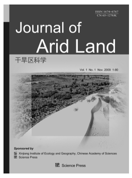
Science Press

Journal of Arid Land

2012, 4(3): 310–319

doi: 10.3724/SP.J.1227.2012.00310

jal.xjegi.com; www.chinasciencejournal.com



Measuring cotton water status using water-related vegetation indices at leaf and canopy levels

QiuXiang YI*, AnMing BAO, Yi LUO, Jin ZHAO

Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, China

Abstract: Drought is one of the major environmental threats in the world. In recent years, the damage from droughts to the environment and economies of some countries has been extensive, and drought monitoring has caused widespread concerns. Remote sensing has a proven ability to provide spatial and temporal measurements of surface properties, and it offers an opportunity for the quantitative assessment of drought indicators such as the vegetation water content at different levels. In this study, sites of cotton field in Shihezi, Xinjiang, Northwest China were sampled. Four classical water content parameters, namely the leaf equivalent water thickness (EWT_{leaf}), the fuel moisture content (FMC), the canopy equivalent water thickness (EWT_{canopy}) and vegetation water content (VWC) were evaluated against seven widely-used water-related vegetation indices, namely the NDII (normalized difference infrared index), $NDWI_{2130}$ (normalized difference water index), NDVI (normalized difference vegetation index), MSI (moisture stress index), SRWI (simple ratio water index), $NDWI_{1240}$ (normalized difference water index) and WI (water index), respectively. The results proved that the relationships between the water-related vegetation indices and EWT_{leaf} were much better than that with FMC, and the relationships between vegetation indices and EWT_{canopy} were better than that with VWC. Furthermore, comparing the significance of all seven water-related vegetation indices, WI and NDII proved to be the best candidates for EWT detecting at leaf and canopy levels, with R^2 of 0.262 and 0.306 for EWT_{leaf}-WI and EWT_{canopy}-NDII linear models, respectively. Besides, the prediction power of linear regression technique (LR) and artificial neural network (ANN) were compared using calibration and validation dataset, respectively. The results indicated that the performance of ANN as a predictive tool for water status measuring was as good as LR. The study should further our understanding of the relationships between water-related vegetation indices and water parameters.

Keywords: artificial neural network; cotton; linear regression; vegetation indices; water parameters

Drought is one of the major environmental threats in the world. Drought monitoring has been an important issue to policy makers and the scientific community. The knowledge of vegetation water conditions can in fact contribute to detect vegetation physiological status (Carter, 1993; Peñuelas *et al.*, 1994), to provide useful information in agriculture for irrigation decisions and drought assessment (Carter, 1993; Peñuelas *et al.*, 1993), and it is important in forestry in determining fire susceptibility (Carlson and Burgan, 2003).

Remote sensing has a proven ability to provide spatial and temporal measurements of surface properties, and offers an opportunity for quantitative assessment of vegetation properties at different levels (Hinzman *et al.*, 1986; McMurtrey *et al.*, 1994; Diker and Bausch, 2003). Together with other parameters, vegetation water content is an important indicator of drought that can be investigated by using remotely sensed data.

The most widely used water-related parameters in remote sensing are the leaf equivalent water thickness (EWT_{leaf}), the canopy equivalent water thickness (EWT_{canopy}), the fuel moisture content (FMC) and vegetation water content (VWC). FMC, defined as the proportion of water over the vegetation dry mass

Received 2011-10-12; accepted 2012-03-19

*Corresponding author: QiuXiang YI (E-mail: yiqx@ms.xjb.ac.cn)

(Marta *et al.*, 2008), has been the most extended measure of fire ignition and fire propagation potential, and it has been widely used for fire danger assessment (Paltridge and Barber, 1988; Viegas *et al.*, 1992). In addition to fire-related applications, the estimation of plant water content is an essential input of vegetation productivity models (Boyer, 1995), and is important to improve water management in irrigated agriculture (Sepulcre-Canto *et al.*, 2006). EWT_{leaf} is calculated as the ratio between the quantities of water and the leaf area. EWT_{leaf} corresponds to a hypothetical thickness of a single layer of water averaged over the whole leaf area (Danson *et al.*, 1992). FMC expresses the amount of water in a leaf relative to the amount of dry matter and differs from EWT_{leaf} which expresses the amount of water in a leaf relative to its area. EWT_{canopy} is calculated as the leaf water content per unit ground area. EWT_{canopy} allows scaling of leaf water content at canopy level by multiplying canopy leaf area index (LAI) with the EWT_{leaf} (Ceccato *et al.*, 2002a). VWC is defined as the quantities of water per unit ground area. VWC is one of the most important parameters for the successful retrieval of soil moisture content from active and passive microwave remote sensing (Jackson *et al.*, 1982; Yilmaz *et al.*, 2008). The expressions for all four water parameters will be presented in the subsequent sections. There is now an extensive amount of literature which shows that leaf or canopy water content, measured as FMC, EWT_{leaf} or EWT_{canopy}, may be estimated from remotely sensed vegetation indices (Gao, 1996; Datt, 1999; Ceccato *et al.*, 2002b; Zarco-Tejada *et al.*, 2003). However, very few studies have explicitly examined the relationships between remotely sensed vegetation indices and these four water parameters of cotton at leaf and canopy levels.

Quite a number of different indices have been developed for the estimation of vegetation water content. These can be broadly divided into spectral indices (based on a ratio, or some other simple mathematical formula, of reflectance at two or more wavelengths, e.g. Peñuelas *et al.*, 1993; Gao, 1996 and Ceccato *et al.*, 2002a), continuum removal (normalizes reflectance spectra in order to allow comparison of individual absorption features from a common baseline (Tian *et al.*, 2001) and spectral curve fitting (using known water absorption coefficients fit to reflectance data over a range of wavelengths, e.g. Gao and Goetz, 1995). Spectral indices are the most widely used technique among the above mentioned methods. Detailed information about the spectral indices adopted in the present research is given in the following sections.

Besides, numerous methods have been developed to estimate water content from reflectance data. They mainly rely on empirical or physical approaches that use regression techniques with hyperspectral indices, and leaf and canopy radiative transfer models (Jacquemoud *et al.*, 1995; Zarco-Tejada *et al.*, 2001; Riaño *et al.*, 2005). Most previous approaches for vegetation water content estimation use the linear regression technique. In recent years, quantitative remote sensing of vegetation biochemicals has been greatly improved by the use of multivariate statistical methods, particularly Artificial Neural Network (ANN). Some comparison studies between regression statistical technique and neural networks have been conducted by many researchers (Gorr *et al.*, 1994; Despagne and Massart, 1998; Kumar, 2005) using various datasets. However, the predictive ability of ANN for water content estimation has not been well demonstrated.

This study initially analysed the relationship between remote sensing indices and EWT, FMC, VWC, and then discussed the method for improving the accuracy in retrieving water parameters at leaf and canopy levels. The study focused on three major aspects: (i) the relationships between remotely sensed water-related vegetation indices and water parameters; (ii) the suitable vegetation indices and water parameters for the estimation of water information; (iii) the suitable models for water content deriving. The objective of this research is to explore further potential of NIR (near-infrared reflectance), SWIR (shortwave-infrared reflectance) wavelengths to estimate FMC, EWT_{leaf}, VWC and EWT_{canopy} using leaf and canopy hyperspectral reflectance, and compare the performance of LR method and ANN technique for vegetation water content deriving based on remotely sensed water-related vegetation indices.

1 Materials and methods

1.1 Study area

Field experiment was conducted during June–October 2010 at an agricultural belt in Shihezi, Xinjiang, Northwest China (85°59′E, 44°19′N), where cotton is a dominant economic crop. The continental arid climate in the study area is characterized by sever aridity, high irradiance levels and rare precipitation, with sharply defined seasons, high annual and diurnal fluctuations in air temperature. The total annual precipitation for the whole study area is about 90 mm. Sites of cotton field were selected for the experiment. Cotton is generally planted from April to May, and harvested from September to October. The whole growth duration is about 180 days. The medium loam soil at the experiment area has the following properties: the field moisture capacity at the depth of 10 cm is 0.33 g/cm^3; the volumetric water content at the depth of 10 cm is 1.59 g/cm^3; and the saturation moisture content is 0.44 g/cm^3. Besides, field sampling was complemented by a water-controlled experiment in order to obtain very low vegetation water content that could not be obtained in the field, except in very extreme situations. There were 48 plots for every field campaign.

1.2 Leaf and canopy hyperspectral measurements

Leaf and canopy hyperspectral measurements were carried out four times from seedling stage until boll stage (the dates are 9 to 12 June, 14 to 18 July, 4 to 8 August, and 8 to 12 September, 2011, respectively). This procedure ensured that the normally occurring variation due to growth stage and measurement factors was included in the models, giving a more realistic basis for model development.

Canopy reflectance was obtained using an Analytical Spectral Devices, FieldSpec Full Range (ASD FieldSpec FR, Analytical Spectral Devices, Inc., Boulder, CO, USA) that acquires continuous spectra from 350 to 2,500 nm. All canopy spectral measurements were taken on clear days with no visible cloud cover between 10:00 am and 14:00 pm (Beijing local time). In each plot, representative plants were selected for canopy spectral measurement. Taking into account the impact of soil background, in the first field campaign, the sensor head was placed about 0.3 m vertically above the canopies. This resulted in a spot size of 13 cm in diameter in each measurement since the ASD sensor has a field of view of 25 degrees. In the other three field campaigns, the sensor head was placed approximately 1 m vertically above the canopies, leading to a spot size of approximately 44 cm in diameter on the canopies.

Leaf reflectance was measured with a leaf clip (ASD, Inc., Boulder, CO, USA) coupled to the ASD FieldSpec FR. The reflectance was measured in the "reflectance" mode against a black background. Fully expanded leaves near the top, middle and bottom parts of sampling plants were respectively excised for leaf reflectance measurements of a total of 266 leaf samples. The reflectance of a white Spectralon ($BaSO_4$) panel was measured before every reflectance was taken, and reflectance was measured in the "reflectance" mode against a black background. Then the reflectance was calculated as the ratio between energy reflected by the crop or leaf and energy incident on the crop or leaf. Every reflectance was an average of ten repeated scans that were automatically acquired by the FieldSpec.

1.3 Plant sampling and water content measurements

After canopy spectra measurements, three average-looking plants per plot were pulled out with their roots, sealed in a plastic bag, and then placed in a cool dark container to avoid water loss as much as possible. Upon being returned to the laboratory, leaves and stems were separated and fresh weight (FW) of leaves and stems was recorded using an analytical balance. Leaf sampling was conducted near the top, middle and bottom parts of every sampling plant, and leaf areas were obtained by photogrammetry. Immediately after photo taking, fresh leaves and stems were then put into an oven to be dried at 105ºC for half an hour and at 70ºC till constant weight (dry weight, DW) was reached. For each site, plant density was estimated by counting the number of plants in two adjacent rows over a transect length of 10 m, and the number of leaves on an average-looking plant per plot was counted to estimate LAI.

The calculations of FWC, EWT_{leaf}, VWC and EWT_{canopy} were as follows:

$$\mathrm{FWC}=\frac{(\mathrm{FW}-\mathrm{DW})}{\mathrm{DW}}\times 100\%, \quad (1)$$

$$\mathrm{EWT_{leaf}}=\frac{\mathrm{FW}-\mathrm{DW}}{\mathrm{dw}\times \mathrm{A}}, \quad (2)$$

$$\mathrm{VWC}=\eta\times((\mathrm{FW}-\mathrm{DW})+(\mathrm{FW_{stem}}-\mathrm{DW_{stem}})), \quad (3)$$

$$\mathrm{EWT_{canopy}}=\mathrm{LAI}\times \mathrm{EWT_{leaf}}. \quad (4)$$

Where, FW is the leaf fresh weight and DW is the leaf dry weight of the same sample (g); dw is the density of water (1 g/cm^3); A is the area of fresh leaf (cm^2); η is plant density, number of plant per ground area (number/m^2); FW_{stem} and DW_{stem} are the stem fresh and dry weight, respectively; LAI is the leaf area index (m^2 leaf/m^2 ground area), and values of LAI were obtained by multiplying the leaf area of an average plant and the plant density (η).

1.4 Water-related vegetation indices

In this study, three ratio water indices and four normalized water indices were adopted (Table 1). The reason why these water-related vegetation indices were used in this study is that the widely used remote sensing satellites for drought detecting at present, such as Landsat 5 Thematic Mapper (TM), MODIS, Advanced Wide Field Sensor (AWiFS), and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), have bands at those wavelengths, and those indices were expected to be the primary candidates for use in vegetation water content estimation.

1.5 Artificial Neural Networks

Artificial Neural Networks (ANNs) are models that learn from a training data set mimicking the human-learning ability. They are robust to noisy data and can approximate multivariate non-linear relations among the variables (Twarakavi *et al.*, 2006). ANNs have been used for a wide range of different learning-from-data applications and input–output correlations of non-linear processes in water resources and hydrology (Hsu *et al.*, 1995; Maier and Dandy, 1996; Ahmad and Simonovic, 2005). Of all the Artificial Neural Networks (ANNs), the back-propagation algorithm is perhaps the most widely used supervised training algorithm for multilayered feed-forward networks, and which was also adopted for ANN analysis in this study. A brief discussion of ANNs can be found in Keiner and Yan (1998).

2 Results and discussion

2.1 FMC, EWT_{leaf}, VWC and EWT_{canopy}

Wide ranges of all four water parameters were established (Fig. 1). From the start to the end of the experiment, EWT_{leaf} and FMC were increased from 0.0099 to 0.066 cm, 121.49% to 762.16%, respectively, and EWT_{canopy} and VWC increased from 0.00844 to 0.2373 cm, 0.1387 to 3.3884 kg/m^2, respectively. Probably due to the rapid increases of LAI, the range of EWT_{leaf} was much smaller than that of EWT_{canopy}.

In order to have the water parameter values and the corresponding spectral water-related vegetation indices equally distributed for model calibration and validation, the grouping of data for calibration and validation was accomplished with Matlab (version, 7.8). The descriptive statistics of water parameters for model calibration and model validation were summarized in Table 2.

2.2 Relationships between water-related vegetation indices and water parameters

The performance of every water-related vegetation index was evaluated by computing its correlation with water parameters. The significance of EWT_{leaf} was assessed in comparison to FMC, and EWT_{canopy} was assessed in comparison to VWC (Fig. 2). The analysis showed that reflectance indices at leaf and canopy levels are both better related to EWT_{leaf} and EWT_{canopy} than to FMC and VWC. Furthermore, the performances of all water-related vegetation indices were generally better at canopy level than at leaf level. The WI and NDII were found to be the best candidates for EWT estimation at leaf and canopy levels, respectively.

There are strong relationships between EWT_{leaf} and $NDII_{1240}$, WI, and SRWI, which is especially true for EWT_{leaf} and WI, with r=0.545 (Table 3); but for leaf FMC, the relationships with all water-related vegetation indices were insignificant, except for $NDWI_{1240}$ and SRWI, with r=0.266 and 0.271, respectively. The reason for more significant relationships between EWT_{leaf} and vegetation indices is probably because EWT_{leaf} is directly related to the water absorption depth and independent of the vegetation fresh matter, but the spectral response to change in leaf FMC is controlled by EWT

Table 1 Definitions of water-related vegetation indices

Water-related vegetation indices	Formula	Full name	References
NDII	$(\rho_{850\ nm}-\rho_{1,650\ nm})/(\rho_{850\ nm}+\rho_{1,650\ nm})$	Normalized Different Infrared Index	Kimes *et al.*, 1981; Hardisky *et al.*, 1983
$NDWI_{2130}$	$(\rho_{858\ nm}-\rho_{2,130\ nm})/(\rho_{858\ nm}+\rho_{2,130\ nm})$	Normalized Different Water Index	Chen and Huang, 2005
$NDWI_{1240}$	$(\rho_{860\ nm}-\rho_{1,240\ nm})/(\rho_{860\ nm}+\rho_{1,240\ nm})$	Normalized Different Water Index	Gao, 1996
NDVI	$(\rho_{858\ nm}-\rho_{648\ nm})/(\rho_{858nm}+\rho_{648\ nm})$	Normalized Different Vegetation Index	Rouse *et al.*, 1974
WI	$\rho_{900\ nm}/\rho_{970\ nm}$	Water Index	Peñuelas *et al.*, 1993, 1997
SRWI	$\rho_{858\ nm}/\rho_{1240\ nm}$	Simple Ratio Water Index	Zarco-Tejada *et al.*, 2001, 2003
MSI	$\rho_{1,600\ nm}/\rho_{820\ nm}$	Moisture Stress Index	Rock *et al.*, 1986; Hunt, 1991

Note: ρ indicates reflectance, and the subscript indicates a particular wavelength in nm.

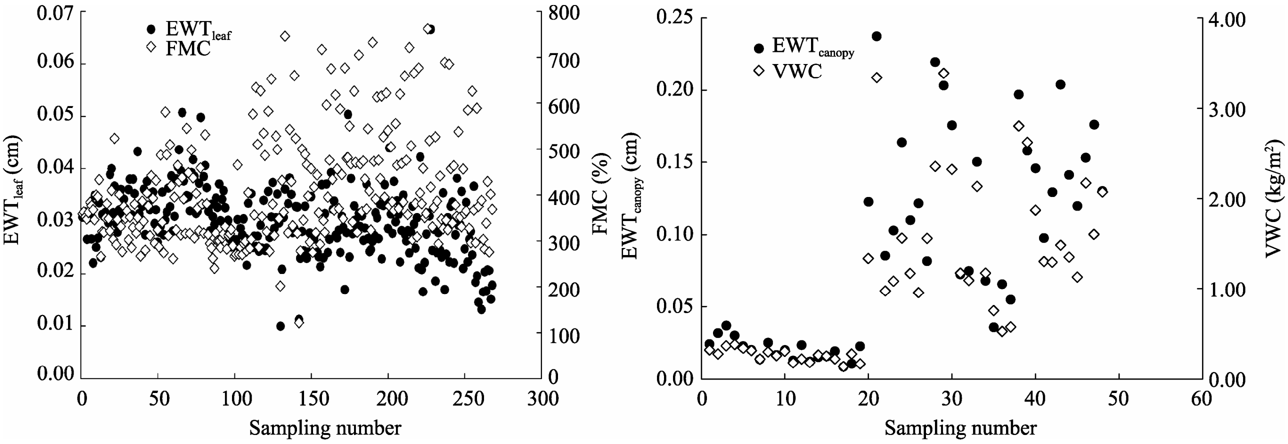


Fig. 1 Distributions of FMC, EWT_{leaf}, VWC and ETW_{canopy}

Table 2 Descriptive statistics of water parameters for model calibration and validation

Water parameters	Group	Number	Maximum	Minimum	Average	Standard deviation
EWT_{leaf}	Calibration	149	0.0666	0.0112	0.0295	0.0072
	Validation	117	0.0436	0.0099	0.0304	0.0059
FMC	Calibration	149	762.1600	121.4900	413.5600	123.1100
	Validation	117	746.0500	201.9800	397.8300	105.4700
EWT_{canopy}	Calibration	24	0.2370	0.0106	0.0959	0.0702
	Validation	20	0.2030	0.0151	0.0908	0.0626
VWC	Calibration	24	3.3380	0.1810	1.1970	0.9040
	Validation	20	3.3880	0.2220	1.1360	0.8430

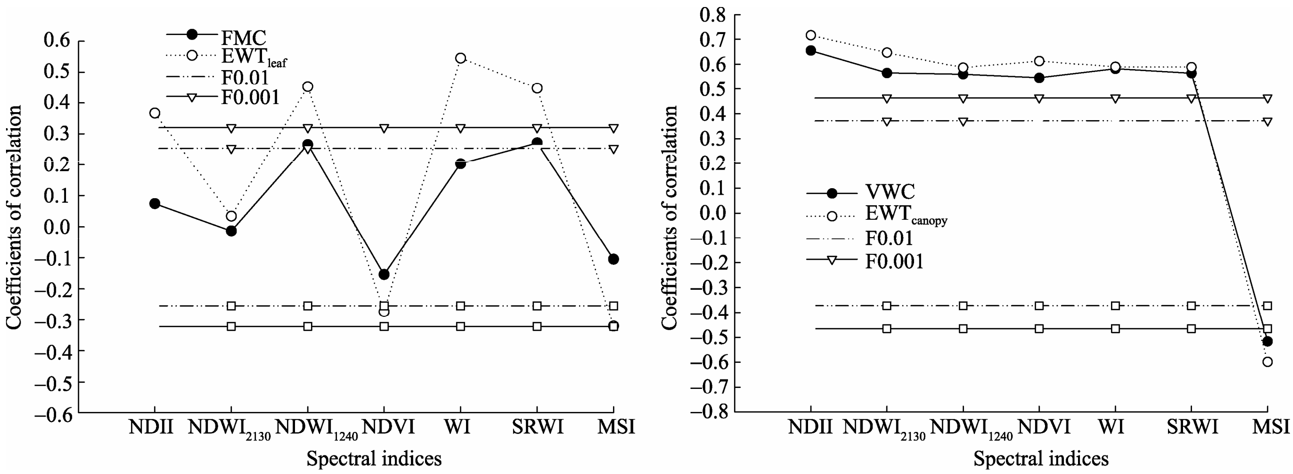


Fig. 2 Correlogram of spectral indices and water parameters

Table 3 Coefficients of correlation among water parameters and water-related vegetation indices

Water parameters	Vegetation index						
	NDII	$NDWI_{2130}$	$NDWI_{1240}$	NDVI	WI	SRWI	MSI
EWT_{leaf}	0.367^{**}	0.034	0.453^{**}	-0.274^{*}	0.545^{**}	0.448^{**}	-0.320^{*}
FMC	0.075	−0.014	0.266^{*}	−0.155	0.203	0.271^{*}	−0.106
EWT_{canopy}	0.717^{**}	0.647^{**}	0.587^{**}	0.613^{**}	0.590^{**}	0.589^{**}	-0.599^{**}
VWC	0.655^{**}	0.565^{**}	0.560^{**}	0.546^{**}	0.582^{**}	0.564^{**}	-0.516^{**}

Note: At leaf level, n=266, when α=0.01, with r=0.254, and when α=0.001, with r=0.3211; at canopy level, n=44, when α=0.01, with r=0.3721, and when α=0.001, with r=0.4648. * indicates significance at P<0.01 level; ** indicates significance at P<0.001 level.

and leaf dry matter content, which means leaf FMC and leaf spectral response may vary as a result of change in one and/or the other (Kimes *et al.*, 1981).

At canopy level, all water-related vegetation indices were significantly related with EWT_{canopy} and VWC, which is especially true for NDII. NDII was related to EWT_{canopy} and VWC, with r=0.735 and 0.676 (Table 3), respectively. Moreover, EWT_{canopy} was linearly related to VWC, with r=0.924. The strong relationship between EWT_{canopy} and NDII over the range of data obtained in the experiment supports the conclusions of previous studies (Ceccato *et al.*, 2002b; Chen *et al.*, 2005). The significant relationship between VWC and NDII was probably caused by the significant correlationships between VWC and canopy EWT. Previous study (Yilmaz *et al.*, 2008) has demonstrated that the relationships between VWC and NDII were indirect; NDII was related to canopy EWT, which in turn was allometrically related to VWC.

2.3 Model development

It was noted that 149 out of 266 samples were used for model calibration at leaf level, and 24 out of 44 samples were used for model calibration at canopy level. The rest were used for model validation (Table 4).

By the above analysis of the relationships, we found that compared to the other spectral indices, WI and SRWI were the best candidates for the estimation of leaf EWT and FMC, and NDII was the best candidate for the estimation of canopy EWT and VWC. As a result, the above mentioned three indices were selected as input variables for model development, and the analysis of the rest spectral indices was not conducted. As was expected, at leaf level, the EWT_{leaf} could be better estimated compared to FMC. At canopy level, the good performance of NDII was obtained for both EWT_{canopy} and VWC, and ANN models were obtained with Matlab (version 7.8). Backpropagation algorithm was employed to train the neural network. In all ANN models, a three-layer network architecture, consisting of one input layer, one hidden layer and one output layer, was established, and a hyperbolic tangent sigmoid transfer function was used at the input layer and the hidden layer and a pure line transfer function was used at the output layer. Besides, the Levenberg-Marquardt training algorithm was used for training the network. The number of neurons for the input layer is equal to the number of input variables introduced in the networks. The output layer contains one neuron. The proper number of neurons in the hidden layer was determined by training ANN with different number of neurons in the hidden layer and computing the correlation coefficient between the output target and the simulated value of the target, and the optimum number of neurons in the hidden layer was determined when the maximum

Table 4 Results of model development and model performance analysis by calibration dataset

Output variable	Input variable	Model expression	*RMSE*	R^2
EWT_{leaf}	WI	$0.515x-0.507$	0.0060	0.035
		1-20-1	0.0060	0.325
FMC	SRWI	$1{,}093x-867.1$	116.5900	0.103
		1-30-1	117.3500	0.099
EWT_{canopy}	NDII	$0.892x-0.269$	0.0394	0.685
		1-3-1	0.0384	0.728
VWC	NDII	$11.43x-3.487$	0.5110	0.680
		1-5-1	0.5700	0.710

Note: All ANN models were established with a three-layer network architecture, consisting of one input layer, one hidden layer and one output layer. The network architecture 1-3-1 represents the number of neurons for input layer, hidden layer and output layer, respectively. *RMSE*, root mean square error; *R*, coefficient of determination.

values of correlation coefficients were obtained. The architectures of all ANN models were estabilished after a time-consuming trial. In order to compare the performance of LR and ANN methods in the process of model development, the *RMSE* and R^2 between the modeled and measured water parameters by calibration dataset were calculated (Table 4). It was observed that ANN method was slightly superior to LR method in accuracy at both leaf and canopy levels. The detailed comparison of the two methods was discussed in model validation section.

2.4 Model validation

The *RMSE* and coefficient of determination (R^2) of all developed models were calculated with validation datasets (Table 5). Besides, linear regression analysis was made on a pairwise basis between measured and modeled values, with slope (a) and intercept (b) of the models reported. The intercept should be 0 and the slope should be 1 for a perfect match.

As can be seen (Table 5), at leaf level, the best result for water content estimation was obtained by EWT_{leaf}-WI-LR and EWT_{leaf}-WI-ANN. It was observed that the models based on leaf EWT always resulted in higher R^2 values and slope (a), lower intercept (b), compared to the models based on FMC. The underperformance of FMC estimation models was perhaps caused by the saturation of the spectral indices when FMC was beyond 500%. At canopy level, the estimation models for canopy EWT and VWC were generally superior to those at leaf level. Furthermore, all models for canopy EWT and VWC could result in a good estimation, which was particularly true for the EWT_{canopy}-NDII-LR and EWT_{canopy}-NDII-ANN models. It should be noted that for calibration dataset, ANN method always performed slightly better than LR method, but for validation dataset, the two methods were competitive in performance. Although the performance of ANN method was not evidently better than LR method, models developed by ANN method also produced encouraging results through high R^2 and low *RMSE* (Table 5).

In order to make the comparison results more convictive and more visual, the measured water parameter values against the modeled water parameter values obtained by estimation models were plotted in Fig. 3.

Ideally, it would be a perfect match if the regression line entirely overlapped the 1:1 line. As was clearly shown in the figure, the efficiency of canopy water estimation models was evident, and the performance difference between canopy EWT and VWC models was small. Additionally, the regression line between the measured and modeled FMC was nearly paralleled with X-axis, indicating the bad performance of estimation models.

3 Conclusions

In this study, the relationships between seven spectral water-related vegetation indices and four ground measured water parameters were established and evaluated. The analysis showed that vegetation indices are better related to EWT_{leaf} and EWT_{canopy} than to FMC and VWC. In fact, all four water parameters were significantly related to all seven spectral indices, except for FMC. Recent investigations have revealed that reflectance is related to changes in leaf EWT rather than to changes in FMC (Datt, 1999; Davidson *et al.*, 2006).

Table 5 Results of model performance analysis and regression statistics describing the relationship between modeled and measured water parameters values

Output variable	Input variable	Type of models	*RMSE*	R^2	*a*	*b*
EWT_{leaf}	WI	EWT_{leaf}-WI-LR	0.005	0.262	0.327	0.020
		EWT_{leaf}-WI-ANN	0.005	0.244	0.338	0.019
FMC	SRWI	FMC-SRWI-LR	106.560	0.047	0.075	392.200
		FMC-SRWI-ANN	108.250	0.046	0.087	389.600
EWT_{canopy}	NDII	EWT_{canopy}-NDII-LR	0.055	0.306	0.432	0.037
		EWT_{canopy}-NDII-ANN	0.061	0.290	0.479	0.025
VWC	NDII	VWC-NDII-LR	0.842	0.168	0.305	0.591
		VWC-NDII-ANN	0.785	0.167	0.239	0.890

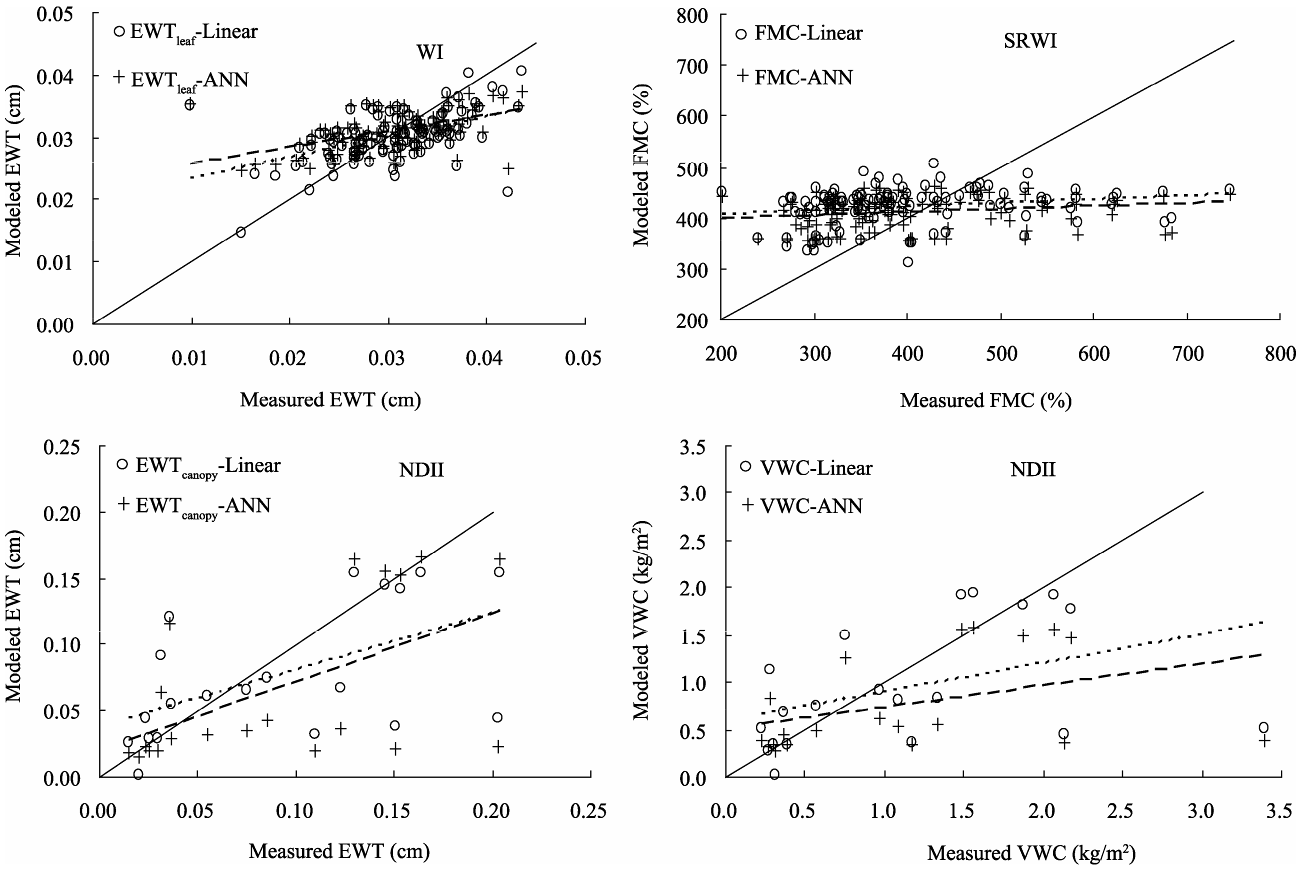


Fig. 3 Scatterplots of modeled versus measured water parameters for linear models and ANN models. The solid lines represent 1:1, the short dashed lines represent regression of linear models, and the long dashed lines represent regression of ANN models.

Among seven water-related vegetation indices, WI and SRWI were selected for model development at leaf level, and NDII was used at canopy level. However, the impacts of cotton growth stages were not considered in the process of correlation analysis, so it is hard to say if the relationships between spectral indices and water parameters would vary with growth stages. More work is needed to verify the result.

Besides, although the accuracy performance of ANN method was slightly better than LR method in the process of model development, the same results were not identified by validation dataset. The under-performance of ANN method in model validation was probably due to the limitations of itself. For neural networks, the process of finding the best result is complicated and we cannot guarantee that the reported result is the optimum because an exhaustive search is excessively time-consuming and there are no well established rules to determine the best network architecture and training methods. All neural network results reported in this study were trained based on our experience by testing a limited number of combinations. In general, we varied the number of hidden neurons to find the best result, and reported the method that gave the highest correlation coefficient. In this respect, further experiments are needed to clearly identify the effectiveness of the ANN technique as an extension to the estimation of water content from hyperspectral indices. However, high R^2 and low *RMSE* indicated that ANN method has the promising potential to improve the estimation of water content by remote sensing. ANN and LR methods may mutually assist each other to obtain a better result.

Finally, this research outlines the first part of a series of studies to investigate the potential and approaches for using optical remote sensing and ANN method to assess vegetation water content. These results set the basis towards establishing operational techniques for the retrieval of water content at top-of-atmospheric level.

Acknowledgements

The work was supported by the West Light Foundation of Chinese Academy of Sciences (XBBS200902), the Knowledge Innovation Project of Chinese Academy of Sciences (KZCX2-YW-BR-12), the National Natural Science Foundation of China (41104130), the West Light Foundation of Chinese Academy of Sciences (XBBS201006), and the China Postdoctoral Science Foundation (20100471681). Our colleagues in Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences are highly appreciated for their work.

References

Ahmad S, Simonovic S P. 2005. An artificial neural network model for generating hydrograph from hydro-meteorological parameters. Journal of Hydrology, 315(1–4): 236–251.

Boyer J S. 1995. Measuring the Water Status of Plants and Soils. Beijing: Academic Press, 56–64.

Carlson J D, Burgan R E. 2003. Review of user needs in operational fire danger estimation: the Oklahoma example. International Journal of Remote Sensing, 24: 1601–1620.

Carter G A. 1993. Responses of leaf spectral reflectance to plant stress. American Journal of Botany, 80: 239–243.

Ceccato P, Gobron N, Flasse S, *et al.* 2002a. Designing a spectral index to estimate vegetation water content fromremote sensing data: Part 1. Theoretical approach. Remote Sensing of Environment, 82: 88–197.

Ceccato P, Flasse S, Gregoire J M. 2002b. Designing a spectral index to estimate vegetation water content from remote sensing data: Part 2. Validation and applications. Remote Sensing of Environment, 82: 98–207.

Chen D Y, Huang J F, Thomas J J. 2005. Vegetation water content estimation for corn and soybeans using spectral indices derived from MODIS near- and short-wave infrared bands. Remote Sensing of Environment, 98: 225–236.

Danson F M, Steven M D, Malthus T J, *et al*. 1992. Highspectral resolution data for determining leaf water content. International Journal of Remote Sensing, 13: 461–470.

Datt B. 1999. Remote sensing of water content in Eucalyptus leaves. Australian Journal of Botany, 47: 909–923.

Davidson A, Wang S, Wilmshurst J. 2006. Remote sensing of grassland-shrubland vegetation water content in the shortwave domain. International Journal of Applied Earth Observation and Geoinformation, 8: 225–236.

Despagne F, Massart D L. 1998. Neural networks in multivariate calibration. Analyst, 123: 157–178.

Diker K, Bausch W C. 2003. Potential use of nitrogen reflectance index to estimate plant parameters and yield of maize. Biosystems Engineering, 85: 437–447.

Gao B C, Goetz F H. 1995. Retrieval of equivalent water thickness and information related to biochemical components of vegetation canopies from AVIRIS data. Remote Sensing of Environment, 52: 155–162.

Gao B C. 1996. NDWI–a normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment, 58: 257–266.

Gorr W L, Nagin D, Szczypula J. 1994. Comparative study of artificial neural network and statistical models for predicting student grade point averages. International Journal of Forecasting, 10: 17–34.

Hardisky M A, Klemas V, Smart R M. 1983. The influences of soil salinity, growth form, and leaf moisture on the spectral reflectance of *Spartina alterniflora* canopies. Photogrammetric Engineering & Remote Sensing, 49: 77–83.

Hinzman L D, Bauer M E, Daughtry C S T. 1986. Effects of nitrogen fertilization on growth and reflectance characteristics of winter wheat. Remote Sensing of Environment, 19: 47–61.

Hsu K I, Gupta H V, Sorooshian S. 1995. Artificial neural network modeling of the rainfall–runoff process. Water Resources Research, 31: 2517–2530.

Hunt E R. 1991. Airborne remote sensing of canopy water thickness scaled from leaf spectrometer data. International Journal of Remote Sensing, 12: 643–649.

Jackson T J, Schmugge T J, Wang J R. 1982. Passive microwave remote sensing of soil moisture under vegetation canopies. Water Resources Research, 18: 1137–1142.

Jacquemoud S, Baret F, Andrieu B, *et al.* 1995. Extraction of vegetation biophysical parameters by inversion of the PROSPECT+SAIL models on sugar beet canopy reflectance data. Application to TM and AVIRIS sensors. Remote Sensing of Environment, 52: 163–172.

Keiner L E, Yan X. 1998. A neural network model for estimating sea surface chlorophyll and sediments from thematic mapper imagery. Remote Sensing of Environment, 66: 153–165.

Kimes D S, Markham B L, Tucker C J. 1981. Temporal relationships between spectral response and agronomic variables of a corn canopy. Remote Sensing of Environment, 11: 401–411.

Kumar U A. 2005. Comparison of neural networks and regression analysis: a new insight. Expert Systems with Applications, 29: 424–430.

Maier H R, Dandy G C. 1996. The use of artificial neural networks for the prediction of water quality parameters. Water Resources Research, 32: 1013–1022.

Marta Y, Emilio C, David R. 2008. Estimation of live fuel moisture content from MODIS images for fire risk assessment. Agricultural and Forest Meteorology, 148: 523–536.

McMurtrey III R F, Chappella E W, Kim M S, *et al.* 1994. Distinguishing nitrogen fertilization levels in field corn (*Zea mays* L.) with active induced fluoresing and passive reflectance measurements. Remote Sensing of Environment, 47: 36–44.

Paltridge G W, Barber J. 1988. Monitoring grassland dryness and fire potential in Australia with NOAA/AVHRR data. Remote Sensing of Environment, 25: 381–394.

Peñuelas J, Filella I, Biel C, *et al*. 1993. The reflectance at the 950–970 nm region as an indicator of plant water status. International Journal of Remote Sensing, 14: 1887–1905.

Peñuelas J, Gamon J A, Fredeen A L, *et al*. 1994. Reflectance indices associated with physiological changes in nitrogen and water limited sunflower leaves. Remote Sensing of Environment, 48: 135–146.

Peñuelas J, Pinol J, Ogaya R, *et al*. 1997. Estimation of plant water concentration by the reflectance water index WI (R900/R970). International Journal of Remote Sensing, 14: 1887–1905.

Riaño D, Vaughan P, Chuvieco E, *et al*. 2005. Estimation of fuel moisture content by inversion of radiative transfer models to simulate equivalent water thickness and dry matter content: analysis at leaf and canopy level. IEEE Transactions on Geoscience and Remote Sensing, 43: 819–826.

Rock B N, Vogelmann J E, Williams D L, *et al*. 1986. Remote detection of forest damage. Journal of Bioscience, 36: 439–445.

Rouse J W, Haas R H, Schell J A, *et al*. 1974. Monitoring vegetation systems in the Great Plains with ERTS. Third Earth Resources Technology Satellite-1 Symposium. Greenbelt: NASA SP-351, 301–307.

Sepulcre-CantóG, Zarco-Tejada P J, Jiménez-Muñoz J C, *et al*. 2006. Detection of water stress in an olive orchard with thermal remote sensing imagery. Agricultural and Forest Meteorology, 136: 31–44.

Tian Q, Tong Q, Pu R, *et al*. 2001. Spectroscopic determinations of wheat water status using 1650–1850 nm spectral absorption features. International Journal of Remote Sensing, 22: 2329–2338.

Twarakavi N K C, Mishra D, Bandopadhyay S. 2006. Prediction of arsenic in bedrock derived stream sediments at a gold mine site under conditions of sparse data. Natural Resources Research, 15(1): 15–26.

Viegas D X, Viegas T P, Ferreira A D. 1992. Moisture content of fine forest fuels and fire occurrence in central Portugal. International Journal of Wildland Fire, 2: 69–85.

Yilmaz M T, Hunt Jr E R, Jackson T J. 2008. Remote sensing of vegetation water content from equivalent water thickness using satellite imagery. Remote Sensing of Environment, 112: 2514–2522.

Zarco-Tejada P J, Miller J R, Noland T L, *et al*. 2001. Scaling-up and model inversion methods with narrow-band optical indices for chlorophyll content estimation in closed forest canopies with hyperspectral data. IEEE Transactions on Geoscience and Remote Sensing, 39: 1491–1507.

Zarco-Tejada P J, Rueda C A, Ustin S L. 2003. Water content estimation in vegetation with MODIS reflectance data and model inversion methods. Remote Sensing of Environment, 85: 109–124.