ESTIMATION OF GREEN WATER FOOTPRINT OF RICE PADDIES IN TAITUNG AREA USING MODIS DATA

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KEY WORDS: rice, Green Water Footprint, evapotranspiration, MOD16, stepwise regression

ABSTRACT: Green Water Footprint (GWF) is a recently developed indicator to identify the utilization and availability of the fresh water resource provided for agricultural products. Based on it accounting for rainwater evapotranspiration, a MODIS Global Terrestrial Evapotranspiration Data Set (MOD16) is applied to estimate GWF for its capable presenting global evapotranspiration status with high accuracy, wide coverage and long-term monitoring. Although the MOD16 product offers aforementioned advantages, current drawback is mainly on its data available time is too slow, for which announced data is about one-year late. This paper therefore aims to overcome the drawbacks and develop a regression method considering multiple variables including weather parameters and Normalized Difference Vegetation Index (NDVI) values in order to improve that the current MOD16 cannot reflect a more near real-time GWF. To demonstrate feasibility of the method we proposed, three representative agricultural areas in Taitung County mainly used for rice planting were selected as the studied sites. The analyzing data covered a prolonged period (from 2003 to 2012) and our regression model further distinguished the first and second cropping seasons in the ten years. The results of stepwise regression analysis reported that temperature and NDVI were significant variables related to MOD16. R^2 values of models derived from the 1^{st} and 2^{nd} cropping data were 0.65 and 0.64, respectively. The regression models were also verified by 10 years' out-of-samples, and the results indicated that overall accuracy of the prediction was above 85%. Since the modelled evapotranspiration value was reliable, it was then used to compute the rice green water footprint of the two cropping seasons. Based on the model, even without values of the latest MOD16, the GWF of rice producing over the same area in 2013 and 2014 were estimated. The potential of a near real-time estimation of GWF of rice was demonstrated.

KEYWORDS: rice, Green Water Footprint, evapotranspiration, MOD16, stepwise regression

1. INTRODUCTION

Water Footprint is an indicator introduced by Hoekstra (2003) to identify the usage and distribution of the fresh water resource. Based on the water resource and usage, it can be classified into three categories, including blue, green and gray water footprints. In which blue water footprint indicates the volume of fresh surface and groundwater, green water footprint means the volume of precipitation on land that does not run off or recharge the groundwater but is stored in the soil or temporarily stays on top of the soil or vegetation, and grey water footprint is freshwater pollution amount that can be associated with the production of a product over its full supply chain. Through the understanding of the three types of the water footprint, the total amount of water used for the production of any products can be estimated. As the volume of water resource is high related with global environmental and climate change, the monitoring and management of water resource becomes a highly important issue all over the world. Water footprint capable of providing total volume of used water therefore becomes a useful indicator to help governments to manage the water resource and also to inform citizen the water consumption amount.

Among all the products, crop is a type of product needs large amount of water and hence the volume of consumed water for cropping has been an essential topic for water resource management. From previous studies it was reported that most of the water for growing crops come from blue water footprint. However it was also noticed that green water contributed for crop growth was ignored. In order to comprehensively understand the total amount of water used during the whole crop growing period, it is critical to identify the amount of green water of crops (Chou et al., 2011). As rice is the most important crops in the daily lives in Asian countries, the computation of green water footprint (GWF) of rice was conducted in this paper.

Green water footprint is referred to the total rainwater evapotranspiration (ET) plus the amount of water incorporating in a product. As the amount existed in the products is only 0.1% ~ 1% of the evapotranspiration value, the evapotranspiration value itself can be used to represent green water footprint (Hoekstra et al., 2011). Evapotranspiration from field can be either directly measured by some instruments at a single position, or indirectly estimated by models based on empirical formulas using data on climates, soil properties and crop characteristics as input. However, these methods are costly, redundant and inconvenient, and inaccurate due to the emergence of extreme weather. To overcome these limitations, estimation of evapotranspiration has been developed using remote sensing technology. The most recent product called "MODIS Global Terrestrial Evapotranspiration Data Set (MOD16)" developed by NASA and USGS in 2011 was one of the remote sensed results showing capability of high measurement accuracy, wide spatial coverage and long-term monitoring. Due to the advantages, MOD16 data was proposed as the tool to estimate evapotranspiration and then to compute green water footprint of rice cropping over test site.

Although the MOD16 product is of great benefit, it is limited by its low temporal resolution, for which it indicates that the data published on-line is about one year delayed. As a result the near real time GWF cannot be derived. To address the issue, a regression method with a number of variables including weather parameters and Normalized Difference Vegetation Index (NDVI) values were applied to model the MOD16. Through the stepwise regression, the best predictor combination used to identify MOD16 was achieved. To demonstrate the method proposed was feasible, three main townships in Taitung County producing rice were selected as the test site for assessing the estimation of GWF using MOD16 and regression method. The data used for analysis covered the period of 2003 to 2012 and the regression modelling was performed separately based on the 1st and 2nd cropping seasons. The data employed and the modelling method are introduced detailed in the Sections 3 and 4 respectively. The resultant GWF of the rice over the test site is reported in the Section 5 and possible improvement can be conducted are discussed in the end.

2. STYDY AREA

Due to a large area of rice paddies and also complete coverage of MOD16 data, three townships, including Chihshang, Guanshan and Luye, in Taitung County in the eastern Taiwan were selected as the study area (shown in Figure 1). These townships located in Taitung Rift Valley plain are at an eastern longitude between 121°05'00" and 121°15'20", and a northern latitude between 22°50'00" and 23°10'00". The overall area is approximately 23,000 ha, and the range of each rice paddy is about 6,500 – 7,000 ha. With its abundant and pure water and rich soil, this area becomes the most important granary of Taitung County (Huang et al., 2003). Regarding the weather condition, due to the natural terrain effect, it was noted that the temperature of this area is lower than the southeast towns. In addition, although this area is close to the Pacific Ocean however it is not affected by ocean currents so that the precipitation and humidity remains stable, although the temperature difference between day and night time is significant.

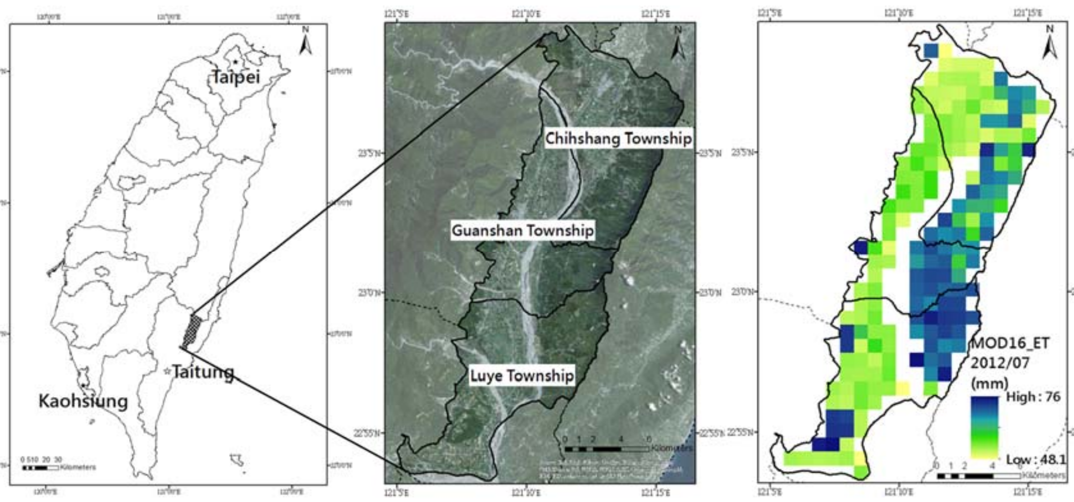

Figure 1. Study area and the corresponding MOD16 data (river area was removed) in July 2012.

3. METARIALS

3.1 MOD16

The MODIS Global Terrestrial Evapotranspiration Data Set (MOD16) provides evapotranspiration value within a regular 1 km^2 ground grid cell with an 8-day, monthly and annual temporal intervals. The MOD16 ET datasets were estimated based on the Penman-Monteith equation and then improved using Mu et al. (2011)'s algorithm, which involved ET difference between day and night, simplified calculation of vegetation cover fraction, added surface stomatal conductance, aerodynamic resistance, wet canopy, soil heat flux, other key environment variables, and etc. (Mu et al., 2013). The MOD16 ET was further validated with ET measured at eddy flux towers and ET estimated from 232 watersheds and therefore a reliable dataset. The monthly MOD16 in July 2012 over the study area is demonstrated in Figure 1. This data was treated as the dependent variable in the regression model applied later.

3.2 MCD12Q1

As the rice paddies were the main focus in this paper, the MODIS Land Cover Type product (MCD12Q1) was introduced to support the selection of cropland. The MCD12Q1 contains five land cover classification schemes with a 500 m^2 spatial resolution and updates the product in a yearly basis. From which the IGBP global vegetation classification scheme was applied. It identifies 17 land cover classes, including 11 natural vegetation classes, three developed and mosaicked land classes, and three non-vegetated land classes. In order to represent the main land cover types over the study area, the 17 land cover classes were re-classified into water, forest, cropland, built-up and barren classes. The grids of cropland class were extracted for sampling and modelling in this study.

3.3 Weather factors

The magnitude of ET was directly affected by weather condition therefore a series of weather factors were employed as independent variables in the regression model. Mean temperature, precipitation, mean wind speed, mean sunshine duration and mean relative humidity collected from 14 observation stations around the test site were collected. Subsequently the Natural Neighbor interpolation was applied to produce gridded weather data. In order to match the size and position of ET grid for regression modelling, it was worthwhile noting that the weather data was interpolated into the grid array corresponding to the MOD16 grid system. The resultant maps of weather data are shown in Fig. 2(a)-(e).

3.4 MOD13Q1

The magnitude of ET was also influenced by land cover. Considering the rice growth phenomenon varies during the growing period, the NDVI value updated monthly through the global MODIS vegetation indices (MOD13Q1) was used to represent the trend of growth of rice (refer to Fig. 2(f)). The value was introduced as an independent variable reflecting land cover change in the regression model.

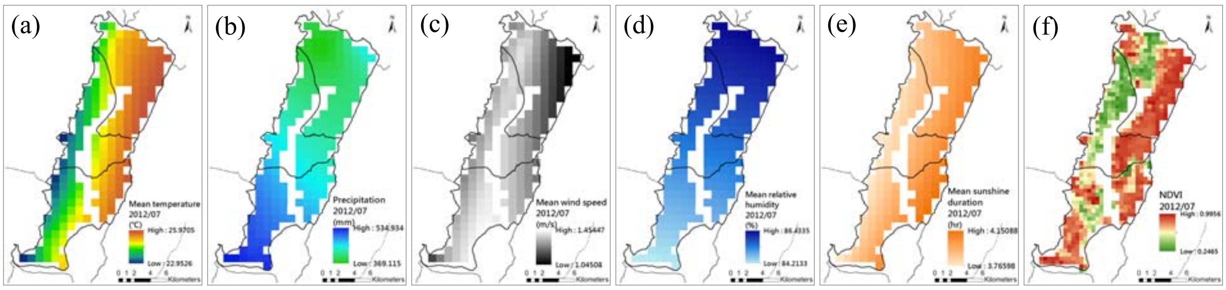

Figure 2. Interpolated maps of weather factors in July 2012 over the test site: (a) mean temperature; (b) mean precipitation; (c) mean wind speed; (d) mean sunshine duration; (e) mean relative humidity; and (f) NDVI.

4. METHODOLOGY

4.1 Model Development

Stepwise regression is a semi-automated process of building a model by successively adding or removing variables based solely on the t-statistics of their estimated coefficients. Every value of the independent variable x is associated with a value of the dependent variable y. Formally, the model can be described as bellow:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad (4.1)$$

where, Y is the dependent variable, X_1,..., X_n are independent variables, β_1,..., β_n are regression coefficients correspondent to each independent variable.

During the model building procedures, variable selection is intended to select the "best" subset of predictors in order to remove the redundant predictors, eliminate the collinearity among predicted variables and explain the data in the simplest way. Stepwise procedure is a combination of the forward and backward selection techniques so that after each step in which a variable was added, all candidate variables in the model are checked to see if their significance has been reduced below the specified tolerance level. If a nonsignificant variable is found, it is removed from the model (Johnson and Wichern, 2002; SAS Institute Inc., 2008). In this study, the significance level used for adding and removing variables was 0.05 and 0.1, respectively.

Stepwise regression has been commonly used in sociology, ecology, and hydrology modeling (Fox, 1991; Huberty, 1989; Ramoelo et al., 2012; Balaghi et al., 2008; Fedorko et al., 2005). Applications where several quantities are to be predicted using a common set of predictor variables are becoming increasingly important in various disciplines (Breiman & Friedman, 1997; Bilodeau & Brenner, 1999). Recent studies further integrated remotely sensed information and stepwise regression algorithm on natural resources management and land-use/land cover assessment. For example, Ramoelo et al. (2012) developed biomass prediction models by applying bootstrapped stepwise regression based on a combination of vegetation index and environmental or ancillary variables. Balaghi et al. (2008) established stepwise regression models to forecast the yields at provincial and national levels based on dekadal (10-daily) NDVI, dekadal rainfall sums and average monthly air temperatures. Fedorko et al. (2005) proposed a method to improve landscape-pollution interaction regression models through the inclusion of a variable that describes the spatial distribution of a land type with respect to the pattern of runoff within a drainage catchment. However, no research focuses on the water footprint estimations for crop cultivation.

Paddy rice is the staple diet in most Asian countries. This study is the first study to model green water consumption for paddy rice growth using remote sensing techniques. In the study area, the 1st crop and 2nd crop periods ranged from January to June, and July to December, respectively. Due to climatic difference, separated models were developed for these two cropping periods. We used evapotranspiration estimated from MODIS MOD16 products for representing green water consumptions by paddy cultivations at 1 km spatial resolution. Monthly MOD16 ET data collected from 2003 to 2012 were adopted as the dependent variable. Independent variables were selected using representations of a range of well-established factors related to ET (Chow et al., 1988), including meteorological factors like air temperature, precipitation, wind speed, day light hours, and vegetation status. On-site observations obtained from weather stations were applied to estimate the spatial variation of these meteorological factors within the study site using natural neighbor interpolation. The amount of vegetation in the study site was obtained from MODIS NDVI (MOD13). In this study, NDVI depicts paddy's growth which affect water vapors released from plantations. R^2 and adjusted R^2 were applied to examine the goodness of fit of the developed models. Through the stepwise procedures, important factors related to ET could be identified, and regression models of ET in 1st and 2nd cropping season would be built.

4.2 Model Validation

We used the 'out-of-sample forecasting' to evaluate the model performance. The whole dataset (78 pure paddy rice pixels per month, about 78km^2 ground area) is divided into two subsets. The first set (70 pure paddy rice pixels per month, about 70km^2 ground area) is for model fitting and is called 'in-sample' whereas the second set (8 pure paddy rice pixels per month, about 8 km^2 ground area; Figure 3) consists of data used to evaluate the forecasting performance and is called 'out-of-sample'. We than used the regression models built based on the in-sample observations, to estimate the ET values of the out-of-sample observations. The predictions of out-of-sample were compared with the MOD16 ET, then the overall accuracy of models validation was evaluated. The equation of the overall accuracy was calculated as follows:

$$OA = 1 - (|preET_{1or2} - ET_{MOD16}|/ET_{MOD16}) \quad (4.2)$$

where, *OA* is the overall accuracy, $preET_{1or2}$ is the predicted ET values, ET_{MOD16} is the ET value from MOD16.

In this study, we first applied out-of-sample forecasting to validate the models developed based on the data from 2003 to 2012. Moreover, MOD16 ET in 2013 and 2014 were further collected and compared with the predictions from the developed models.

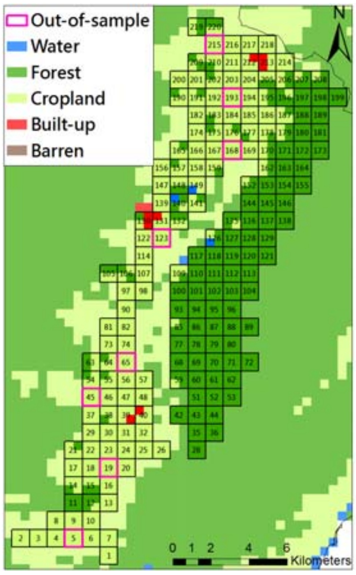

Figure 3. Spatial distribution of out-of-sample grids

4.3 Estimation of Green Water Footprint

According to the Water Footprint Assessment Manual (Hoekstra et al., 2011), all process water footprints are supposed per unit of product, namely in water per mass. Usually the process water footprints in agriculture or forestry as m^3/ton, which is equivalent to liter/kg. The green component in the process water footprint of growing a crop or tree ($WF_{proc,green}$, m^3/ton) is calculated as the green component in crop water use (CWU_{green}, m^3/ha) divided by the crop yield (Y, ton/ha):

$$WF_{proc,green} = \frac{CWU_{green}}{Y} \text{ [volume/mass]} \tag{4.3}$$

The green component in crop water use (CWU_{green}, m^3/ha) is calculated by accumulation of daily evapotranspiration (ET, mm/day) over the complete growing period:

$$CWU_{green} = 10 \times \sum_{d=1}^{1gp} ET_{green} \text{ [volume/area]} \tag{4.4}$$

in which ET_{green} represents green water evapotranspiration. The factor 10 is meant to covert water depths in millimeters into water volumes per land surface in m^3/ha. The summation is done over the period from the day of planting (day 1) to the day of harvest ($1gp$ stands for length of growing period in days). Since different crop varieties can have substantial differences in the length of the growing period, this factor can significantly influence the calculated crop water use.

Due to the high cost of measuring evapotranspiration directly, evapotranspiration can be estimated by means of a model based on empirical formulas in general. However, it's also hard to estimated evapotranspiration of 'green water' or 'blue water' individually, the CROPWAT model developed by the Food and Agriculture Organization of United Nations (FAO, 2010) is an alternative way to model evapotranspiration of green water and blue water. This model offers two options to calculate evapotranspiration: one option is the '**crop water requirement option**' (assumed that there are no water limitations to crop growth), and it calculates: (i) crop water requirements (CWU) during the full length of the growing period under particular climatic circumstances; (ii) effective precipitation over the same period; (iii) irrigation requirement. The other option is the '**irrigation schedule option**' (allowing the specification of the actual irrigation over the growing period), and it does not work with the concept of effective precipitation. Instead, the model includes a soil water balance which keeps track of the soil moisture content over time using a daily time step. On account of this reason, 'irrigation schedule option' requires input data on soil type, and it will much more complex than the 'crop water requirement option'. Therefore this study used the 'crop water requirement option' to model and estimate green water evapotranspiration.

The crop water requirement is the water needed for evapotranspiration under ideal growth conditions, and 'ideal conditions' means that adequate soil water is maintained by rainfall and irrigation so that it is does not limit plant growth and crop yield. Basically, it is calculated by multiplying the reference crop evapotranspiration (ET_0) by the crop coefficient (K_C): $CWR = K_C \times ET_0 = ET_C$. It is assumed that the crop water requirements are fully met, so that actual crop evapotranspiration (ET_C) will be equal to the crop water requirement: $ET_C = CWR$.

The reference crop evapotranspiration (ET_0) is the evapotranspiration rate from a reference surface without short of water. The reference surface represents a hypothetical surface with extensive green grass cover with specific standard characteristics and therefore the only factors affecting ET_0 are climate parameters. Consequently the actual crop evapotranspiration (ET_C) is must calculated by multiplying ET_0 by K_C. Nevertheless, this study would use the 'MODIS Global Terrestrial Evapotranspiration Data Set' (MOD16) which is equal to the actual crop evapotranspiration on crop land. In other words, this study used the MOD16 data in the study area where are all crop lands, and it meant that the MOD16 data was no necessary to multiply K_C as well as was the actual crop evapotranspiration.

Effective precipitation (P_{eff}) is the part of the total amount of precipitation that is retained by the soil in order that it is potentially available for meeting the water need of the crop. It is often less than the total precipitation because not all precipitation can actually be appropriated by the crop, such as surface run-off or percolation. There are various ways to estimate effective precipitation based on the total amount of precipitation; USDA SCS method (addressed by the United States Department of Agriculture, Soil Conservation Service) is often used.

The irrigation requirement (IR) is calculated as the difference between crop water requirement and effective precipitation. The irrigation requirement is zero if effective precipitation is larger than the crop water requirement: $IR = max(0,\ CWR - P_{eff})$, which is assumed that the irrigation requirements are fully met. Green Water Footprint (ET_{green}), namely evapotranspiration of precipitation, can be equal to the minimum of total crop evapotranspiration (ET_C) and effective precipitation (P_{eff}):

$$ET_{green} = \min\left(ET_C, P_{eff}\right) \quad \text{[length/time]} \tag{4.5}$$

As mentioned above, Green Water Footprint of rice can be calculated by:

$$WF_{rice,green} = \frac{10 \times min\{ET_C, P_{eff}\} \times A}{Y} \tag{4.6}$$

This study would use MOD16 data and value estimated by stepwise regression model as the actual crop evapotranspiration (ET_C), instead of past calculation by multiplying the reference crop evapotranspiration (ET_0) by the crop coefficient (K_C). Effective precipitation (P_{eff}) would be estimated by USDA SCS method:

$$\begin{gathered} P_{eff} = \{P_{total} \times (125 - 0.2 \times P_{total})\}/125, P_{total} \leq 250\ mm \\ P_{eff} = 125 + 0.1 \times P_{total}, P_{total} > 250\ mm \end{gathered} \tag{4.7}$$

in which P_{total} represents the total amount of precipitation. On the other hand, the amount of water incorporating in rice is very low, so that the calculation of equation (4.6) stands for Green Water Footprint of rice.

5. RESULTS

5.1 Stepwise Regression for ET

A total number of 4200 samples were applied for model development. Table 1 and Table 2 show the results of the developed regression models. Adjusted R^2 values of regression models derived from the 1st and 2nd cropping season were 0.65 and 0.64 respectively, and indicated that the developed models had an intermediate-high explanatory power for paddy ET variation. Both these models reached the 0.05 significance level (p = .000). The results of stepwise procedures reported that 'temperature' and 'NDVI' were significant predictors to ET. Both variables were positive associated with ET. Temperature was more important than NDVI since its standardized coefficient was larger in both models. On the other hand, the rest of the four weather variables including precipitation, mean wind speed, mean sunshine duration, and mean relative humidity did not reach the statistical significance, therefore been excluding from the models. The developed regression models of 1st and 2nd cropping seasons are showed as the following equations:

$$ET_1 = -24.731 + 4.887\text{T} + 22.821\text{NDVI} \tag{5.1}$$

$$ET_2 = -56.149 + 5.704T + 29.813NDVI \tag{5.2}$$

in which ET_1 represents evapotranspiration over 1st cropping season; ET_2 represents evapotranspiration over 2nd cropping season; T represents mean monthly temperature; NDVI represents monthly NDVI.

Table 1. ANOVA of stepwise regression

Model	R	R^2	adjusted R^2	Std. Error of the estimate	F	Sig.
1st Cropping Season	.803	.645	.645	14.499	4216.524	**.000**
2nd Cropping Season	.798	.637	.637	16.073	4076.948	**.000**

Table 2. Coefficients of the developed ET models

1st Cropping Season					2nd Cropping Season				
Entered Variable	Unstandardized Coefficients		Standardized Coefficients	Sig.	Entered Variable	Unstandardized Coefficients		Standardized Coefficients	Sig.
	B	Std. Error	β			B	Std. Error	β	
(Constant)	-24.731	1.231		**.000**	(Constant)	-56.149	1.655		**.000**
Temp.	4.887	.069	0.716	**.000**	Temp.	5.704	.070	0.737	**.000**
NDVI	22.821	1.483	0.155	**.000**	NDVI	29.813	1.465	0.184	**.000**

5.2 Results of Out-of-sample Forecasting

For each cropping season of each year, 48 out-of-sample were used to verify the model predictions. The results are showed in Table 3. The averaged overall accuracy from 2003 to 2012 was above 0.85 indicated that the developed models could provide highly accurate ET predictions. Table 4 showed the model validations based on ET data from 2013 to 2014, and similar results were obtained in accuracy assessment (0.87 and 0.86 for 2013 and 2014, respectively). This result again demonstrated the applicability of our models.

Table 3. Overall accuracy from 2003-2012 validation

Model	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Avg.
1st crop	0.886	0.879	0.875	0.872	0.879	0.874	0.877	0.751	0.795	0.889	**0.857**
2nd crop	0.850	0.860	0.850	0.846	0.862	0.885	0.870	0.832	0.792	0.882	**0.853**

Table 4. Overall accuracy from 2013-2014 validation

Model	2013	2014	Avg.
1st crop	0.854	0.889	**0.872**
2nd crop	0.848	0.864	**0.856**

5.3 Result of Estimation of Green Water Footprint

Since the ET value has been precisely estimated through regression model, it was then used to compute GWF of rice over the test site in 1st and 2nd cropping seasons between 2003 and 2012. The result was compared against the GWF calculated using the MOD16 product. As listed in Table 5, the estimation accuracy of GWF achieves 0.993 and 0.999 respectively in the two cropping season, validating the reliability of the proposed method for deriving GWF. In order to compute the overall GWF volume, the harvested area was calculated and the yield per cropping season was collected from the Agriculture and Food Agency, Council of Agriculture, Executive Yuan in Taiwan. The results of 1st and 2nd cropping season of rice Green Water Footprint are shown in Table 5 and their trend in the period of 2003-2012 are shown in Figure 4.

Table 5. Comparison of the 1st and 2nd crop of rice Green Water Footprint derived from MOD16 and modelled ET value based on the regression models (unit: m^3/ton)

Cropping Season	Calculation	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Ave.	Overall Accuracy
1st crop	MOD16	279.6	311	403.2	433.2	266.2	419.1	305.6	297.4	335.1	421.9	**347.2**	**0.993**
	Regression Model	279.6	311	391.3	421.2	268.7	416.6	314.9	306	357.7	428.6	**349.6**	
2nd crop	MOD16	834.2	853.7	1137	909.3	1128	985.7	1045	960.3	1153	773.3	**977.9**	**0.999**
	Regression Model	868.6	828.4	1048	862.8	1168	980.5	1008	990.8	1248	762.2	**976.6**	

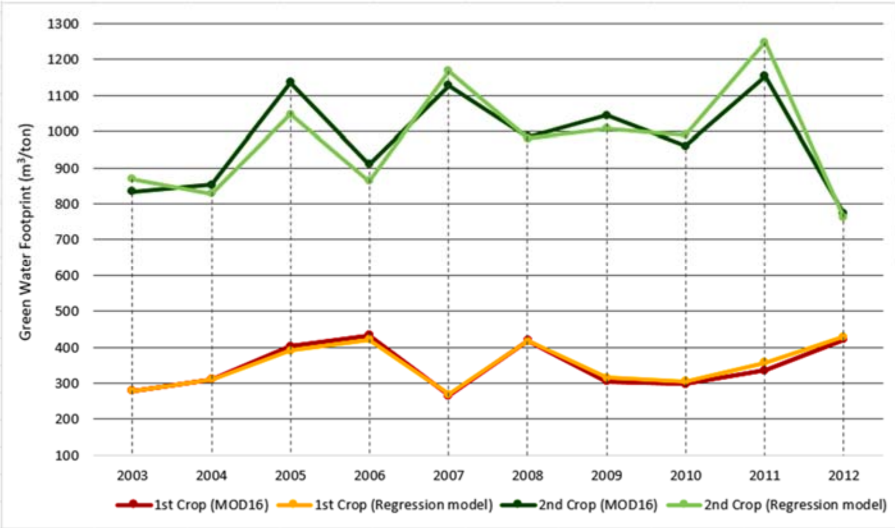

Figure 4. Trend of 1st and 2nd crop of rice Green Water Footprint in the period of 2003-2012

The results of the calculation and trend showed that 2nd crop of rice Green Water Footprint obviously larger than 1st crop of rice Green Water Footprint. The average of 1st crop of rice Green Water Footprint was 347.2 m^3/ton; the average of 2nd crop of rice Green Water Footprint was 977.9 m^3/ton. Comparing the estimation of MOD16 with regression models, both were of similar trends no matter in 1st crop or 2nd crop, and the overall accuracy was quite high. The results indicated that the usage of MOD16 evapotranspiration data set and the application of stepwise regression analysis was feasible for estimating GWF.

6. CONCLUSION

MOD16 evapotranspiration data was an ideal product for estimating green water footprint. However, it was limited by its temporal delay of announcement of data accessibility. Therefore this paper aimed to provide an alternative method to compute green water footprint. To achieve this, we applied stepwise regression modelling method to establish a model capable of computing accurate ET value. The model was then successfully used to estimate the GWF of rice and hence the reliability was proved as well. In addition, this study tried to predict evapotranspiration in 2013 and 2014 by the regression model, the overall accuracy of estimation in 2013 and 2014 achieved 87% and 86% respectively. All the results indicated that the usage of MOD16 data and stepwise regression modelling could accurately and immediately evaluate Green Water Footprint of rice. Since the method was proved reliable, it can be applied to measure GWF of various agricultural products. Moreover, the GWF itself can be treated as an indicator for agricultural irrigation and water resource management.

REFERENCES

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56. Rome: FAO - Food and Agriculture Organization of the United Nations.

Anderson, S., Aziz, O., Tootle, G., Grissino-Mayer, H., & Barnett, A. (2012). Using Pacific Ocean climatic variability to improve hydrologic reconstructions. Journal of Hydrology, 434–435(0), 69-77.

Balaghi, R., Tychon, B., Eerens, H., & Jlibene, M. (2008). Empirical regression models using NDVI, rainfall and temperature data for the early prediction of wheat grain yields in Morocco. International Journal of Applied Earth Observation and Geoinformation, 10(4), 438-452.

Bilodeau, M., & Brenner, D. (1999). Theory of Multivariate Statistics. US: Springer.

Breiman, Leo., & Friedman, J. H. (1997). Predicting multivariate responses in multiple linear regression. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 59(1), 3-54.

Chen, S. S. (2013). Applied Time-Series Econometrics for Macroeconomics and Finance. Taipei: Tunghua.

Chou, C. E., Zuo, J. D., Lee, G. E., Chu, M. C., Yang, H. Y., Chen, S. T., & Chang, Y. Z. (2011). Promoting Water Footprint Concepts and a Pilot Study. Taipei: Water Resources Agency, Ministry of Economic Affairs.

FAO. (2015). CROPWAT 8.0 model. From www.fao.org/nr/water/infores_databases_cropwat.html

Fedorko, E. J., Pontius, R. G. J., Aldrich, S. P., Claessens, L., Hopkinson, C. J., & Wollheim, W. M. (2005). Spatial distribution of land type in regression models of pollutant loading. Journal of Spatial Hydrology, 5(2), 60-80.

Fox, J. (1991). Regression diagnostics: An introduction Sage University Papers Series on Quantitative Applications in the Social Sciences (Vol. series no. 07-079). Newbury Park, CA: Sage.

Hoekstra, A. Y. (2003). Virtual water trade-Proceedings of the international expert meeting on virtual water trade. Paper presented at the Proceedings of the International Expert Meeting on Virtual Water Trade, Delft, the Netherlands.

Hoekstra, A. Y., Chapagain, A. K., Aldaya, M. M., & Mekonnen, M. M. (2011). The Water Footprint Assessment Manual - Setting the Global Standard. UK: Earthscan.

Huang, C. L., & Chiang, J. K. (2003). Development of the New Rice Variety Tai-tung 30. Reserach Bulletin of Taitung District Agricultural Improvement Station, 14, 49-68.

Huberty, C. J. (1989). Problems with stepwise methods-better alternatives. Social Science Methodlogy, 1, 43-70.

Johnson, R. A., & Wichern, D. W. (2002). Applied Multivariate Statistical Analysis (5th ed.). US: Prentice-Hall, Inc.

Jung. T. S. (2013). Statistical Products and Services Solution. Taipei: Wu-Nun.

Mu, Q., Zhao, M., & Running, S. W. (2011). Improvements to a MODIS global terrestrial evapotranspiration algorithm. Remote Sensing of Environment, 115(8), 1781–1800.

Mu, Q., Zhao, M., & Running, S. W. (2013). MODIS Global Terrestrial Evapotranspiration (ET) Product (NASA MOD16A2/A3) - Algorithm Theoretical Basis Document Collection 5 Washington, DC: National Aeronautics and Space Administretion.

Ramoelo, A., Cho, M., Mathieu, R., Skidmore, A., Schlerf, M., & Heitkönig, I. (2012). Estimating grass nutrients and biomass as an indicator of rangeland (forage) quality and quantity using remote sensing in Savanna ecosystems. Paper presented at the 9th International Conference of the African Association of Remote Sensing and the Environment (AARSE), El Jadida, Morroco.

SAS Institute Inc. (2008). SAS/STAT® 9.2 User's Guide. Cary, NC: SAS Institute Inc.

Shen, H. & Liu, W. Z. (2011). Simulating Spatial Distribution of Precipitation over the Loess Plateau Based on macro-geographical Factors. Agricultural Research in the Arid Areas, 29(1), 237-241.

Shiau, W. L. (2007). Multivariate Analysis -SPSS+LISREAL (SEM). Taipei: Gotop.

Solano, R., Didan, K., Jacobson, A., & Huete, A. (2010). MODIS vegetation index user's guide (MOD13 Series) version 2.00: The University of Arizona.

USGS (US Geological Survey) (2013). Land processes distributed active archive center (LP DAAS), Vegetation Indices Retrieved August 8, 2015, from https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products _table/mod13q1