit similar problems as the spring planted Miscanthus, which could be estimated using long-term weather scenarios. A lack of timeliness in planting but also harvesting due to limited machinery was a serious problem for the establishment phase of this crop and in need of serious investment.

5. Conclusion

- On-farm yields of quasi mature Miscanthus stands (~5 years old) varied between 2.4 and 20 Mg ha^{-1} and currently average at a long-term equilibrium yield of around 10 Mg ha^{-1}.
- Yields on medium and light textured soils are more predictable than on heavy, clay-textured soils, which have the highest yield potential but also the highest yield uncertainty.
- Satellite imagery of plant cover was well correlated to yield, but, canopy cover (shoot density) should be augmented with information on canopy height which also determines total biomass.
- Improved spatial and temporal resolution of new satellite data that combines estimates of crop cover and height would facilitate better early productivity forecasts.
- To obtain continued improvement in crop productivity and efficiency of the biomass supply chain, it is crucial to develop diagnostic and predictive tools based on field-specific soil and satellite-derived information to support the reporting, and national statistics, of biomass yields.

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[3] http://www.geostore.com/environment-agency/.

[4] Full project title: “Impact of Spatio-Climatic Variability on Environment-Hosted Land-based Renewables: Microclimates”.

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