Bulgarian Journal of Agricultural Science, 20 (No 6) 2014, 1289-1294
Agricultural Academy

EFFECT OF TEMPERATURE ON MOISTURE SORPTION ISOTHERMS AND MONOLAYER MOISTURE CONTENT OF BERMUDA GRASS (*CYNODON DACTYLON)*

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Abstract

AL-MAHASNEH, M., F. ALKOAIK, A. KHALIL, R. FULLEROS and A. EL-WAZIRY, 2014. Effect of temperature on moisture sorption isotherms and monolayer moisture content of bermuda grass (*Cynodon dactylon)*. *Bulg. J. Agric. Sci*., 20: 1289-1294

Bermuda grass is widely grown in Saudi Arabia as a turf grass. It is highly tolerant to drought and hot weather. It can be compressed to form pellets, which can be used as livestock, or energy pellets similar to charcoals. Drying is required to process the grass into a safe storage condition. Moisture sorption isotherms are required to design and optimize the drying process of the grass. Therefore, moisture sorption isotherms were studied using gravimetric methods at temperatures ranging from 20 to 40°C. Both conventional analytical moisture sorption isotherms (MSI) and artificial neural networks (ANNs) were used to model the relationship between equilibrium moisture content (EMC) and equilibrium relative humidity (ERH). The results showed that Modified Halsey equation was the best representative of MSIs. However, ANNs were also found to outperform MSI analytical models with $R^2 = 0.991$ and a root mean square error (RMSE) = 1.17. Monolayer moisture content was also found to decrease linearly with EMC from 0.074 to 0.047 (decimal w.b.) over the temperature range investigated.

Key words: equilibrium relative humidity; drying; Bermuda grass; artificial neural networks

Introduction

Bermuda grass (*Cynodon dactylon*) is a fast-growing, popular turf grass widely grown in warm climates all over the world. It is used for recreational parks and sports fields. The grass is a highly suitable turf grass in Saudi Arabia due to its high tolerance to hot and dry conditions. Bermuda grass is available in large amounts from recreational sites and sport fields in Saudi Arabia. Due to the fluffy nature of this biomass, it is normally stored in open fields at ambient conditions. Loss of harvested grass due to the microbial bio-degradation and self-ignition resulting from internal heat developed in biomass represents a difficult problem. In addition, some allergic microbes are released into air at relatively high concentrations resulting in some potential health hazards. Bermuda grass can be used as a source of energy by direct incineration or after conversion into pellets where it can be used to replace conventional charcoals, or alternatively, it can be used as a feedstock either before or after drying (Jirjis, 1995; Çağlar, 2013).

Water content plays an important role in physical, biochemical and thermochemical conversion of biomass into fuel. Water content affects harvesting, transportation and storage of biomass. Biomass with higher water content results in higher transportation costs and higher char yield in pyrolysis (Jirjis, 1995; Hashemi et al., 2008; Singh, 2004; Arabhosseini et al., 2010). Storage and processing of dried biomass is easier and safer as compared to wet biomass. Water content plays an important role in deterioration of biomass during storage. It has been reported that a water content of 17.7% is needed for long-term storage of most biomass materials (Arabhosseini et al., 2010). A wide range of ambient temperatures and relative humidity affects biomass from har-

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vesting to final storage. Establishing the relationship between temperature and relative humidity is of great importance for determining the best handling, drying and storage practices that best preserve biomass quality and value. Biomass can easily adsorb or desorbs humidity due to their hygroscopic nature (Singh, 2004). The ability of a material to gain or lose humidity is determined by equilibrium moisture content (EMC). In addition to environmental temperature and humidity, EMC of a biomass depends on agronomic factors such as species, type and maturity, physical parameters such as specific surface area, porosity, feedstock to wood ratio and microstructure (Chakraverty, 1981; Arslan and Togrul, 2005; Krupin´ et al., 2007) and type of post-treatments such as harvesting and grinding (Moreno et al., 2004).

Bermuda grass has high initial moisture content, which makes it largely susceptible to fast deterioration especially in a relatively hot environment such as Saudi Arabia. Drying is therefore, required for proper handling and use of the grass. Drying of agricultural commodities is an energy intensive process, due to the strong binding between water and solid particles. Therefore, it requires a considerably high amount of energy. Drying of low value commodities such as grass can be costly and unfeasible. A detailed analysis of water sorption isotherms of Bermuda grass will therefore be required to optimize the drying operation. The objectives of this study were:

- To investigate the moisture sorption isotherms of Bermuda grass over a temperature range between 20 and 40°C, which covers the normal handling and processing temperature period?
- To compare between conventional analytical methods and neural network to model MSIs of Bermuda grass.

Materials and Methods

Sample preparation

Bermuda grass samples were collected from local Riyadh area recreational parks (Riyadh, Saudi Arabia). Samples were dried in oven at 105°C to final moisture of 6% (w. b.). The dried samples were ground using a hammer mill using a 4 mm sieve. The ground material was stored in 2 l sealed plastic bags at 4°C inside a refrigerator until further use. Moisture content of the samples were measured based on the ASABE Standard method for forage (ASAE, 2003).

Experimental procedure

Moisture sorption characteristics were determined using the static gravimetric method, where 0.5 g of the ground samples were placed in an aluminum cup inside a glass desiccators with seven saturated salt solutions with ERH values ranging from 8 to 90% (Table 1). A laboratory grade salt solution stocks were prepared by adding distilled water to the required salt until saturation. Biomass samples were kept above the saturated salt solution. Relative humidity was held constant by assuring a slightly oversaturated salt solution. All samples were placed inside a thermostatic chamber to maintain a constant temperature. Three temperatures representing the handling and storage temperature range were used: 20, 30 and 40°C. The samples were regularly weighed until weight became constant (less than 0.0001 g). All measurements were obtained in triplicates.

Modeling moisture sorption

Five common isotherm models adopted by the ASAE standard D245.5 (ASAE, 1996) were used in this study: modified Chung-Pfost model, modified GAB model, modified Halsey model, modified Henderson model and modified Oswin model. The models selected for this study are presented in Table 2. In addition to the above conventional analytical models, a feed forward artificial neural network (FF-ANN) with back propagation algorithm was also used to predict equilibrium relative humidity of Bermuda grass. The results obtained from analytical models and artificial neural networks were compared.

Table 1
Equilibrium relative humidity (ERH) of the seven saturated salt solutions used

Saturated salt solution	Chemical formula	ERH, %		
		40°C	30 °C	20 °C
Sodium Hydroxide	NaOH	8.9	7.6	6.3
Magnesium chloride	$MgCl_2$	33	32.4	31.6
Potassium carbonate	K_2CO_3	43.2	43.2	41
Sodium bromide	NaBr	59.1	57.3	56
Potassium Iodide	KI	69.9	67.9	69.1
Potassium Chloride	KCl	86	84	83
Barium Chloride	BaCl	89	89	89

Statistical Analysis

Non-linear regression analysis was used to find parameter estimates of the MSI models selected. SAS PROC NLIN version 9.2 was used for this purpose (SAS Institute Inc, Cary, NC). PROC NLIN is a regression procedure that uses the cost minimization function (least square difference between measured and predicted EMC) to obtain parameter estimates. The procedure is an iterative technique based on Gauss-Newton method or similar algorithms to achieve minimization. The model inputs were ERH and temperature and the output was the corresponding measured EMC of the grass samples. In addition to conventional analytical MSI models, an artificial neural network analysis was performed using SPSS (ver.18, SPSS Inc., IL), where ERH and temperature were used as network inputs and EMC was assigned to the network output. Adequacy of each model used was examined by using three statistical parameters, the standard error of parameters estimates (SE), which provide information about the accuracy of model parameters estimates, mean square error (MSE) which provides a measure of overall model error and the coefficient of determination (R^2), which provides information about the goodness of fit for each model as follows:

$$SE = \sqrt{\frac{\sum\left(Y-\overline{Y}\right)^2}{df}} \tag{1}$$

$$MSE = \frac{1}{n}\sum\left(Y-\overline{Y}\right)^2 \tag{2}$$

$$R^2 = 1-\frac{ESS}{TSS} \tag{3}$$

where: Y and $\overline{Y}$ are the observed and predicted EMC in % (w. b.), n is the number of observations, df is the degrees of freedom (number of observations minus the number of model parameters) and ESS and TSS are the error and total sum of squares, respectively.

Monolayer moisture content (M_m) can also be obtained by applying a linearized form of the modified BET equation for ERH values below 0.45 as follows:

Table 2

Five common isotherms equations and one neural network model used for estimating equilibrium moisture content

Model name	Equation
Modified Chung-Pfost	$M = \frac{-1}{C}\, h\left[\frac{(ERH)(T+B)}{-A}\right]$
Modified GAB	$M = \frac{A\left(\frac{C}{T}\right)B*ERH}{(1-B*ERH)\left(1-B*ERH+\left(\frac{C}{T}\right)B*ERH\right)}$
Modified Halsey	$M = \left[\frac{-\exp(A+BT)}{ln\,(ERH)}\right]^{\left(\frac{1}{C}\right)}$
Modified Henderson	$M = \left[\frac{h\,(1-ERH)}{-A(T+B)}\right]^{\left(\frac{1}{C}\right)}$
Modified Oswin	$M = (A+BT)\left[\frac{ERH}{1-ERH}\right]^{\left(\frac{1}{C}\right)}$
Sigmoid function (Neural Network)	$Y = \frac{1}{1+e^{-x}}$

Where: M- moisture content, % db; ERH-equilibrium relative humidity (decimal); T-temperature °C; A, B and C are constants.

$$\left(\frac{ERH}{(1-ERH)(EMC)}\right)=\frac{1}{M_m}+\left[\frac{(C-1)ERH}{(C)M_m}\right], \qquad (4)$$

where A, B and C are model constants and M_m is the monolayer moisture content (% w. b.).

Results and Discussion

Moisture sorption isotherms of bermuda grass

The measured EMC values for Bermuda grass at different ERH and temperatures are shown in Figure 1. It can be observed that the relationship between EMC and ERH followed type II (sigmoidal curve) isotherms for all temperatures (Arabhosseini et al., 2010). The highest and lowest EMC were 27.7 and 2.37% (w. b.) corresponding to the combination of 20°C with 0.884 ERH and 40°C with 0.063 ERH, respectively. The type II isotherm observed suggested that sorption occurred according to a multi-layer mechanism through ought equilibrium relative humidity range. The effect of temperature observed as a slight decrease in moisture content with the increase in temperature at constant equilibrium relative humidity can be attributed to the decrease in water molecules binding strength at the water-solid interface. The temperature increase can cause a reduction of the number of active moisture binding sites, which can be attributed to the decreased attraction forces between water and binding sites at higher temperatures leading to lower equilibrium moisture content. Hossain et al. (2001), reported that as temperature increases, water molecules move to higher energy levels, which cause them to break away from water binding sites on solid particles. Larger water binding forces are usually associated with higher requirements of drying energy, but it is also associated with faster spoilage due to the availability of greater free water fraction that can be used by various spoilage microbes. A safe ERH for perishable materials would be less than 0.6, which is equivalent to an EMC of about 8 to 10% (Figure 1). Similar trends were observed for corn stover (Igathinathane et al., 2008), flax straw, hemp stalk, reed canary grass (Nilsson et al., 2005), and switch grass and prairie cord grass (Karunanithy et al., 2013).

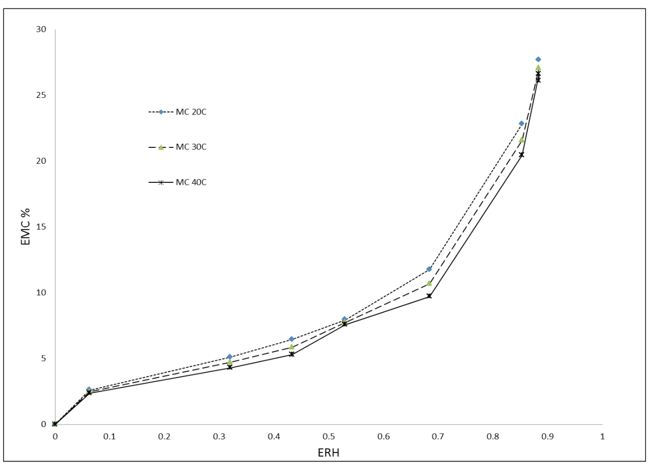

Fig. 1. Moisture sorption isotherms of Bermuda grass using Halsey model

Fitting of Isotherm Using Analytical Models and ANNs

The results of isotherm models fit are shown (Table 3). Out of the five models used, only modified Halsey and modified Oswin models were found to yield satisfactory results as observed by overall mean square error (MSE), coefficient of determination (R^2) and parameters standard error of estimates (SE). The results from the other three models were unsatisfactory and therefore were not included. The results showed that modified Halsey model has slightly outperformed modified Oswin model with MSE and R^2 of 2.18 and 0.973 compared to 2.5 and 0.969, respectively. Artificial neural network (ANN) analysis was also performed. The network settings, architecture and output are shown in (Table 4). The table shows that input data were partitioned into training, validation and testing data sets. Training data were used to train the network, validation data set were used to prevent model over fitting and a testing data set was used as independent data to test model capability to predict new observations. The best ANN obtained had one hidden layer containing 5 neurons and a sigmoid activation function. A Scaled Conjugate Gradient (SCG) optimization algorithm with initial λ and σ corresponding to 0.0000005 and 0.005 was used. The ANN output showed that ERH and temperature were responsible for 90 and 10% of the variation in EMC values predicted by the network, respectively. Furthermore, overall R^2 and MSE were 0.989 and 1.17, respectively. A plot of ANN predicted versus observed EMC is shown in Figure 2. The plot showed a high correlation with R^2 = 0.991. The fitting performance obtained by ANN was slightly better than that obtained by applying the modified Halsey model because ANNs have better computational capabilities and flexibility, and can model the non-linear moisture sorption isotherms better. In addition, ANNs have the capabilities to cross-validate the results yielding better accuracy and reliability. The modified Halsey model, on the contrary, has the advantage of providing an explicit equation for the prediction of new unseen observations. While this can be done also with ANNs, it can be computationally expensive. The systematic error of residual plots in modified Halsey model, which propagated towards higher values of ERH, indicated that ANNs model was better since residuals plot from ANN appeared to be more random with a slight tendency to overestimate EMC especially at higher values. ANN model was therefore chosen as the best model to predict EMC.

Monolayer moisture content was obtained at different temperatures from Eq. 4. The results of M_m values were observed to decrease linearly with increase in temperature. It decreased from 0.074 (decimal w. b.) at 20°C to 0.047 (decimal w. b.) at 40°C. The linear decrease in M_m values observed with increase in temperature was due to the increased mobility of water particles on solid sorption sites. Water particles tend to leave the sorption sites as excitation energy increases because of temperature increase. Similar values and trends of M_m were reported for spices and corn fodder, but smaller values were observed for coffee and sunflower hulls (Menkov et al., 1999).

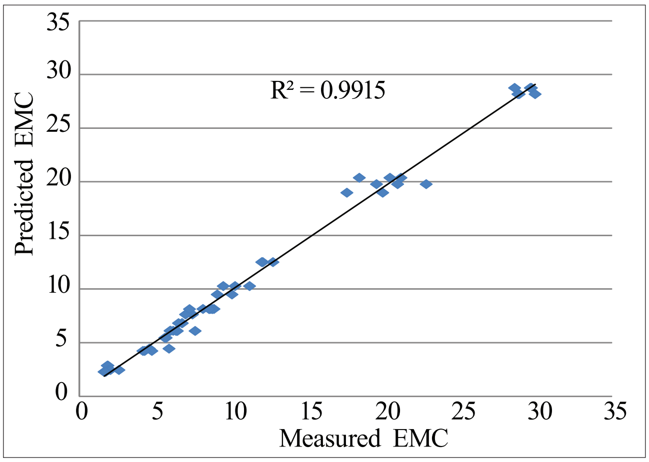

Fig. 2. Relationship between predicted and measured EMC for temperatures 20-40°C using ANN

Conclusion

Equilibrium moisture content for Bermuda grass was observed to decrease with increase in temperature at constant equilibrium relative humidity. Both conventional analytical moisture isotherms models and artificial neural networks

Table 4
Settings and architecture of feed forward artificial neural network

Parameter	Value
Input variables	ERH, Temperature
Output variable	EMC
Partition	
Training samples	35
Validation samples	13
Testing samples	8
Number of Hidden layers	1
Number of neurons	5
Activation function	Sigmoid
Dependent variable rescaling	Standardized
Training mode	Batch
Optimization algorithm	Scaled Conjugate Gradient
Initial λ	0.0000005
Initial σ	0.0005
Minimum relative error change	0.0001
Network Output	
Input variables importance	
ERH	90%
Temperature	10%
Mean Square Error	1.17
Overall R2	0.989
Residual type	random

Table 3
Fitted moisture sorption isotherms for Bermuda grass

Parameter	Modified Halsey	Modified Oswin
Constants		
A	1.76 (0.14)*	4.981 (0.470)
B	0.013 (0.002)	0.640 (0.013)
C	0.313 (0.040)	1.576 (0.054)
Performance Parameters		
MSE	2.178	2.502
R^2	0.973	0.969
Residuals	Systematic	Systematic

*Standard error of parameter estimate

were found to model the relationship between EMC and ERH well. ANNs, were found to yield a better model fit. Finally, the mono-layer moisture content was found to decrease linearly with increase in temperature. These information, provide a useful tool for the design and optimization of Bermuda grass post-harvest handling and drying operations.

Acknowledgments

The authors would like to thank the Deanship of Scientific research at King Saud University for funding the work through the research group project No. RGP-VPP-134.

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Received December, 17, 2013; accepted for printing, June, 2, 2014.