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Mapping field-scale yield gaps for maize: An example from Bangladesh

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ABSTRACT

Accurate estimation of the size and spatial distribution of the yield gap has many practical applications, including relevance to precision agriculture and technology targeting. The objectives of this study were to illustrate a methodology to create a yield gap map and to discuss its potential uses to provide optimal crop management recommendations to the farmers. We used the HybridMaize crop simulation model to estimate potential yield for maize grown in the winter season in northwestern Bangladesh. This is a high yielding environment, where farmers achieve yields as high as 12 Mg/ha. The model predicted a mean potential yield of 12.87 Mg/ha. We used a RapidEye satellite image acquired around tasseling to identify the maize fields, calculate ground cover and its regression to actual yield from farmers' fields. Next, the regression was applied to all the maize pixels in the image to calculate actual yield. In the last step, we created a yield gap map based on the difference between potential and actual yield. Yield gap maps will enable agronomists to identify production constraints on farmers' fields with large yield gaps. Alternatively, by learning from the farmers with the highest actual yields and analyzing their data, it will be possible to generate region or field specific, optimized crop management recommendations.

1. Introduction

Knowledge of the size of the gap between the potential and actual yield has various applications. They range from tailoring agricultural policies aiming at improving the livelihood of resource-constrained farmers to prioritizing research and extension work. Information on the spatial variability of the yield gap will also support the development of region, field or site specific recommendations, including 'real time' adjustments to management practices in response to weather events that change yield potential in a given season. There are various methodologies to estimate potential and actual yield, which then allow for a calculation of the gap between the two (Van Ittersum et al., 2013). One way to estimate potential yield is to conduct field experiments under well-managed, controlled conditions to restrict any limitations to yield. In such experiments, potential yield of any crop variety should not be limited by factors other than climate. However, it is a challenging task to omit any factor that limits and reduces growth and yield under field conditions. An alternative method is to use process based crop simulation models. Some of them have been calibrated and validated for a wide range of environments (Bouman and van Laar, 2006; Timsina and Humphreys, 2006). Their main strength is that they can take into account varying weather conditions among years and interactions with the environment and management, and thus are able to quantify the magnitude and variability of the potential yield. Moreover, they can also be used to assess whether a given year for which the actual yield data are available is representative or not. Data on actual yield are typically based on crop statistics. Formal and informal surveys, trade statistics as well as expert opinions are used for its estimation. Crop statistics are generally summarized and aggregated at various levels of administrative districts. These are political boundaries, and generally they do not delineate agro-ecological zones. Hence, there might be large differences in the yield gaps within an administrative district and they may not be representative for an agro-ecological zone or a field within that district.

In this paper, we are describing a method that makes use of remote sensing and crop modeling to predict the magnitude of the yield gap for maize at the field level. The case study with maize is set in northwestern Bangladesh. Maize has great potential in that country. Total area of maize production in 2010 was 152,000 ha with an average yield of 5.8 Mg/ha (FAOSTAT; http://faostat3.fao.org; verified October 31, 2012). When grown in the winter months (Rabi season), maize yields of up to 12 Mg/ha have been reported (Ali et al., 2008). Such high yields can be achieved with

Abbreviations: HI, harvest index; LAI, leaf area index; MSE, mean squared error; NDVI, normalized difference vegetation index; PAR, photosynthetically active radiation; PVI, perpendicular vegetation index; WDVI, weighted difference vegetation index.

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4–5 irrigations, which is about 1/10 of the irrigation water requirements of ponded rice grown in the same region and season. Knowledge of the yield gap will serve to set up demonstration trials at key locations and to improve management recommendations. Hence, the objectives of this study are to illustrate a methodology to create a yield gap map and to discuss its potential uses to provide optimal crop management recommendations to the farmers.

2. Theory

In order to estimate actual yield of maize for an entire region, we are using remote sensing derived ground cover as an estimate of the light intercepted by the crop, which in return tends to be closely related to yield.

2.1. Estimation of ground cover with remote sensing

Optical sensors on satellites that are used for earth observation measure the amount of light reflected from the earth's surface. Reflectance from the bare soil usually steadily increases with wavelength. Plants, however exhibit a rather distinctive reflective pattern between wavelengths in the visible and near infrared spectrum. Healthy, unstressed plants use most of the light in the visible spectrum for photosynthesis and reflect only a small portion of it. However, in the near infrared spectrum, most of the light is scattered back from the interfaces of cell walls and intercellular air spaces (Slaton et al., 2001). These distinctive properties are being used in most algorithms that aim at estimating ground cover (GC), leaf area index (LAI) and other canopy properties such as chlorophyll content from remote sensing. The most commonly used vegetation index is the normalized difference vegetation index (NDVI). However, it tends to be strongly influenced by soil background conditions and to saturate when LAI exceeds 2. Huete (1987) demonstrated the strong influence of soil background on vegetation indices. The perpendicular vegetation index (PVI) developed by Richardson and Wiegand (1977) seeks to limit the effects of differences in soil moisture content on the index. The mathematically related weighted difference vegetation index (WDVI) described by Clevers (1989) assumes that the soil line runs through the origin.

The capability of WDVI to predict ground cover was widely tested in the 1980s and early 1990s in the Netherlands (Bouman et al., 1992). They found linear relationships between ground cover and WDVI throughout the growing season for potato, sugar beet, barley, wheat and oats. They reported that the average estimation accuracy of ground cover from WDVI was of the same magnitude as that of conventional methods, i.e., about 5% (absolute value) in most cases.

Most methods to predict ground cover require remote sensing data that have been calibrated to reflectance because they are making use of the soil line. However, Maas and Rajan (2008) described an elegant way to calculate ground cover based on digital numbers (DN), i.e., uncalibrated imagery. That approach is based on a visual analysis of the so-called tasseled cap. This is a plot of the DNs of the red (x-axis) versus those of the NIR (y-axis) band. That plot exhibits the two key features needed to calculate ground cover: the full canopy point and the soil line. At the full canopy point, the ground cover approximates 100%. This approach works well in regions with a diverse cropping pattern, where some fields have reached a full canopy, whereas other ones have bare soil.

2.2. The relation between ground cover and yield

Per definition, ground cover is the percentage ground covered by green leaves when seen from above. It is therefore a measure of the amount of light or photosynthetically active radiation (PAR) that is intercepted by a plant canopy. Monteith and Moss (1977) showed that cumulative light interception throughout a season is closely related to biomass production. In line with their findings, several studies demonstrated that cumulative intercepted PAR derived from remote sensing can be used to accurately estimate above ground biomass (Casanova et al., 1998; Christensen and Goudriaan, 1993). However, in order to estimate cumulative intercepted radiation, several satellite images as well as the date of crop emergence and maturity for each field are required. This approach is not very practical for a country like Bangladesh, where skies tend to be hazy during the winter months and typical field sizes are less than 1 ha.

The LAI, and thus ground cover of maize reaches its peak just before tasseling. It then declines at a slow and steady rate (Odenweller and Johnson, 1984). Hence, there is a period of several weeks around tasseling during which LAI does not change much. This offers a rather long window for the estimation of LAI. In maize, it has been shown that the amount of light intercepted around the silking phase is a key determinant of grain set (D'Andrea et al., 2008; Kiniry and Knievel, 1995; Lizaso et al., 2001). Hence, even if there are differences in sowing date among maize fields in a given region, an image taken around the time when the majority of the fields has reached tasseling or soon thereafter, can potentially serve as good indicator of the spatial variability of yield. However, the slope and intercept of the relation between ground cover and yield changes from year to year, since temperature and solar radiation have a strong impact on grain filling. It is therefore necessary to calibrate that equation.

3. Materials and methods

3.1. Study area

The study was conducted in the Rangpur district, in northwestern Bangladesh. That area is intensively cropped with rice during the rainy season. Winter (Boro) rice, potato, wheat and increasingly maize, as well as lentils, mustard, jute and other crops are grown during the remainder of the year under irrigated as well as rainfed conditions.

3.2. General crop production practices for maize

Maize in Rangpur is most commonly grown in the following cropping patterns: maize–fallow–transplanted monsoon (T. Aman) rice, potato–maize/relay maize–T. Aman rice, maize–relay jute/jute–T. Aman rice, or maize–pre monsoon (Aus) rice–T. Aman rice. In most of the areas, however, T. Aman–maize–fallow and T. Aman–potato–maize are the predominant cropping patterns. In T. Aman–maize–fallow system, maize is generally planted during November and December (called Rabi maize) and harvested during April and May, thus the growth duration of Rabi maize is around 150 days. In the T. Aman–potato–maize system, maize is sown as a relay crop 20–35 days after planting potato in January or it is grown after the early harvest of potato in late February to early March (called Kharif-1 maize), thus the growth duration of kharif-1 maize is around 110–115 days. The long duration, and hence the late variety of Rabi maize results in delay in planting of main Kharif season rice resulting in reduced rice yield while delay in harvesting of kharif-1 maize results in crop damage and poor grain quality due to storm and heavy rainfall at crop maturity (Ali et al., 2008; Timsina et al., 2011). Short duration hybrids are required in NW Bangladesh to intensify the cropping systems but they must have high yield potential too.

Most maize in Rangpur is grown on deep fertile alluvial soils supplemented by large amounts of NPK fertilizer. Maize farmers apply N fertilizer rates of around 200 kg N/ha in three splits: 1/3 N as a basal dressing during land preparation, 1/3 at the 8 leaf stage and the remaining 1/3 at tasseling. Maize is planted in rows at approximately 53,000–66,000 plants/ha on conventionally tilled land. Some farmers maintain a higher plant population of up to 80,000 plants/ha. Soil ridges are made after hand weeding.

Almost 100% of the maize area is planted with hybrid maize seed each year, mainly with single cross and double cross hybrids (Ali et al., 2008). Almost all the maize is sole cropped but farmers are interested to intercrop maize with very early harvested vegetables, including potato, red-amaranth, spinach, radish, coriander and French bean. Irrigation scheduling is well developed, with around 80–85% of farmers providing the optimal 2–4 irrigations at appropriate stages of crop development.

3.3. Ground truth data

In a survey maize yield data from the 2010/2011 season were collected in June of 2012 for more than 40 farmers' fields. Additionally, sowing and harvest dates as well as the names of varieties/hybrids were recorded. The coordinates of one point within a field were recorded with a GPS. The yield data set was first checked for plausibility. Some fields had to be eliminated due to geo-location inconsistencies that could not be resolved. All in all, yield data from 30 fields passed the quality control. Next, field boundaries were created using a RapidEye satellite image and GoogleEarth (http://www.google.com/earth/index.html; verified October 31, 2012) as a reference.

3.4. Estimation of potential yield

Potential yield was estimated with the HybridMaize model (Yang et al., 2004, 2006). The model requires only a few parameters when used to simulate growth and yield under non-limiting conditions. They were: start from planting on (m/d): 12/1 (DOY = 335); seed brand: generic (default name when the name of the maize hybrid being simulated is not known); cumulative thermal time from emergence to maturity (total GDD10C): 1360; cumulative thermal time from emergence to silking (GDD10C to silking): 680; plant population ($\times$1000/ha): 80; seed depth (cm): 5; water regime: optimal (fully irrigated). Base temperature for all thermal time calculations is 10 °C. Neither potential nutrient deficiencies nor yield reducing effects due to pests were simulated. HybridMaize requires the following weather parameters on a daily basis: maximum and minimum temperature and solar radiation.

The HybridMaize model has been validated against a range of data sets in Indonesia, Philippines and Vietnam (Witt et al., 2006) and used extensively to predict yield potential of maize for 29 locations in nine countries in Asia, including three locations in Bangladesh (Timsina et al., 2010, 2011).

The weather data for the long-term simulations were satellite derived and are being provided by NASA (http://power.larc.nasa.gov/; verified 31 October 2012). They were selected using the coordinates of the city of Rangpur (25.700°N; 89.230°E), which is in the center of the study area. NASA recommends not using them for long-term simulations that run across January 1, 2008. Hence, they were limited to the period 1987–2007. In addition, data measured near the city of Rangpur by the Rangpur office of the Meteorological Department of Bangladesh were used to simulate growth for the 2010/2011 growing season.

3.5. Remote sensing

An optical remote sensing image was obtained from RapidEye AG. The image had been acquired on March 26, 2011 and covered 644 km^2. The native resolution of the RapidEye images is 6.5 m, but during the geo-rectification process they are resampled to 5.0 m. The RapidEye images have five bands: blue, green, red, red-edge and NIR.

The image was used to identify the maize fields and to calculate ground cover as well as calibrated yield. For crop identification an object-based approach was used. First, segments were created with eCognition (Definiens Imaging GmbH). Segments with an average ground cover of less than 5% were excluded for the subsequent classification steps in order to keep the number of segments low. There were still more than 170,000 segments left for classification. Next, two training classes, "Maize" and "Others" were created. The Maize class consisted of 100 segments and Others of 250. They were created based on a visual analysis of the image. The classification algorithm used was Random Forest, implemented in WEKA (Hall et al., 2009). Random Forest has been shown to be able to handle data sets with a non-uniform distribution. However, it cannot detect crop type specific interactions among the information contained in the spectral bands, which can be useful for separating the various crop types. Hence, in addition to digital numbers of the 5 bands, GC, NDVI and the ratio of the digital numbers of [NIR/(blue + green + red)] were used as input for the classification. The visual quality control revealed that the main source of errors was the misclassification of rice fields as maize. However, this could easily be corrected for, since rice production typically takes place in large pockets, because it requires access to a suitable irrigation infrastructure.

Ground cover was calculated using the methodology described by Maas and Rajan (2008). The study area certainly contained pixels with dense vegetation, since some crops, such as the maize fields in question had reached the peak of their canopy development. Moreover, it contained wetland and evergreen forest. The other key feature, the soil line could also be easily detected, since many potato fields had been freshly harvested and contained no green vegetation. For the subsequent prediction of yield, the average ground cover of each field was extracted.

3.6. Prediction of actual yield with ground cover

Actual yield was predicted by regressing ground cover derived from remote sensing versus reported yield of 30 fields. The confidence limits of the prediction were assessed using a stratified 10-fold cross-validation approach. Standard procedure for this approach is to divide the data set into ten parts (Witten et al., 2011). Each part is held out in turn, and the learning scheme is trained on the remaining nine-tenths. The error rate is determined based on the hold-out part.

Actual yield of maize for the entire study area was then calculated by applying the regression line to all the maize pixels in the image.

4. Results

4.1. Estimation of potential yield with HybridMaize

The HybridMaize model estimated an average yield of 12.87 Mg/ha (Table 1) across the 20 years. The highest yield was simulated for 2002, with 15.04 Mg/ha, while 1991 was the worst year with 10.96 Mg/ha. In that year, the harvest index was particularly low. In all years, the simulated harvest index was below 0.50. Changing the sowing date between December 1 and December 31 led to a decline in yield with time (Table 2). Noteworthy is the steady increase of the coefficient of variability of yield from 9% for the first sowing date to 14% for the last date. We also wanted to test whether the 2010/2011 weather conditions were

Table 1
Potential yield of maize grown in the Rangpur district, Bangladesh estimated with the HybridMaize model. Weather data spanning 20 years from 1987 until 2007 were used. Sowing date was set to December 1.

Rank	Year	Grain yield[a] (Mg/ha)	Stover (Mg/ha)	Harvest index	Growth duration (days)		
					Vegetative	Reproductive	Total
Best yield	2002	15.04	13.29	0.49	83	54	137
75% percentile	1993	13.68	15.21	0.43	66	55	121
Median yield	2000	13.00	14.62	0.43	74	50	124
25% percentile	2006	12.23	13.97	0.43	65	53	118
Worst yield	1991	10.96	16.97	0.35	80	44	124
Long-term mean		12.87	14.11	0.44	73	49	122
Long-term CV (%)		9	9	8	7	8	5

[a] Grain yield at 15.5% moisture content.

Table 2
Potential yield of maize grown in the Rangpur district, Bangladesh estimated with the HybridMaize model. Sowing date was varied from December 1 to December 31. As input, either 20 years or the actual 2010/2011 weather data were used. The 20 years covered the period from 1987 until 2007.

Sowing date	20 years		2010/2011 season
	Grain yield[a] (Mg/ha)	CV (%)	Grain yield[a] (Mg/ha)
December 1	12.87	9	12.85
December 11	12.58	10	12.65
December 21	12.58	12	11.87
December 31	12.48	14	10.89

[a] Grain yield at 15.5% moisture content.

comparable to the long-term data. It turned out that the predicted yield (12.85 Mg/ha) for that season was almost identical with the long-term average yield. Late sowing dates, however showed a slightly sharper decline in yield than the long-term average. December 1 is the earliest practically feasible sowing date. Hence, the simulated average yield of 12.87 Mg/ha was assumed to represent potential yield for the study area.

4.2. *Estimation of actual yield with remote sensing and ground truth data*

Ground cover data derived from remote sensing in conjunction with ground truth data were used to establish a function to predict yield for all maize pixels in the image. The results of the calibration of the model with the average yield of 30 fields are shown in Fig. 1. In order to obtain a more reliable estimate of the accuracy of the prediction, a 10-fold cross validation was performed. Fig. 2 shows the results of calculating a regression line using 9 sets to train the algorithm, while the remaining set was used to calculate the mean squared error (MSE). This procedure was repeated ten times. This resulted in an average MSE of 1.15 Mg/ha.

In order to assess the spatial variability of the yield gap at the regional level, the function that had been derived in the calibration step was applied to all the maize pixels in the remote sensing image. The satellite image did not cover the entire Upazilas (administrative sub-districts), hence the comparisons to the official statistical data shown in Table 3 are to be seen with caution. For two sub-districts Rangpur Sadar and Gangachara, yield was over predicted by 1.1 and 0.9 Mg/ha respectively as compared to the yield data estimated by the Bangladesh Bureau of Statistics, while for Mithapukur, yield was underestimated by 0.5 Mg/ha. The map (Fig. 3) also shows that in general, smaller yield gaps were observed for the Mithapukur Upazila. There were large pockets especially in the Gangachara and Rangpur Sadar sub-districts that had very low ground cover or bare soil. Most likely, these were potato fields that had been harvested before the satellite image was acquired.

5. Discussion

The estimated yield potential of maize of 12.87 Mg/ha is in-line with other published results in previous studies and seems to be plausible (Timsina et al., 2010, 2011). Ali et al. (2008) reported

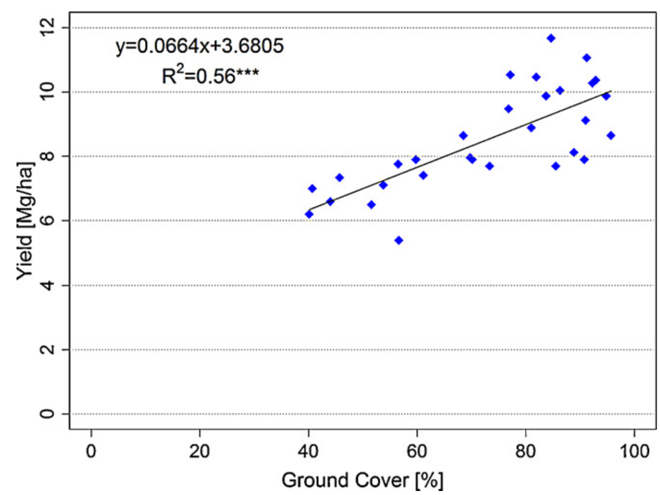

Fig. 1. Calibration of the model predicting maize yield as a function of ground cover in the Rangpur District, Bangladesh. Ground cover was derived from a satellite image acquired on March 26, 2011. The observed yield data consisted of the average yield of 30 farmers' fields from the 2010/2011 growing season.

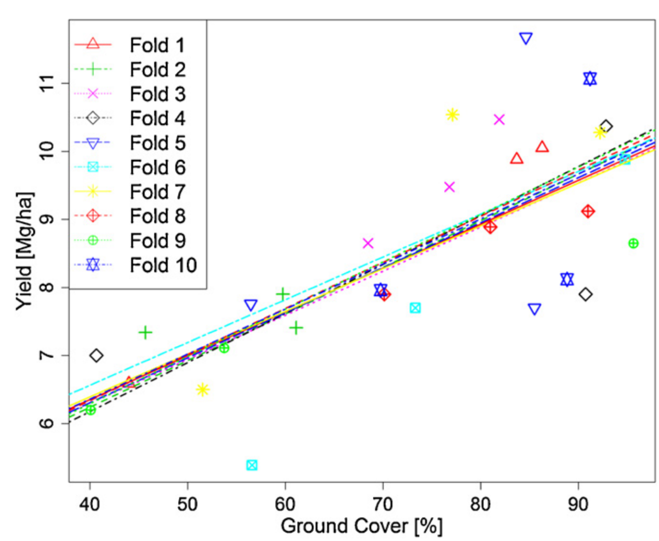

Fig. 2. Outcome of the 10-fold cross-validation used to establish the confidence limits of the prediction of actual yield with remote sensing derived ground cover estimates. The resulting mean square error was 1.15 Mg/ha.

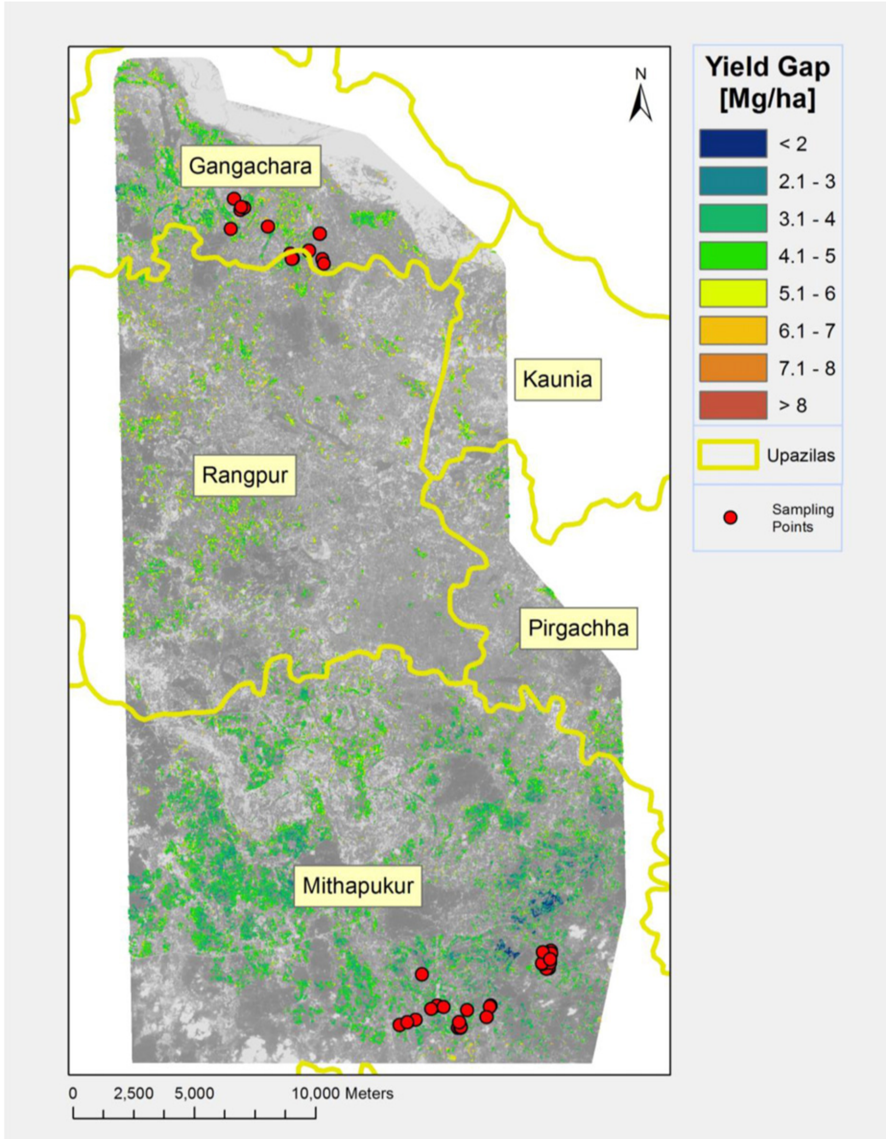

Fig. 3. Map depicting the spatial variability of the yield gap within three Upazilas (sub-districts) in the Rangpur district, Bangladesh. Potential yield was estimated with the HybridMaize model, actual yield data estimates were generated based on ground cover calculated from satellite data and yield data of 30 famer's fields. The mean squared error of the prediction of actual yield was 1.15 Mg/ha.

yields as high as 11–12.5 Mg/ha from on-farm experiments conducted in northwestern Bangladesh.

The cumulative thermal time used to characterize a hybrid has a big impact on the yield estimates generated by HybridMaize. Since the Rabi season maize crop is usually followed by another crop before the Kharif-1 or Aus rice crop, we chose a somewhat shorter duration hybrid, so that the Rabi maize would fit well into the cropping system. The simulated harvest indices were relatively low when compared to values reported in the literature (Lorenz et al., 2010). This might be due to the relatively high temperatures during the grain filling period, shortening its duration when expressed in days as compared to other maize productions regions such as the corn belt in the USA.

The actual yields that are currently being achieved by the farmers are generally high, though there is quite some spatial variability in the actual yield data. It seems that especially in the sub-districts of Gangachara and Rangpur Sadar where maize yields tended to be lower, farmers prefer to grow Rabi-rice if water for irrigation is available. Maize is a relatively new crop for Bangladesh, and the demand for rice is much higher than for maize as rice is a staple crop and is a primary source of food for every Bangladeshi. However, maize is an important feed source for poultry and fish and is now increasingly being used as a food crop, especially by the rural poor.

The proposed methodology of using ground truth data for yield collected from farmers' fields to calibrate a ground cover map to estimate actual yield is rather challenging and time consuming.

Table 3
Yield estimates of maize at the Upazila (administrative sub-district) level within the Rangpur district of Bangladesh in the 2010/2011 Rabi growing season. The remote sensing estimates did not cover the entire Upazilas, and therefore, may not be fully representative for a given Upazila.

Upazila	Average yield (Mg/ha)	
	Bangladesh Bureau of Statistics	Remote sensing
Gangachara	7.0	7.9
Mithapukur	9.0	8.5
Rangpur Sadar	6.5	7.6

There are issues with geo-location accuracies of the data points, as well as potential in-accuracies of the yield estimates provided by the farmers. However, it allows to create maps with an MSE of 1.15 Mg/ha for an area of several hundred square kilometers based on the input of a rather small number of fields.

The size of the yield gap in the study area was variable, but for some of the fields, it was less than 2.5 Mg/ha. One of the potential uses of a yield gap map is to learn from the farmers with the highest yields what their management practices were, in order to establish up-to date management recommendations. Alternatively, it might also be worthwhile to visit the low yielding fields in order to identify the production constraints. This information could greatly enhance the efficacy of the extension work and would allow agronomists to generate region or even field specific recommendations.

6. Conclusions

Generating an accurate yield gap map at the field level is challenging. While potential yield estimates under non (water) limiting conditions can be relatively easily generated with a crop simulation model, an accurate estimation of the actual yield at the field level is prone to errors. The method described in this paper allowed to spatially extend the yield data of maize from initially 40 farmers' fields to a region of 600 km^2 with a MSE of 1.15 Mg/ha. For practical applications such as identifying the causes of yield gaps in a given region and improving information and knowledge provided by the extension services, this accuracy should be sufficient.

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References

Ali, M.Y., Waddington, S.R., Hodson, D., Timsina, J., Dixon, J., 2008. Maize–Rice Cropping Systems in Bangladesh: Status and Research Opportunities. CIMMYT, Mexico, D.F.

Bouman, B.A.M., van Kasteren, H.W.J., Uenk, D., 1992. Standard relations to estimate ground cover and LAI of agricultural crops from reflectance measurements. Eur. J. Agron. 1, 249–262.

Bouman, B.A.M., van Laar, H.H., 2006. Description and evaluation of the rice growth model ORYZA2000 under nitrogen-limited conditions. Agric. Syst. 87, 249–273, http://dx.doi.org/10.1016/j.agsy.2004.09.011.

Casanova, D., Epema, G.F., Goudriaan, J., 1998. Monitoring rice reflectance at field level for estimating biomass and LAI. Field Crops Res. 55, 83–92.

Christensen, S., Goudriaan, J., 1993. Deriving light interception and biomass from spectral reflectance ratio. Remote Sens. Environ. 43, 87–95.

Clevers, J.G.P.W., 1989. The application of a weighted infrared-red vegetation index for estimating leaf area index by correcting for soil moisture. Remote Sens. Environ. 29, 25–37.

D'Andrea, K.E., Otegui, M.E., Cirilo, A.G., 2008. Kernel number determination differs among maize hybrids in response to nitrogen. Field Crops Res. 105, 228–239, http://dx.doi.org/10.1016/j.fcr.2007.10.007.

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., Witten, I.H., 2009. The WEKA data mining software: an update. SIGKDD Explor. 11, 1.

Huete, A.R., 1987. Soil-dependent spectral response in a developing plant canopy. Agron. J. 79, 61–68.

Kiniry, J.R., Knievel, D.P., 1995. Response of maize seed number to solar radiation intercepted soon after anthesis. Agron. J. 87, 228–234.

Lizaso, J.I., Batchelor, W.D., Adams, S.S., 2001. Alternate approach to improve kernel number calculation in CERES-Maize. Trans. ASAE 44, 1011–1018.

Lorenz, A.J., Gustafson, T.J., Coors, J.G., Leon, N.d., 2010. Breeding maize for a bioeconomy: a literature survey examining harvest index and stover yield and their relationship to grain yield. Crop Sci. 50, 1, http://dx.doi.org/10.2135/cropsci2009.02.0086.

Maas, S.J., Rajan, N., 2008. Estimating ground cover of field crops using medium-resolution multispectral satellite imagery. Agron. J. 100, 320–327.

Monteith, J.L., Moss, C.J., 1977. Climate and the efficiency of crop production in Britain. Phil. Trans. R. Soc. Lond. B 281, 277–294, http://dx.doi.org/10.1098/rstb.1977.0140 (and Discussion).

Odenweller, J.B., Johnson, K.I., 1984. Crop identification using Landsat temporal–spectral profiles. Remote Sens. Environ. 14, 39–54.

Richardson, A.J., Wiegand, C.L., 1977. Distinguishing vegetation from soil background information. Photogram. Eng. Remote Sens. 43, 1541–1552.

Slaton, M.R., Hunt, E.R., Smith, W.K., 2001. Estimating near-infrared leaf reflectance from leaf structural characteristics. Am. J. Bot. 88, 278–284.

Timsina, J., Humphreys, E., 2006. Performance of CERES-Rice and CERES-Wheat models in rice–wheat systems: a review. Agric. Syst. 90, 5–31, http://dx.doi.org/10.1016/j.agsy.2005.11.007.

Timsina, J., Jat, M.L., Majumdar, K., 2010. Rice–maize systems of South Asia: current status, future prospects and research priorities for nutrient management. Plant Soil 335, 65–82, http://dx.doi.org/10.1007/s11104-010-0418-y.

Timsina, J., Buresh, R.J., Dobermann, A., Dixon, J., 2011. Rice–Maize Systems in Asia: Current Situation and Potential. IRRI as an IRRI-CIMMYT Joint Publication September 2011, 235 pp.

Van Ittersum, M.K., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P., Hochman, Z., 2013. Yield gap analysis with local to global relevance – a review. Field Crops Res. 143, 4–17.

Witt, C., Pasuquin, J.M.C.A., Dobermann, A., 2006. Towards a site-specific nutrient management approach for maize in Asia. Better Crops. 90, 28–31.

Witten, I.H., Eibe, F., Hall, M.A., 2011. Data Mining: Practical Machine Learning Tools and Techniques, third ed. Morgan Kaufmann, Burlington, MA.

Yang, H., Dobermann, A., Cassman, K.G., Walters, D.T., 2006. Features, applications, and limitations of the Hybrid-Maize simulation model. Agron. J. 98, 737, http://dx.doi.org/10.2134/agronj2005.0162.

Yang, H.S., Dobermann, A., Lindquist, J.L., Walters, D.T., Arkebauer, T.J., Cassman, K.G., 2004. Hybrid-maize – a maize simulation model that combines two crop modeling approaches. Field Crops Res. 87, 131–154, http://dx.doi.org/10.1016/j.fcr.2003.10.003.