BIOSYSTEMS ENGINEERING 169 (2018) 71–84

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/issn/15375110

Research Paper

Modelling the influence of crop density and weather conditions on field drying characteristics of switchgrass and maize stover using random forest

Amit Khanchi [a,*], Stuart Birrell [a], Robert B. Mitchell [b]

[a] Department of Agricultural and Biosystems Engineering, Iowa State University, Ames, IA 50011, USA
[b] USDA-ARS, Wheat, Sorghum and Forage Research Unit, University of Nebraska, Lincoln, NE 68583, USA

ARTICLE INFO

Article history:
Received 7 August 2017
Received in revised form
21 November 2017
Accepted 2 February 2018

Keywords:
Field drying
Random forest
Switchgrass
Weather forecasting
Crop density
Drying models

Field drying trials were conducted using both field baskets as well as grab sampling techniques to study drying behaviour of switchgrass and maize (corn) stover (CS). Environmental conditions such as hourly solar radiation, vapour pressure deficit (VPD), average wind speed, rainfall amount, harvesting method, and field operations such as swath density were used as variables for model development. A powerful classification-based algorithm, which uses a collection of decision trees called random forest (RF) was utilised to predict moisture content (MC) of switchgrass and CS on wet basis. RF predicted the MC of switchgrass and CS with a coefficient of determination of 0.77 and 0.79, respectively. Rainfall, hours after harvest, average change in solar radiation in past 12 h, average solar radiation in past 12 h, and swath density were found to be the important variables affecting the MC of CS. Drying CS in low density (LD) and medium density (MD) swaths facilitated quick drying even in moderate drying conditions. Rainfall events ranging from 1.5 to 7.5 mm were experienced during the switchgrass drying period which delayed crop drying by one day to several days depending on the weather conditions after rainfall. Several rewetting events were also observed due to dew at night which increased the MC in LD switchgrass and CS by 5–15%. The models developed in the current study will help in decision-making of switchgrass and CS collection after harvest, based on forecast weather conditions in lower Midwestern states.

1. Introduction

The potential of biofuels to reduce pollution, benefit the economy, and provide energy security is well documented (Acheampong, Ertem, Kappler, & Neubauer, 2017; Carneiro et al., 2017; Chen & Smith, 2017). The updated billion ton study estimates an availability of 370 Mt of dry biomass from forest resources and 1 Gt from croplands under high yield and large scale planting scenarios (Perlack & Stokes, 2011).

* Corresponding author.
E-mail addresses: amitkhanchi1@gmail.com, amit@iastate.edu (A. Khanchi).
https://doi.org/10.1016/j.biosystemseng.2018.02.002

Switchgrass (*Panicum virgatum* L.) has a potential to be a leading bioenergy crop for bioethanol production. Crop residues such as maize (corn) stover (CS) have also been recognised as a major contributor to bioenergy and bio-based applications (Yu, Igathinathane, Hendrickson, & Sanderson, 2014). Maize stover consists of the stalk, leaf, cob, and husk portion of the plant and has a potential annual yield of 130 Mt and can produce 38.4 GL of bioethanol (Kim & Dale, 2004). As of May 2017, ten biorefineries have been funded by the bioenergy technologies at pilot, demonstration, and pioneer scales to produce biofuels from agricultural residues and energy crops in the US (USDOE, 2017). Overall, twenty-six biorefineries have been funded at different scales to produce biofuels from all renewable resources such as algae, woody biomass, municipal solid waste, vegetable and yard waste, agricultural residues and energy crops in the US (USDOE, 2017).

Moisture content (MC) of biomass is an important factor that influences the downstream handling operations for biofuel production. Depending on the plant maturity stage at harvest, the moisture in the plant might be high to avoid microbial spoilage during storage and transportation. In order to avoid microbial spoilage, a MC of less than 20% is desirable (Shinners, Binversie, Muck, & Weimer, 2007). At early maturity stages, a MC of 65–70% in switchgrass (Khanchi et al., 2013) and 34–52% in CS (Shinners et al., 2007; Womac, Igathinathane, Sokhansanj, & Pordesimo, 2005) has been reported at harvest. During harvest, several field and mechanical operations are applied for quick drying of crops. Windrows of varying densities can be obtained by controlling the windrow-forming shield at the back of the harvester. Dedicated machines such as tedders are also used to spread the crop evenly on the field which helps to capture maximum solar radiation for rapid drying. However, spreading the crop also exposes it to unfavourable events such as rainfall, which can prolong the field drying period and reduce dry matter and quality of the crop (Khanchi & Birrell, 2017b).

Temperature, relative humidity, solar radiation, wind, soil moisture, and rainfall are the major environmental factors that affect the drying of crops in the field. The drying process is driven by differences between the vapour pressure of biomass material and that of surrounding air. The solar radiation supplies most of the energy for evaporation of water (Atzema, 1992). The radiation is able to penetrate up to 5 cm into the swath, after which the heating effect is reduced and the crop dries slowly (Atzema, 1992) in the bottom layers. Therefore, drying in a low-density swath or tedding is recommended to promote more even and quick drying. Previous studies on drying of grass have concluded that, of all of the weather parameters studied, solar radiation is a more important factor than vapour pressure deficit or wind speed in determining the drying rates (McGechan & Cooper, 1995; Wright, Frost, Patterson, & Kilpatrick, 2001). However, at night, vapour pressure deficit (VPD) is the most important factor in determining the drying rates of crops (Khanchi & Birrell, 2017a). When the crop is moistened by rainfall or dew, most of the water is adsorbed on the surface and is called free water (Atzema, 1992). The moisture gain by rain or dew is also influenced by the conditioning of the crop material. During conditioning, the crop passes through conditioning rolls which break open the stems, resulting in faster drying of crops. Highly conditioned biomass loses and gains moisture more easily than unconditioned biomass. All of these factors should be considered while implementing any field operation for biomass drying.

Models predicting the drying behaviour of CS and switchgrass are limited in the literature. Models have been previously developed for other crops such as alfalfa (*Medicago sativa* L.) (Dyer & Brown, 1977; Hayhoe & Jackson, 1974; Kemp, Misener, & Roach, 1972) and ryegrass (*Lolium perenne*) (Wright et al., 2001) which utilise environmental variables and pan evaporation to predict the drying of crops. In the case of CS, models were developed by Womac et al. (2005) and Manstretta and Rossi (2015). Womac et al. (2005) developed models for the southeast U.S. and found that moisture measured in the morning was significantly greater than moisture in the afternoon. They also concluded that conditioning resulted in a 10% higher moisture reduction than unconditioned stover. However, conditioned stalk also gained greater moisture after rainfall. Manstretta and Rossi (2015) developed models to study the effect of weather on moisture fluctuations in maize stalk residues as an important inoculum source for plant disease in Italy. In the absence of rainfall, they also found a diurnal pattern with decreasing MC during the day and increasing moisture at night. Shinners et al. (2007) compared wet and dry maize stover harvest but no models were developed during the study. They observed that out of four trials, only in one trial did the stover reach a safe storage moisture level (20%) in four days after grain harvest. In the other trials, the ambient temperature was low and there were frequent rainfall events which kept the stover at a higher MC during the 10 day drying period. All these studies show the significance of environmental conditions on final MC of CS. In the case of switchgrass, field drying studies are even more limited. Shinners, Boettcher, Muck, Weimer, and Casler (2010) studied the effect of three swath densities and two conditioning treatments. They found that switchgrass dried more quickly when it was placed in a wide swath. However, there was no significant difference observed between the roller and impeller conditioning treatments. Popp et al. (2015) studied the influence of weather on the predicted moisture content of field-chopped energy sorghum and switchgrass. They concluded that the weather, and specifically rainfall, impacts harvesting cost by affecting the seasonal production capacity. Additionally, they found that temperature impacted the rate of drying and suggested artificial drying instead of longer field drying periods when the drying conditions are not favourable.

The models developed to predict the MC in crops, using environmental factors and field operations, use multiple linear regression (MLR) as a common prediction technique. MLR is popular due to simplicity in application, computational efficiency, and ease of interpretation (Zhang et al., 2017). MLR can detect a linear relationship between the response variable and the environmental variables used for moisture prediction. However, MLR models can result in errors when the relationships are inter-correlated, complex and nonlinear (Zhang et al., 2017). In past studies (Khanchi & Birrell, 2017a; Khanchi et al., 2013; Wright, Frost, & Kilpatrick, 2000) an interaction between solar radiation and wind speed was observed while predicting the drying rate of switchgrass and other crops. Prediction techniques such as classification and regression tree (CART) modelling, generalised linear modelling, and artificial neural networks (ANN) have been used to detect nonlinear relationships between the response variable and environmental predictors (Zhang et al., 2017). Random forest (RF) was developed as an extension for CART models and is a relatively new prediction approach with several advantages (Breiman, 2001). RF is resistant to overfitting, insensitive to noise, provides an unbiased measure of error rates (Zhang et al., 2017), incorporates interaction between predictors, and outperforms more recent algorithms such as ANN or weighted k nearest neighbours (Cánovas-García, Alonso-Sarría, Gomariz-Castillo, & Oñate-Valdivieso, 2017). Other advantages of RF include a measure of the importance of variables, availability in the open-source program R, non-parametric approach (Cánovas-García et al., 2017), and ability to capture complex and nonlinear relationships with a small size of training data (Brokamp, Jandarov, Rao, LeMasters, & Ryan, 2017). The RF model building process is similar to CART models but differs by including a combination of many trees. The details of RF model building and concepts can be found elsewhere (Brokamp et al., 2017; Cánovas-García et al., 2017; Zamorano, Popov, Rodríguez, & García-Maraver, 2011; Zhang et al., 2017). To date, a few studies have used RF to predict response variables using environmental conditions (Grimm, Behrens, Märker, & Elsenbeer, 2008; Guo et al., 2015; Rossel & Behrens, 2010). However, RF has not been used to predict MC in switchgrass and CS with environmental conditions and swath density as variables.

The drying models developed in this study on field drying data will assist in better management of field operations and will be useful for logistics planning and further research related to drying of biomass. In the previous study (Khanchi & Birrell, 2017a), drying models for switchgrass and CS were developed in lab conditions. These lab models were based on a wide range of data and are applicable to the entire harvesting period of switchgrass and maize stover. But, due to the complexity of field trials, the models developed for the present study are applicable to environmental conditions and maturity stage tested during the study (Table 1). Additionally, the models developed in this study include rainfall as a variable which was lacking in the lab drying study. The specific objectives of the present study were to conduct field trials for both switchgrass and CS to evaluate the effect of environmental conditions and swath density on drying characteristics, model development, validation, and measure environmental variable significance.

Table 1 – Range of hourly environmental conditions recorded during the drying study.

Environmental variable	Maize stover	Switchgrass
Solar radiation (W m^{-2})	0 to 584	0 to 745
Temperature (C)	−2 to 25	5 to 33
RH (%)	35 to 100	17 to 98
VPD (Pa)	0 to 2100	16 to 3800
Wind speed measured at 3 m height (m s^{-1})	0 to 9.46	0.3 to 8.7
Rainfall (mm)	0 to 4.6	0 to 7.6

2. Materials and method

2.1. *Maize stover and switchgrass harvesting*

CS drying experiments were performed in 2014 and 2015 at agricultural farms (41°58′37″N 93°46′14″W) owned by Iowa State University in Boone, IA. In 2014, switchgrass drying experiments were conducted at agricultural farms (42°00′46″N 93°46′42″W) owned by Iowa State University in Boone, IA and in 2015, experiments were conducted at the University of Nebraska Eastern Nebraska Research and Extension Centre (41°09′01″N 96°27′13″W) at Ithaca, NE. Four drying trials were conducted on CS beginning on Oct 25 2014, Nov 4 2014, Oct 20 2015, and Oct 30 2015, and five drying trials were conducted on switchgrass beginning on Oct 20 2014, Sep 16 2015, Sep 28 2015, Oct 6 2015, and Oct 9 2015, respectively. The range of environmental conditions recorded during the field drying study of CS and switchgrass is given in Table 1.

CS was collected by using a conventional harvesting method and a modified harvesting technique. The modified harvesting technique had a high degree of conditioning as well as shattering compared to the conventional harvesting method and will be referred to as “biomass harvesting” in the following sections. For conventional harvesting, a John Deere 9870 combine was used with a 608 C Stalkmaster Model maize head and a John Deere 9860 combine with a modified 612 C maize head was used for biomass harvest. In 2014, switchgrass was harvested by a Vermeer mower conditioner (Model no. MC 840 DiscPro, Vermeer Corp., Pella, IA) having a cutting width of 3.2 m. In 2015, switchgrass was harvested by Kuhn disc mower (Model no. GMD 400, Kuhn North America, Inc, Brodhead, WI) with a cutting width of 1.5 m. After mowing, two windrows were merged together by a rake to form a 1.5 m wide windrow, resulting in a material collected from an equivalent cutting width of 3.0 m. In both years, no conditioning treatment was used for switchgrass.

2.2. *Field moisture measurement by drying trays and hand grab sampling*

For large scale mass change or moisture measurements in the field, steel baskets of different dimensions were constructed. To simulate material in low density (LD) swath, baskets measuring 2.44 by 2.44 by 0.15 m were utilised whereas, to simulate high density (HD) windrows, trays measuring 1.22 by 1.22 by 0.31 m (Figs. 1 and 2) were used. For simulating MD windrows, biomass was placed in 1.83 by 2.44 m area of the 2.44 by 2.44 m trays.

The field arrangement of CS and switchgrass trays of different densities is shown in Figs. 3 and 4, respectively. In each experiment, the switchgrass field was divided into 6 replicate blocks, with each block having a separate row for low, medium and high density swaths with a tray placed randomly in each row. The steel trays were lined with galvanised hardware cloth with a mesh size of 6.35 mm to provide adequate ventilation and to avoid biomass falling through the trays during the drying and lifting process. In the case of CS, LD trays were filled by collecting material available from a 2.44 by 2.44 m area of the field and was evenly spread in

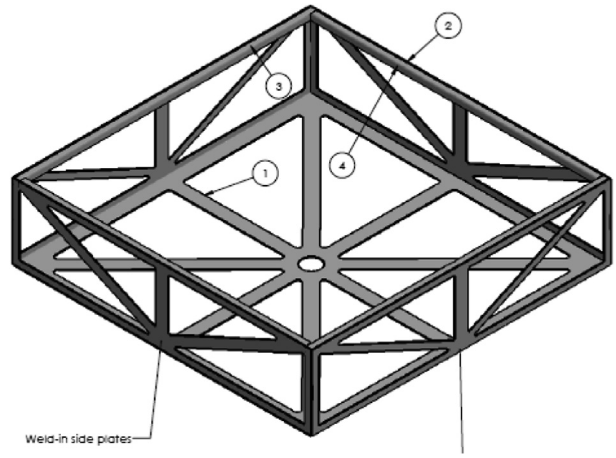

Fig. 1 – Steel trays used for high density (HD) windrow drying measuring 1.22 by 1.22 by 0.31 m.

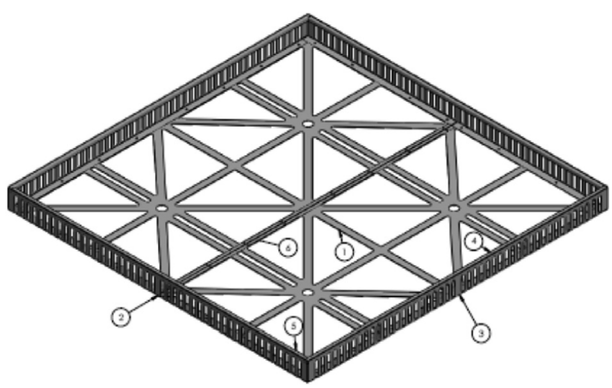

Fig. 2 – Steel trays used for low (LD) and medium density (MD) swaths measuring 2.44 by 2.44 by 0.15 m.

the trays. For preparing MD trays, CS was raked into a windrow approximately 1.83 m wide. The CS was then filled into the MD trays by displacing the 2.44 m length of this 1.83 m wide windrow. For preparing HD trays, two 1.83 m wide windrows were raked into a single high density windrow and the CS was filled in the HD trays by replacing 1.22 m length of high density windrow (Fig. 3). The average wet density of CS filled in LD, MD, and HD trays for conventional harvest were 0.88, 2.74, and 8.39 kg m^{-3}, respectively. Similarly, for biomass harvest, the density of CS in LD, MD and HD trays were 0.65, 1.92, and 6.01 kg m^{-3}, respectively. In the case of switchgrass, a portion of the windrow measuring 2.44 m in length and 1.5 m in width was filled into LD, MD and HD trays according to the surface density mentioned previously in this section. The resulting average density of switchgrass filled in LD, MD, and HD trays were 1.8, 2.3, 6.7 kg m^{-3}, respectively.

The CS and switchgrass-laden baskets were flagged as they visually blended well with the windrows formed during the field operations. The open design of the baskets allowed minimum hindrance to wind flow and the side walls of the baskets helped to prevent material from blowing away in windy situations. During day 1 of switchgrass field trials, the trays were weighed initially and then around 17:00 h. From day 2, the trays were weighed at 9:00, 13:00, and 17:00 h until they reached a MC of below 15%. In the case of CS, trays were weighed or hand grab samples were collected twice a day at 10:00 and 17:00 h. When drying conditions were not favourable (VPD < 500 Pa), samples were collected once a day at 17:00 h.

A 453.6 kg capacity load cell (Model no LC 101-1K, Omega Engineering Inc., CT) with a repeatability of ± 0.01% of full scale output, connected to a digital display (Model no. DP41-S-DC-S2, Omega Engineering Inc., CT) was used to measure the gravimetric mass change of the biomass trays. A steel frame was constructed to lift the trays. One end of the frame was connected to the load cell via chains and the other end was connected to the trays by hooks (Fig. 5). The tray connected to the load cell was lifted by a telehandler.

When the trays containing biomass were first weighed, an initial sample was also collected and analysed for MC by oven drying method (ASAE, 2003). The MC at each subsequent time was then estimated from the mass at that time and the initial MC of the crop at the start of the study. It was assumed that the dry matter of the tray remained constant throughout the drying period and the change in mass was only due to addition or

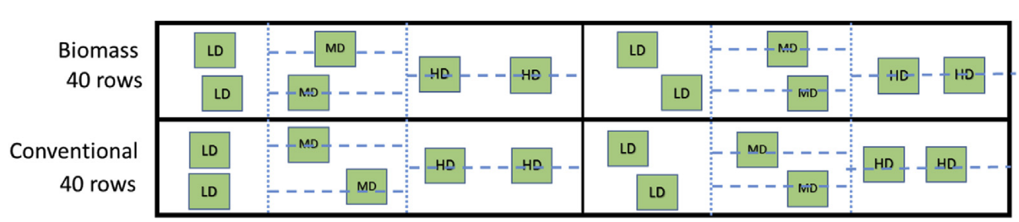

Fig. 3 – Experimental field layout and placement of drying trays for field moisture relationship of maize stover. LD, MD, and HD represent low density, medium density and high density, respectively.

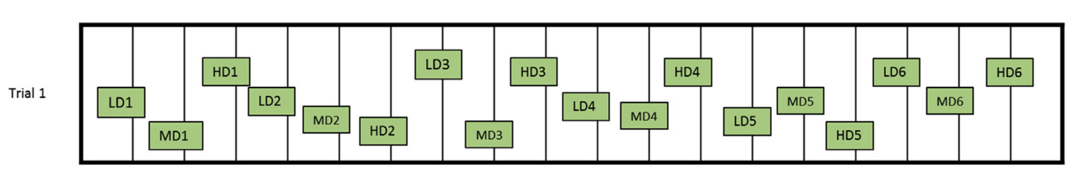

Fig. 4 – Experimental field layout and placement of drying trays for field moisture relationship of switchgrass. LD, MD, and HD represent low density, medium density and high density, respectively.

Fig. 5 – A typical mass measurement of drying basket containing conventionally harvested maize stover using a load cell attached to a reading scale inside the telehandler.

removal of moisture. During drying days with extremely windy conditions, only hand grab sampling was performed as lifting the trays risked part of the biomass blowing away, resulting in errors during tray sampling. Hand grab samples were collected across the whole width of the windrow and the samples were placed in plastic bags and transported to lab immediately for moisture analysis by oven drying method (ASAE, 2003).

2.3. *Environmental variable monitoring during field drying*

Weather parameters such as air temperature, relative humidity, wind speed, wind direction, and solar radiation were collected at 1 min intervals by a portable weather station set up at the field site. Air temperature and humidity were measured by two shielded temperature and humidity data loggers (Model no UX 100-011, Onset Computer Corp., MA). Wind speed and direction were measured by a wind speed and direction sensor set (Model no S-WSET-A, Onset Computer Corp., MA) connected to a HOBO Micro station (Model no H21-002, Onset Computer Corp., MA) for data logging. The solar radiation intensity was measured by a pyranometer (Model no. LP 02, Hukseflux Thermal Sensors, Netherlands) with a detection range of 285–3000 nm.

2.4. *Statistical analysis and model development*

In this study, RF was utilised for finding the importance of variables and predicting MC from environmental conditions, while CART (Classification and Regression Tree) was used to identify threshold values and visual classification of variables predicting the MC of switchgrass and CS.

RF and CART (decision trees) are non-parametric techniques which can select the best features to differentiate the dependent variable, whether quantitative (regression) or qualitative (classification) (Gao, 2009). The calibration of a classification tree starts with a single node which is split into two nodes by using the predictor feature and threshold value to minimise heterogeneity measurement (Gini index) in the resulting nodes (Cánovas-García et al., 2017). The splitting process continues until all terminal nodes are homogeneous. Next, the tree is pruned by using an independent training data set to improve accuracy and avoiding overfitting (Gao, 2009). However, decision trees have a problem of high variance and sensitivity to training data. If the training data is slightly different, the node splitting process might result in a completely different tree. Ensemble learning algorithms such as RF attempt to solve these issues (Cánovas-García et al., 2017). CART differs from RF by providing a single tree compared to a collection of many such trees in RF (Zhang et al., 2017). In RF, the split variable at each node is also chosen from a random subset of the available features, which reduces correlation among trees and gives good results (Cánovas-García et al., 2017).

RF gives the importance of variables by measuring the decrease in heterogeneity (mean decrease in Gini index or MDGI), which is obtained for each variable by averaging its importance in all the trees (Cánovas-García et al., 2017). For each tree, the prediction error (Mean Squared Error or MSE) on the out-of-bag portion of the data is recorded. In the next step, prediction accuracy is recorded after permuting each prediction variable. The difference between the two accuracies are averaged over all trees and normalised by the standard error. If the standard error is zero for a variable, the division process stops. After permutation, the variable which shows the highest difference becomes the most important variable. Smaller and negative values indicate that the variable is not important in predicting the dependent variable.

CART was implemented by using the package *rpart* in R (R Core Team, 2017). The RF model was implemented in R by using the package *random forest* and method of *cross-validation*. The RF model was implemented by splitting the data into training and validation sets. The validation set is also called out-of-bag (OBB) data, which is a random subset of data that is not involved in the model building or tree development process. The mean square error (MSE_{OBB}) of the model was estimated from the equation below (Zhang et al., 2017).

$$MSE_{OBB} = N^{-1}\sum_{i=1}^{n}\left(Z_i - i^{OOB}\right)^2 \quad (1)$$

where Z_i is the measured value of variable and i^{OOB} is the average of all OBB predictions. The categorical and continuous variables of time, time of day (morning, afternoon and evening), hours after harvest (HAH), average VPD of past 12 h, change in VPD in past 12 h, average hourly solar radiation of past 12 h, change in solar radiation in past 12 h, average wind speed in past 12 h, swath density, and rainfall were used to predict the MC of switchgrass. The VPD of air was calculated by using temperature (T) and humidity (Rh) data in the equation below.

$$VPD(Pa) = \left(1 - \frac{Rh}{100}\right)\left(6.11 * exp\left(\frac{17.47 * T}{239 + T}\right)\right) * 100 \quad (2)$$

The change in VPD and solar radiation in past 12 h was calculated from hourly solar radiation and hourly VPD values at the time, t, and at t-12 h from Eq. (3).

$$\textit{Change in past 12 h} = \frac{Value_t - Value_{t-12}}{12} \quad (3)$$

In the case of CS, the harvesting method was also included as a categorical variable in MC prediction in addition to the above mentioned variables for switchgrass. Variable significance was evaluated for both switchgrass and CS. The R program used for predicting MC using the above mentioned variables and maize stover and switchgrass datasets is given in Supplementary material as File S1, File S2, and File S3, respectively.

3. Results and discussion

3.1. Field experiments and observations

In 2015, trials 2 to 5 were conducted on switchgrass and trials 8 to 9 were conducted on CS and are discussed below. Hourly weather variations for these trials are provided in detail in Supplementary material (File S4). Trials conducted in 2014 are not shown here but they were used for model development and their field moisture variation data and weather conditions are presented in Supplementary material (File S2 and File S3). During trial 2 of switchgrass, an average daily temperature of 19.5 °C and an average daytime hourly radiation of 380 W m^{-2} was observed. Under these favourable conditions, switchgrass dried to a safe storage MC of 20% after one and a half days of field drying. Drying conditions were good and trays of different densities dried at a similar rate. Some moisture gain at night was observed and the morning moisture observations were higher than the previous evening MC with trays in LD gaining the most moisture (Fig. 6). Since LD was more spread out, they gained more moisture at night compared to HD trays, but LD trays also lost that gained moisture quickly due to faster drying rates during the daytime. A slight rainfall of 1.5 mm was observed the next day, but all the treatments were below 20% moisture after 24 h of drying.

In trial 3 of switchgrass, an average daily temperature of 16 °C and a day time average radiation intensity of 460 W m^{-2} was observed. An average moisture content ranging from 30 to 35% was observed at the end of the first day of drying. Rainfall of 7.8 mm was observed which increased the moisture to 55% in HD compared to 65% in LD and MD trays (Fig. 7). Even though the LD trays gained the highest moisture, they also dried quickly and lost the adsorbed moisture, which was reduced to 25% at the end of the second day. The rainfall of 7.8 mm delayed the collection of switchgrass by one day. At the end of the second day, a low VPD of 97 Pa was observed which resulted in rewetting of switchgrass with dew at night and early morning. In the morning, rewetting resulted in 13, 11 and 4.5% moisture increase in LD, MD, and HD trays, respectively, over the previous day's evening moisture.

In trial 4 of switchgrass, an average daily temperature of 18.7 °C and an average day time radiation intensity of 350 W m^{-2} was observed. LD and MD trays reached a safe storage moisture after 26 h of drying but HD trays were at 27%. A 1.5 mm rainfall was also observed at night which increased the morning moisture of LD, MD, and HD trays by 22.5, 18.0, and 8.5% over the previous evening MC (Fig. 8). After the rainfall, switchgrass reached a final moisture of 26, 23 and 20% in LD, MD, and HD trays, respectively at the end of the day. Some error might have occurred during the weighing of trays. The conditions were windy and wind speed of up to 6 m s^{-1} was recorded during weighing which resulted in higher masses than expected.

In trial 5 of switchgrass, an average daily temperature of 16.4 °C and an average day time hourly solar radiation intensity of 390 W m^{-2} were recorded. At the end of the first day, LD and MD trays reached a MC of 32.7 and 33.5%, respectively compared to a MC of 41.5% in the HD trays (Fig. 9). During trial 5, HD trays remained at a higher MC than LD and MD trays

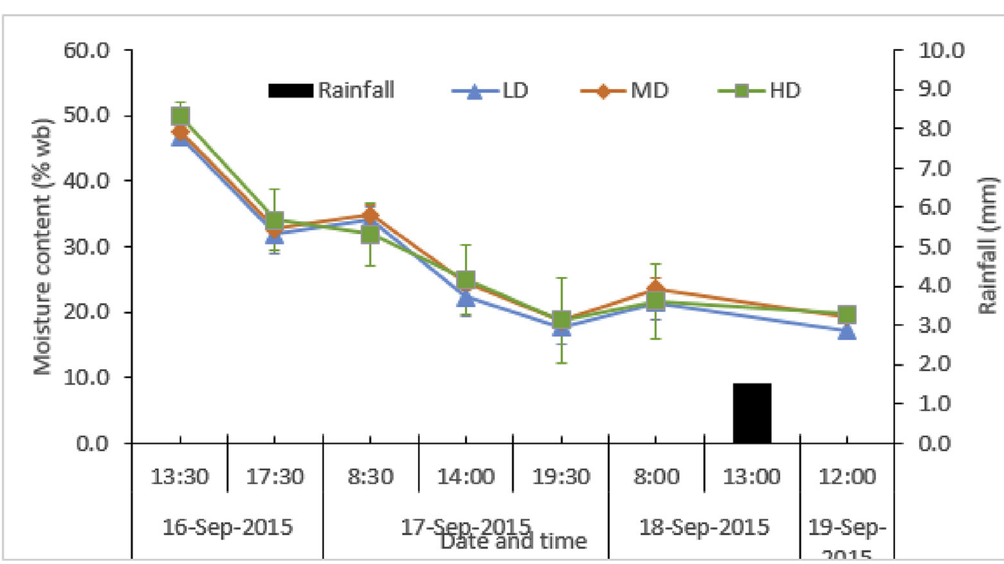

Fig. 6 – Moisture variation with standard error bars in low (LD), medium (MD) and high density (HD) trays of switchgrass during field drying in Ithaca, NE (Trial 2).

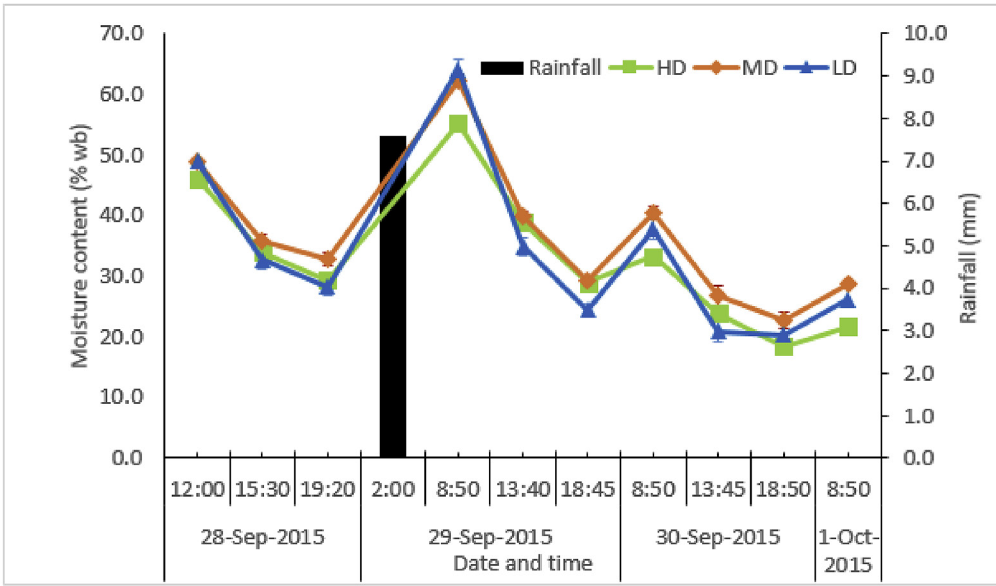

Fig. 7 – Moisture variation with standard error bars in low (LD), medium (MD) and high density (HD) trays of switchgrass during field drying in Ithaca, NE (Trial 3).

showing the significance of drying in spread swath compared to a narrow windrow during unfavourable or moderate conditions. A VPD as low as 25 Pa was recorded during the early morning of the second day which resulted in rewetting of switchgrass and increased MC in morning readings. Switchgrass placed in LD, MD and HD trays gained 3, 9.6, and 10.4% more moisture than the prior evening readings. A similar rewetting event due to dew at night and early morning was observed because of low VPD (36 Pa) which resulted in a moisture increase of 4.0, 9.2, and 10.6% the next morning. Only LD and MD reached a safe MC of 17% after 3 days of drying.

During trial 8 of CS, an average hourly temperature of 14 °C and an average hourly day time radiation intensity of 211 W m^{-2} was observed during the drying period. CS placed in HD windrows did not reach a safe storage MC during the entire drying period. However, CS placed in LD and MD were below 20% at the end of day 1 (Fig. 10). On day 2, a rainfall of 5.8 mm increased the MC of CS placed in LD swaths to above 70% compared to 50% in HD swaths. The average air temperature was 13 °C between the two rainfall events which resulted in slower drying rates. Another rainfall event of 7.0 mm increased the MC to 70% in the LD swaths compared to 50–55% in the HD windrows. Soil moisture was high which prevented the telehandler from entering the field. Moisture was determined by the hand grab sampling method and some differences were also observed between replications due to

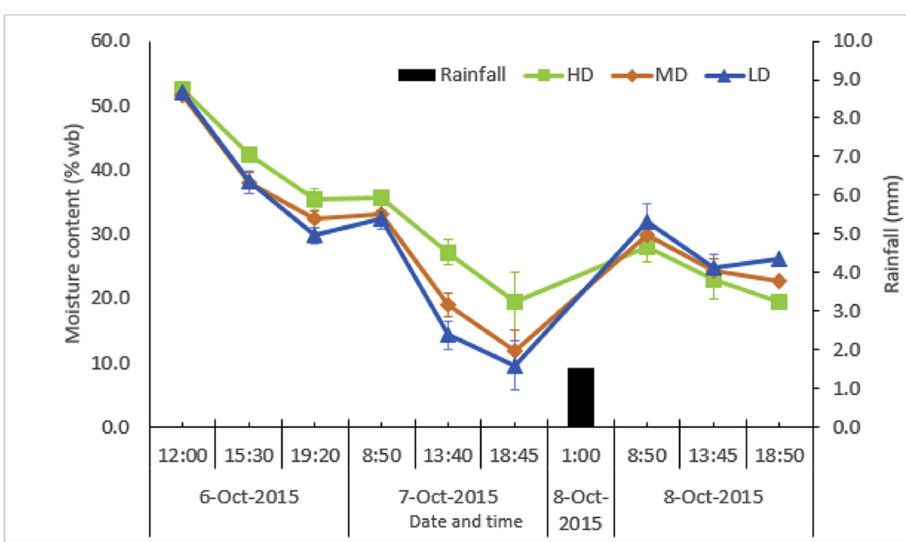

Fig. 8 – Moisture variation with standard error bars in low (LD), medium (MD) and high density (HD) trays of switchgrass during field drying in Ithaca, NE (Trial 4).

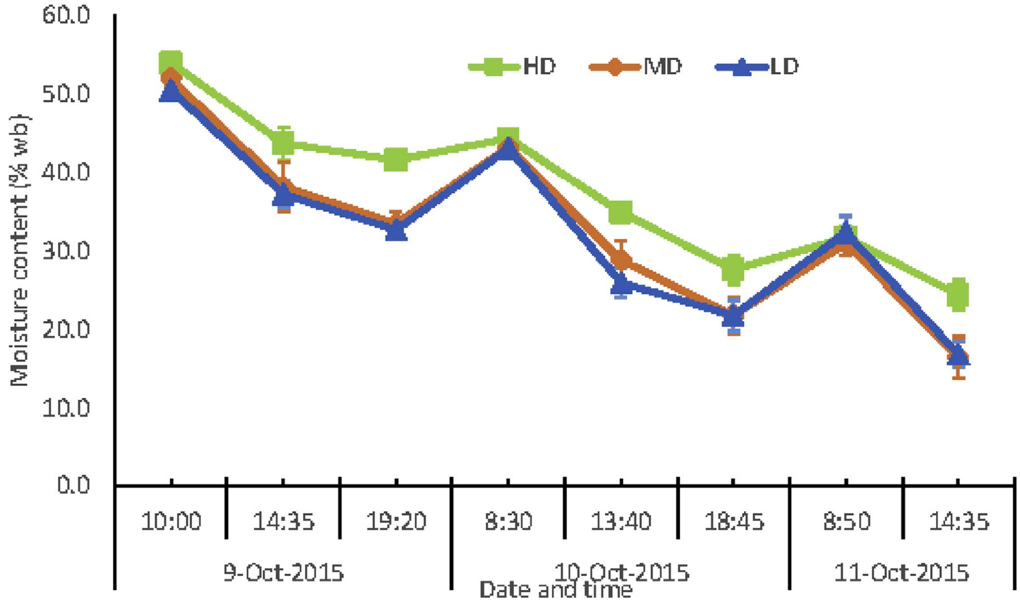

Fig. 9 – Moisture variation with standard error bars in low (LD), medium (MD) and high density (HD) trays of switchgrass during field drying in Ithaca, NE (Trial 5).

variation caused by rainfall. The hand grab samples were collected from different locations of the swath compared to a single location while tray sampling which could increase the variation between replications.

During trial 9 of CS, an average temperature of 12 °C and an hourly day time radiation intensity of 271 W m^{-2} was recorded which was similar to conditions of trial 8 but different than trials 2 to 5 of switchgrass. On day 1, an average air temperature of 9.5 °C and an average radiation intensity of 313 W m^{-2} was observed and all the treatments reached a safe storage moisture of less than 18% by the end of the day. On day 2, rainfall of 7.0 mm was received which increased the MC of CS to 65–70% in LD swaths compared to 43–58% in the HD windrows (Fig. 11). Drying conditions were poor and samples were collected once a day at 16:00 h. On the fifth day after rainfall, a MC ranging from 16 to 36% between treatments was recorded.

Overall, depending on the environmental conditions, switchgrass dried to less than 20% in a 1.5–3-day drying period. Rainfall up to 7.4 mm during the drying period increased the drying time by a day and a half. However, drying time can be extended by several days if the drying conditions are not favourable after rainfall. In the case of CS after rainfall, most of the treatments did not reach a safe storage moisture of less than 20% after four days of field drying. Shinners et al. (2007) also reported that after rainfall when the average temperature was 5 °C, CS did not reach a safe storage MC after 15 days of field drying. Under these conditions, the environment becomes a constraint and the crop will not dry to a safe storage moisture even if it is conditioned or dried in LD or MD swaths. Being unconditioned might have helped switchgrass to resist moisture uptake during low rainfall or low VPD conditions. However, a rainfall event of 7.4 mm increased the MC of switchgrass in the

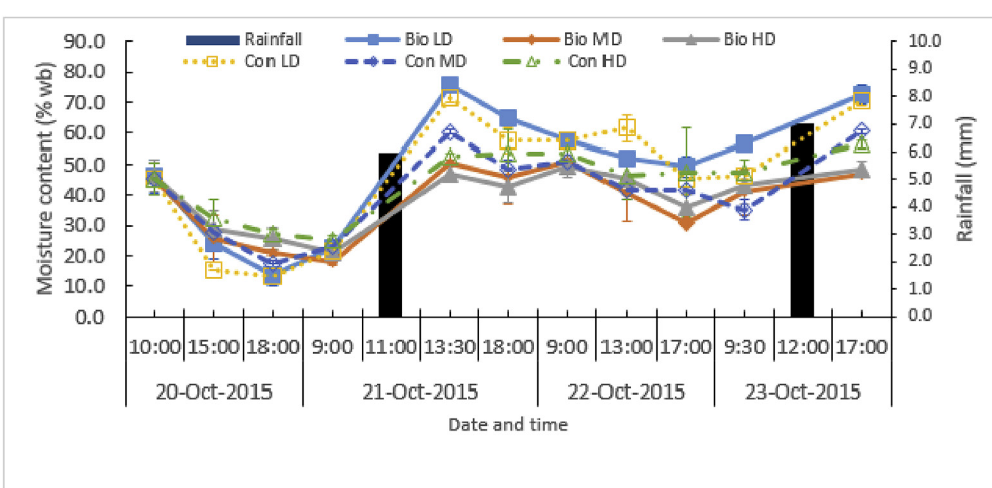

Fig. 10 – Moisture variation with standard error bars in low (LD), medium (MD) and high density (HD) trays of maize stover harvested by conventional (con) and biomass (bio) methods during field drying in Boone, IA (Trial 8).

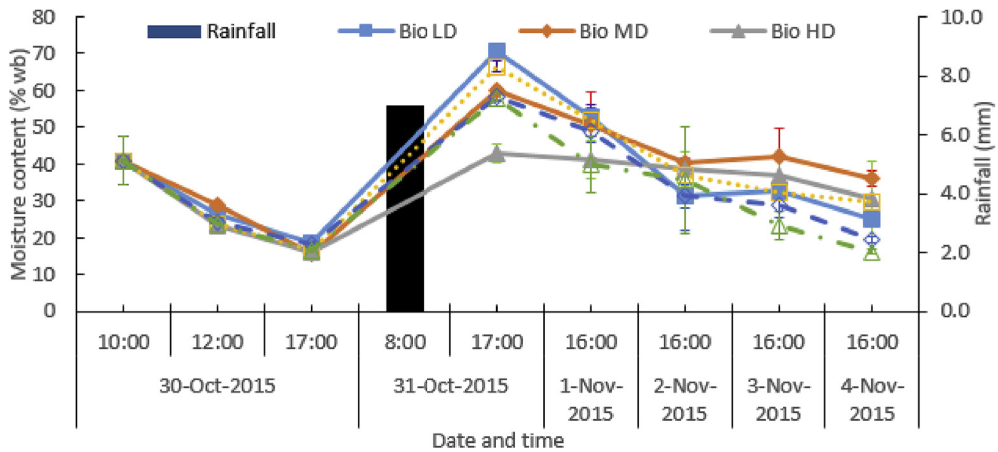

Fig. 11 – Moisture variation with standard error bars in low (LD), medium (MD) and high density (HD) trays of maize stover harvested by conventional (con) and biomass (bio) methods during field drying in Boone, IA (Trial 9).

LD swaths by up to 68% (Fig. 7). CS being highly conditioned reached a MC of up to 76% and was saturated with water after 6–7 mm of rainfall. Similar moisture uptake up to 68% was observed for shredded CS by Shinners et al. (2007). Low initial MC at harvest and being highly conditioned helped CS to reach safe storage moisture in 1–2 days even in moderate drying conditions before rainfall. Under moderate drying conditions, drying in the LD and MD swaths was helpful to reduce the moisture quickly compared to HD windrows. However, HD windrows also showed a benefit by gaining less moisture during rainfall as well as low VPD conditions at night which helped in achieving drying times similar to the LD and MD swaths in some cases. The amount of moisture gain due to rainfall or dew at night also depends on the MC of the crop before the rainfall event. Crops at later stages of drying gain more moisture after rainfall than crops at early stages of drying. A significant moisture gain due to dew was observed in the early morning samples of switchgrass and CS. Depending on the duration of dew and swath density, morning moisture was up to 15% higher than the previous evening moisture. However, dew moisture was lightly adsorbed on the surface and dried quickly before afternoon readings.

3.2. *Random forest models to predict MC of switchgrass and maize stover*

The parameters and results of RF model are shown in Table 2. In this study, the number of trees in the forest (N_{tree}) and the number of variables tried at each split (M_{try}) were set and optimised to 200 and 2 for switchgrass and 200 and 7 for CS, respectively. A root mean square error (RMSE) and R^2 value of 5.79% and 0.77 for switchgrass and 6.54% and 0.79 for CS, respectively were obtained when the model was fitted to the data.

Table 2 – Parameters and results of the RF model.

Crop	Model parameters		Model results	
	N_{tree}	M_{try}	RMSE (% wb)	R^2
Switchgrass	200	2	5.80	0.77
Maize stover	200	7	6.58	0.79

N_{tree} is the number of trees in the forest, M_{try} is the number of variables tried at each split, RMSE is the root mean square error.

The program used for RF model development is given in Supplementary material (File S1). The field drying data set for CS and switchgrass is also provided in Supplementary material as File S2 and File S3, respectively. For future moisture content prediction of switchgrass and CS, the same R program given in Supplementary material (File S1) can be utilised. The weather conditions for the unknown MC data can be arranged similarly, as that arranged in known datasets (File S2 and S3 of Supplementary material). The R program uses the dataset File S2 and S3 to predict MC of CS and switchgrass, respectively, for unknown or forecasted weather conditions.

3.3. *Validation of random forest models*

The performance of RF models was tested by splitting the switchgrass and maize stover data randomly into a test and a validation set. For switchgrass, 80% of the data was used for model development and 20% was used for model validation. Similarly, 70% of the CS field drying data was used for model development and 30% was used for validation. The results of validation are presented below in Figs. 12 and 13 for switchgrass and CS, respectively. A perfectly fitted model will have an R^2 value of 1, slope of 1, and intercept of 0 (Wright et al., 2001). In the case of switchgrass, an R^2 value of 0.76, a slope of 1.024 and an intercept of 0.75 was achieved. Some error might have occurred during the experimental field readings as well as model development. When the trays were lifted for measurement in windy conditions, some material was blown from the trays which might have contributed to the error. A root mean square error of 6.37% and 6.66% in moisture content was obtained while predicting the MC of the validation set for switchgrass and CS, respectively.

3.4. *Variable importance*

The measured importance of the predictor variables derived from the RF model for switchgrass and CS are given in Figs. 14 and 15, respectively. Hours after harvest (HAH) was the most

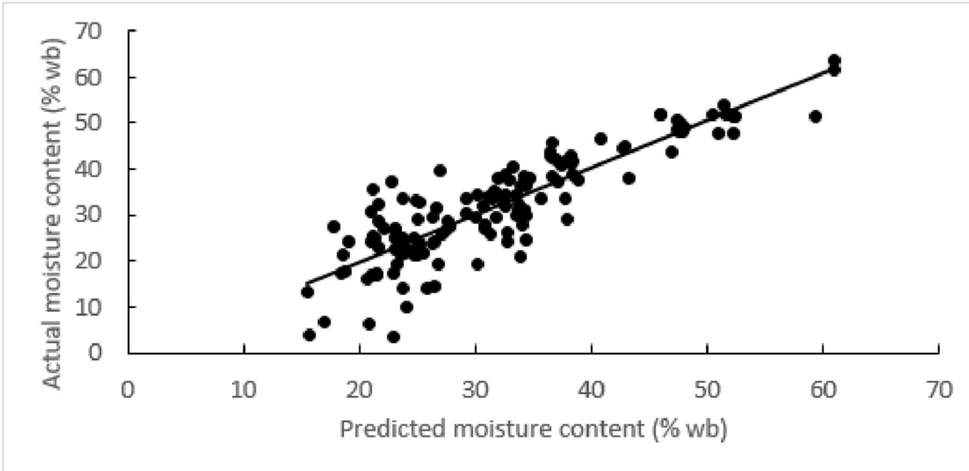

Fig. 12 – Plot between predicted vs actual moisture content of switchgrass. The line is the regression equation (y = 1.024x − 0.7463) between actual and predicted moisture content with an R^2 of 0.76.

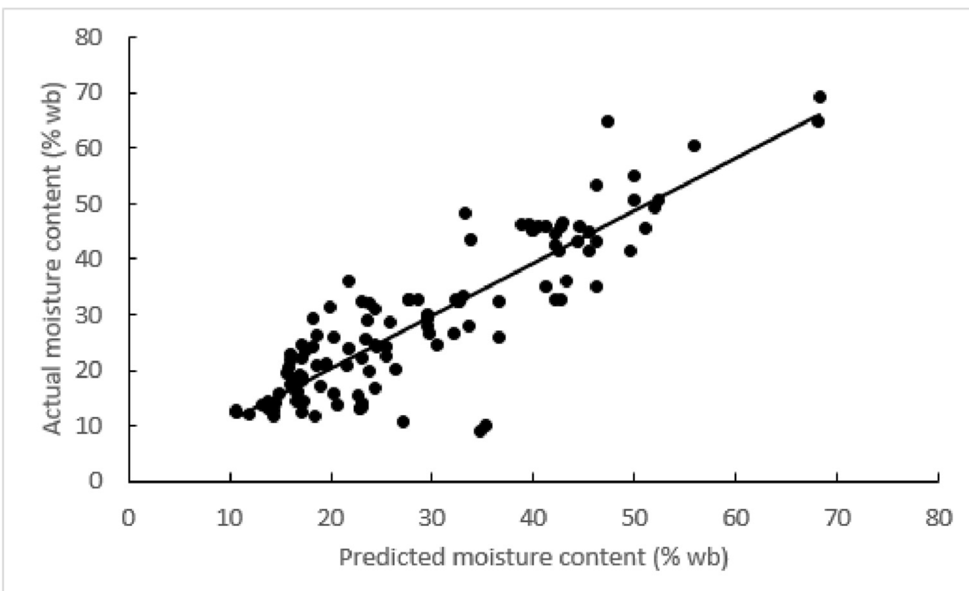

Fig. 13 – Plot between predicted vs actual moisture content of maize stover. The line is the regression equation (y = 0.9479x + 1.4502) between actual and predicted moisture content with an R^2 of 0.77.

important variable to explain the variation in moisture content of switchgrass. As expected under favourable weather conditions, an increase in drying time reduces the MC of the crop. Environmental variables of solar radiation, wind speed, and VPD were next in importance with minor differences between each other. Solar radiation has also been reported to be the most important environmental variable in the drying of other crops (Khanchi & Birrell, 2017a; Rotz & Chen, 1985; Wright et al., 2000).

In case of CS, rainfall was the most important variable explaining the variation in MC. CS, being extensively conditioned during harvest, was more severely affected by rainfall than switchgrass. The open or exposed tissues of CS due to conditioning gained more moisture during the rainfall event than unconditioned switchgrass. After harvesting, CS also collapsed into a dense swath, compared to the airy structure of switchgrass, which helped in the quick drying of switchgrass. Additionally, environmental conditions experienced during CS drying after rainfall were not favourable compared to switchgrass during the experiments which resulted in little effect of rainfall on switchgrass compared to CS. All these factors increased the importance of rainfall in the case of CS compared to switchgrass. HAH was the second most important variable for CS and had nearly the same importance as rainfall. From the environmental variables, solar radiation was more important than VPD and wind speed. During CS

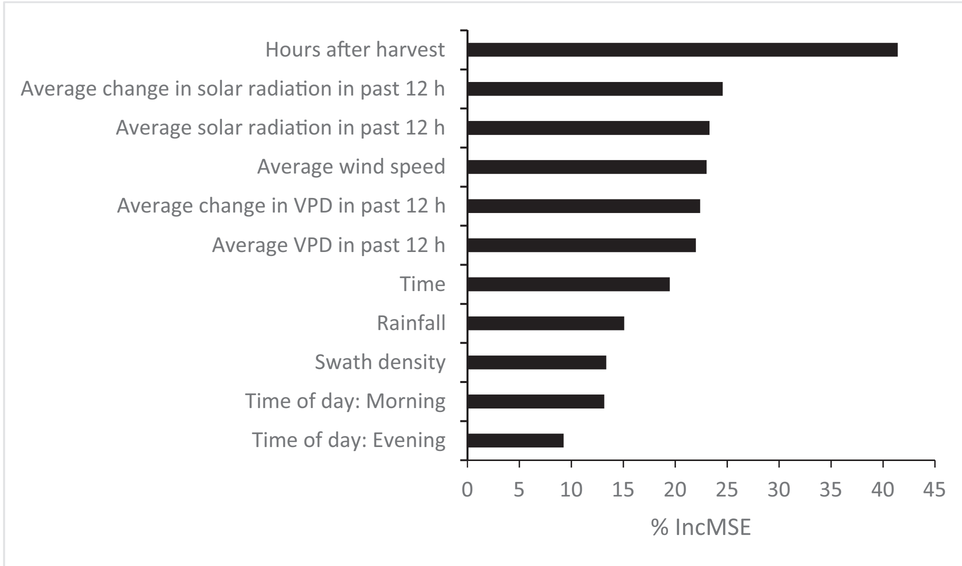

Fig. 14 – Variable importance derived from random forest model for estimating the moisture content of switchgrass. VPD: vapour pressure deficit, Average change in VPD and solar radiation in past 12 h calculated from equation: ***Change in past 12 h*** $= \frac{Value_t - Value_{t-12}}{12}$.

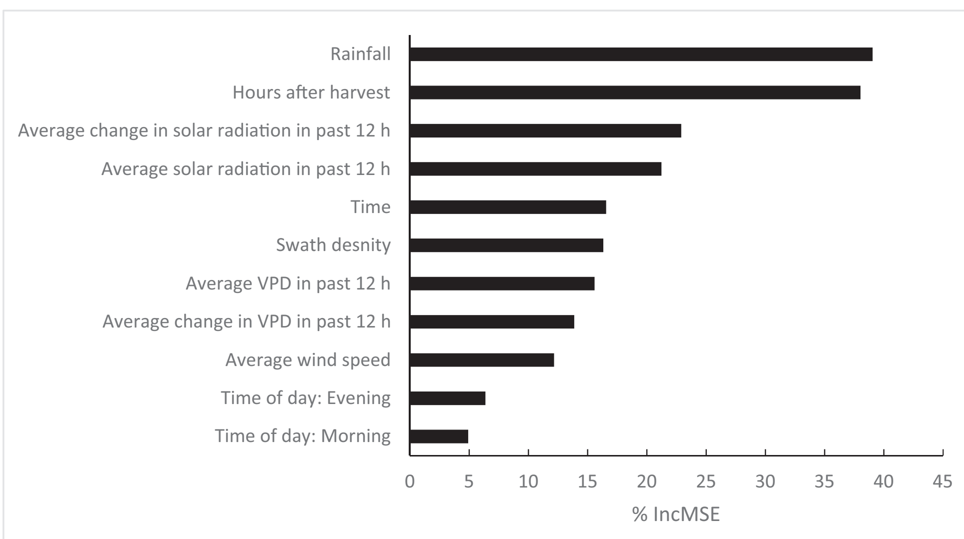

Fig. 15 – Variable importance derived from random forest model for estimating the moisture content of maize stover. VPD: vapour pressure deficit, Average change in VPD and solar radiation in past 12 h calculated from equation: ***Change in past 12 h*** $= \frac{Value_t - Value_{t-12}}{12}$.

harvest (late October and early November), low VPD conditions were observed which decreased the importance of VPD and wind speed compared to switchgrass (mid September to mid October). Interestingly, swath density had more positive effect on CS drying than was found for switchgrass. Due to favourable drying conditions during switchgrass harvesting period, all density treatments dried at a faster rate reducing the importance of density. However, during CS drying, high density treatments did not reach a safe storage moisture after rainfall events showing the importance of drying in low density swaths during unfavourable weather conditions.

The regression tree structure generated by the CART model for moisture content prediction of switchgrass and CS is given in Figs. 16 and 17, respectively. The CART model also indicated that HAH and rainfall were the most important factors influencing the MC of switchgrass and CS, respectively. The starting node in the switchgrass regression tree structure (Fig. 16) gives the mean MC of 32.4% from 694 observations (N). The first split in MC data was based on the most important variable, HAH and was divided into observations greater than or equal to 22.3 h (resulting in mean MC of 22.4% from 348 observations) and less than 22.3 h (resulting in mean MC of

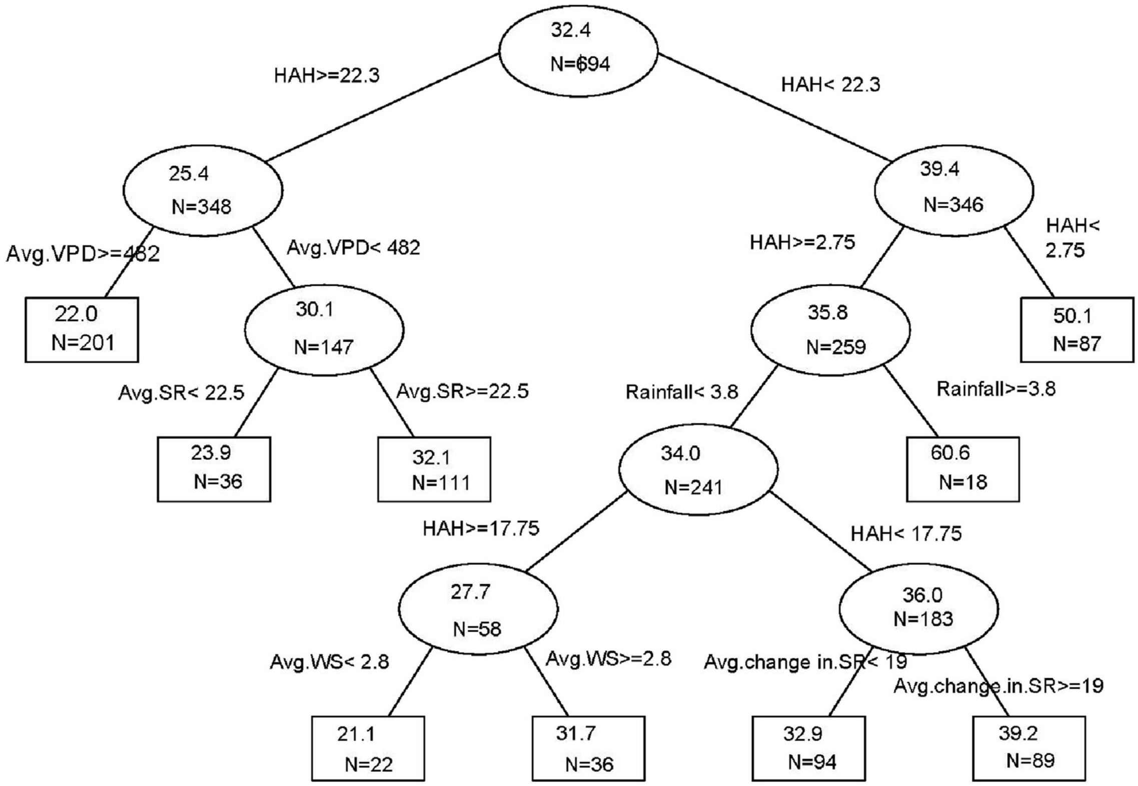

Fig. 16 – Regression tree structure for moisture content estimation of switchgrass using environmental variables. HAH: Hours after harvest, Rainfall (mm), Avg. change in VPD and Avg. change in SR: Average change in vapour pressure deficit and solar radiation, respectively in past 12 h given by equation, $Change\ in\ past\ 12\ h = \frac{Value_t - Value_{t-12}}{12}$, Avg. WS: Average wind speed ($m\ s^{-1}$), Avg. SR and Avg. VPD: Average solar radiation and average vapour pressure deficit in past 12 h, respectively.

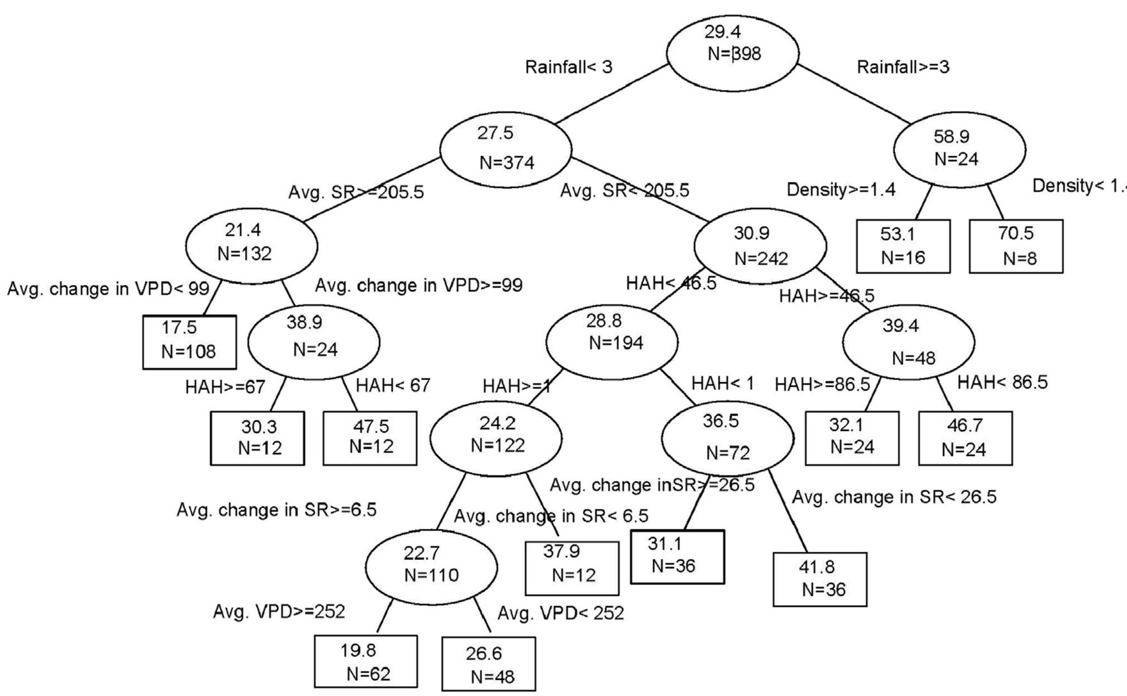

Fig. 17 – Regression tree structure for moisture content estimation of maize stover using environmental variables. HAH: Hours after harvest, Rainfall (mm), Avg. change in VPD and Avg. change in SR: Average change in vapour pressure deficit and solar radiation, respectively in past 12 h given by equation, $Change\ in\ past\ 12\ h = \frac{Value_t - Value_{t-12}}{12}$, Avg. WS: Average wind speed ($m\ s^{-1}$), Avg. SR and Avg. VPD: Average solar radiation and average vapour pressure deficit in past 12 h, respectively.

39.4% from 346 observations). Each node was further divided based on the next important variable for that split and gave the resulting mean MC of observations in the rectangular box at the end. This graphical splitting of data by CART model gives the advantages of visually identifying the threshold values, important variables, and the expected range of MC for different environmental conditions.

In our past studies, we found that increase in wind speed did not always increase the drying rate of crops (Khanchi & Birrell, 2017a; Khanchi et al., 2013). At high radiation intensity, the wind speed and solar radiation were inversely related, contrary to what one might expect. At high intensities, increasing the wind speed carried away part of the heat generated by solar radiation. However, at low and medium radiation intensities, increasing the wind speed improved the drying rates. Therefore, if we are presenting the model as MLR, the interaction term will be positive or negative which means that it will either improve the drying rate or decrease the drying rate. When the interaction term is negative, and we are calculating for low radiation and high wind conditions, during which the interaction should have a positive effect on drying rate will be shown as negative. Whereas, classification-based models such as RF will provide a response based on the radiation intensity rather than always giving a positive or negative effect on the dependent variable. At low or medium radiation intensities, air temperature also plays a role as increasing the wind speed has little to no effect on crop drying if the air temperature is below a certain value. Therefore, MLR models are not capable of handling all these complex interactions of weather conditions. If we use MLR to predict nonlinear relationships the error in prediction is higher than classification-based models, which is the reason for using it in this study. In other studies, RF models also provided superior results with lower error indices than MLR when environmental data was predicted with both modelling techniques (Chagas, Junior, Bhering, & Filho, 2016; Guo et al., 2015; Zhang et al., 2017). Another advantage of RF models over MLR is that the RF provides relative importance of variables, unlike MLR, in which only highly correlated predictive variables are used in the model through stepwise selection (Chagas et al., 2016).

4. Conclusions

A new classification-based algorithm on decision trees called Random Forest was used to predict MC of switchgrass and CS. Due to the superiority of RF models to handle nonlinear data, a satisfactory RMSE and correlation coefficients were achieved for both CS and switchgrass when the model was fitted to independent data. Variable importance was also evaluated and out of environmental conditions, solar radiation was the most important factor for both CS and switchgrass field drying. Solar radiation was also the most important factor in several lab and field drying studies of crops. Due to extensive conditioning during harvest, rainfall had a significant impact on MC modelling of CS. When compared to switchgrass, CS absorbed more moisture at a similar amount of rainfall suggesting that CS should be raked to a higher density when rainfall is expected. VPD was the third most important environmental variable after solar radiation and rainfall which was similar to the results when CS was dried in lab conditions (Khanchi & Birrell, 2017a). From the field observations, it can be concluded that switchgrass and CS should be dried in LD or MD swaths under moderate weather conditions to quickly bring the moisture to a safe storage level. Under good drying conditions, drying differences between LD, MD, and HD swaths were minimal. Further analysis is required to evaluate if the field operations such as tedding to spread the crop are economic.

Acknowledgements

We would like to acknowledge the financial support from the CenUSA Bioenergy project funded by Agriculture and Food Research Initiative Competitive Grant No. 2011-68005-30411 from the USDA National Institute of Food and Agriculture. We also would like to acknowledge the assistance offered by Ethan Thies, Zach Buscher, Harishchandra Jadhav, Jordan Leach, Ben Fann, and Bill Bickmeier for assisting in weighing of trays and field experiments.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.biosystemseng.2018.02.002.

REFERENCES

Acheampong, M., Ertem, F. C., Kappler, B., & Neubauer, P. (2017). In pursuit of sustainable development goal (SDG) number 7: Will biofuels be reliable? *Renewable and Sustainable Energy Reviews, 75*, 927–937.

ASAE. (2003). *ASAE standard S358.2 moisture measurement-forages*. St. Joseph, MI, USA: American Society of Agricultural and Biological Engineers.

Atzema, A. J. (1992). A model for the drying of grass with realtime weather data. *Journal of Agricultural Engineering Research, 53*, 231–247.

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32.

Brokamp, C., Jandarov, R., Rao, M. B., LeMasters, G., & Ryan, P. (2017). Exposure assessment models for elemental components of particulate matter in an urban environment: A comparison of regression and random forest approaches. *Atmospheric Environment, 151*, 1–11.

Cánovas-García, F., Alonso-Sarría, F., Gomariz-Castillo, F., & Oñate-Valdivieso, F. (2017). Modification of the random forest algorithm to avoid statistical dependence problems when classifying remote sensing imagery. *Computers & Geosciences, 103*, 1–11.

Carneiro, M. L. N. M., Pradelle, F., Braga, S. L., Gomes, M. S. P., Martins, A. R. F. A., & Turkovics, F. (2017). Potential of biofuels from algae: Comparison with fossil fuels, ethanol and biodiesel in Europe and Brazil through life cycle assessment (LCA). *Renewable and Sustainable Energy Reviews, 73*, 632–653.

Chagas, C. D. S., Junior, W. D. C., Bhering, S. B., & Filho, B. C. (2016). Spatial prediction of soil surface texture in a semiarid region using random forest and multiple linear regressions. *Catena, 139*, 232–240.

Chen, M., & Smith, P. M. (2017). The U.S. cellulosic biofuels industry: Expert views on commercialization drivers and barriers. *Biomass and Bioenergy, 102*, 52–61.

Dyer, J. A., & Brown, D. M. (1977). A climatic simulator for field-drying hay. *Agricultural Meteorology, 18*(1), 37–48.

Gao, H. (2009). *Digital analysis of remotely sensed imagery*. McGraw-Hill.

Grimm, R., Behrens, T., Märker, M., & Elsenbeer, H. (2008). Soil organic carbon concentrations and stocks on Barro Colorado Island — digital soil mapping using Random Forests analysis. *Geoderma, 146*(1–2), 102–113.

Guo, P. T., Li, M. F., Luo, W., Tang, Q. F., Liu, Z. W., Lin, Z. M., et al. (2015). Digital mapping of soil organic matter for rubber plantation at regional scale: An application of random forest plus residuals kriging approach. *Geoderma, 237–238*, 49–59.

Hayhoe, H. N., & Jackson, L. P. (1974). Weather effects on hay drying rates. *Canadian Journal of Plant Science, 54*(3), 479–484.

Kemp, J. G., Misener, G. C., & Roach, W. S. (1972). Development of empirical formulae for drying of hay. *Transactions of ASAE, 15*(4), 723–725.

Khanchi, A., & Birrell, S. (2017a). Drying models to estimate moisture change in switchgrass and corn stover based on weather conditions and swath density. *Agricultural and Forest Meteorology, 237–238*, 1–8.

Khanchi, A., & Birrell, S. J. (2017b). Effect of rainfall and swath density on dry matter and composition change during drying of switchgrass and corn stover. *Biosystems Engineering, 153*, 42–51.

Khanchi, A., Jones, C. L., Sharma, B., Huhnke, R. L., Weckler, P., & Maness, N. O. (2013). An empirical model to predict infield thin layer drying rate of cut switchgrass. *Biomass and Bioenergy, 58*, 128–135.

Kim, S., & Dale, B. E. (2004). Global potential bioethanol production from wasted crops and crop residues. *Biomass and Bioenergy, 26*(4), 361–375.

Manstretta, V., & Rossi, V. (2015). Modelling the effect of weather on moisture fluctuations in maize stalk residues, an important inoculum source for plant diseases. *Agricultural and Forest Meteorology, 207*, 83–93.

McGechan, M. B., & Cooper, G. (1995). A simulation model operating with daily weather data to explore silage and haymaking opportunities in climatically different areas of Scotland. *Agricultural Systems, 48*(3), 315–343.

Perlack, R. D., & Stokes, B. J. (2011). U.S. Billion ton update: Biomass supply for a bioenergy and bioproducts Industry. In *U.S. D.o. Energy* (p. 227). Oak Ridge, TN: Oak Ridge National Laboratory.

Popp, M. P., Searcy, S. W., Sokhansanj, S., Smartt, J. B., & Cahill, N. E. (2015). Influence of weather on the predicted moisture content of field chopped energy sorghum and switchgrass. *Applied Engineering in Agriculture, 31*, 179–190.

R Core Team. (2017). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Rossel, R. A. V., & Behrens, T. (2010). Using data mining to model and interpret soil diffuse reflectance spectra. *Geoderma, 158*(1–2), 46–54.

Rotz, C. A., & Chen, Y. (1985). Alfalfa drying model for the field environment. *Transactions of ASAE, 28*(5), 1686–1691.

Shinners, K. J., Binversie, B. N., Muck, R. E., & Weimer, P. J. (2007). Comparison of wet and dry corn stover harvest and storage. *Biomass and Bioenergy, 31*(4), 211–221.

Shinners, K. J., Boettcher, G. C., Muck, R. E., Weimer, P. J., & Casler, M. D. (2010). Harvest and storage of two perennial grasses as biomass feedstocks. *Transactions of ASABE, 53*(2), 359–370.

USDOE. (2017). *Integrated biorefineries*. https://www.energy.gov/eere/bioenergy/integrated-biorefineries. (Accessed 13 July 2017).

Womac, A. R., Igathinathane, C., Sokhansanj, S., & Pordesimo, L. O. (2005). Biomass moisture relations of an agricultural field residue: Corn stover. *Transactions of ASAE, 48*, 2073–2083.

Wright, D. A., Frost, J. P., & Kilpatrick, D. J. (2000). The influence of weather factors on the drying rate of cut perennial ryegrass herbage under controlled conditions. *Grass and Forage Science, 55*(4), 331–342.

Wright, D. A., Frost, J. P., Patterson, D. C., & Kilpatrick, D. J. (2001). PA–Precision Agriculture: Development of a model to predict drying Rates of cut ryegrass. *Journal of Agricultural Engineering Research, 79*, 23–35.

Yu, M., Igathinathane, C., Hendrickson, J., & Sanderson, M. (2014). Moisture sorption kinetics of switchgrass, big bluestem, and bromegrass biomass. *Transactions of ASABE, 57*(4), 1219–1230.

Zamorano, M., Popov, V., Rodríguez, M. L., & García-Maraver, A. (2011). A comparative study of quality properties of pelletized agricultural and forestry lopping residues. *Renewable Energy, 36*(11), 3133–3140.

Zhang, H., Wu, P., Yin, A., Yang, X., Zhang, M., & Gao, C. (2017). Prediction of soil organic carbon in an intensively managed reclamation zone of eastern China: A comparison of multiple linear regressions and the random forest model. *The Science of the Total Environment, 592*, 704–713.