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A Method for Evapotranspiration Retrievals From a Mesoscale Model Based on Weather Variables for Soil Moisture Deficit Estimation

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Abstract

Reference Evapotranspiration (ETo) and soil moisture deficit (SMD) are vital for understanding the hydrological processes. Precise estimation of ETo and SMD are required for developing appropriate forecasting system and hydrological modelling. In this study, the surface temperature downscaled from Weather Research and Forecasting (WRF) model is used to estimate ETo using the boundary conditions provided by the European Center for Medium Range Weather Forecast (ECMWF). In order to understand the performance, the Hamon method is employed to estimate the ETo using the temperature from meteorological station and WRF derived variables. After estimating the ETo, a range of linear and non-linear models are utilized to retrieve SMD. The performance statistics such as RMSE, %Bias, and Nash Sutcliffe Efficiency indicates that the simplistic linear model is efficient for SMD estimation in comparison to other complex models. Findings of this study also showed that the technique is performing better during the growing season than the non-growing season for SMD.

Keywords: *Evapotranspiration; soil moisture deficit; WRF; Noah Land Surface model; Seasonality*

1. Introduction

Local, regional or global scale monitoring of Evapotranspiration (or ET) is vital for assessing climate and human-induced affects on natural and agricultural ecosystems [1,2]. There are numerous methods available for assessment of ET based on different conditions of soil, water, plants and land cover [3-7]. Allen et al. in 1998, provided a standard method for ET estimation using the standardised FAO-56 Penman-Monteith model [8] for grasses and given the term reference ETo. ETo can be represented as the sum of water that can be evaporated from the soil surface and transpired from vegetation when the soil water is sufficient to meet the atmospheric demand [8]. Many studies already conducted have documented that ETo fluxes at various scales have direct effect on water balance and hydrological cycle [9]. The regional variations in ETo also influences the soil water content and irrigation water demand [10]. Therefore, accurate estimation of ETo are needed for an improved monitoring of climate, water resources, drought and flood [11,12].

There are many methods to estimate ETo, among them the most simplest one is proposed by Hamon [13]. Hamon method requires temperature data for calculation of ETo, which can be downscaled using the advanced numerical weather prediction (NWP) model such as Weather Research and Forecasting (WRF) model. WRF model is well tested by a number of users with satisfactory performance and hence used in this study also for dynamical downscaling of surface temperature [14-16].

In real conditions, the soil water content usually varies because of changing meteorological conditions, crop suction and evaporation losses from the soil surface. The amount of water content required to bring back the soil moisture to field capacity can be described by using the term Soil Moisture Deficit (SMD) [17,18]. The prolonged deficiency of soil moisture SMD leads to drought conditions, while very low SMD may cause flooding problem during extreme rain events. Moreover, monitoring of SMD is an alternative method for irrigation scheduling and represents the usage of an optimal amount of water at appropriate time to avoid any agricultural losses [19]. The relationship between the SMD, ETo, rainfall etc are well documented in the previous studies by [19,20]. Therefore, ETo can be used for estimation of SMD using appropriate models.

In purview of the above, this work is focused on the following objectives: 1) to perform a performance evaluation of the WRF downscaled temperature for ETo estimation 2) to derive SMD using the WRF and observed ETo through several linear and non-linear models, and 3) to evaluate the impression of seasonality on SMD retrieval with special reference to growing and non-growing season. This article is divided into following sub-sections. After introduction, Section 2 provides a description of the study area and datasets, theoretical backgrounds of WRF-Noah LSM model, probability distributed model, Hamon's method and the statistical indices computed to evaluate the method. Section 3 delivers the results and discussion followed by conclusions in Section 4.

2. Materials and Methodology

2.1 Study area and datasets

The Brue catchment (135.5 Km^2) is used as a study area, having an elevation of 105 m above mean sea level, positioned in the south-west of England (51.11 °N and 2.47 °W) (**Figure 1**). All the measured dataset were provided by the Natural Environment Research Council and the British Atmospheric Data Centre, United Kingdom. For benchmark SMD, a probability distributed model or PDM is employed using the locally measured flow, rainfall and Evapotranspiration. PDM is used in UK for both operational and design purposes and successfully employed in other parts of the world [21,22]. The calibration of the model involves two years of hourly data from 1st February 2009 to 31st January 2011 is used, while for validation one year of data is taken into account for the period 1st February 2011 to 31st January 2012. The SMD obtained during the validation is considered for all the models development. The overall analysis of PDM indicated a satisfactory performance with NSE value of 0.84 and 0.81 during the calibration and validation respectively. The detailed information on PDM calibration, validation, sensitivity and uncertainty analysis over Brue is reported in [20]. The flowchart of the methodology used in present study is depicted through **Figure 2**.

Figure 1 Geographical location of the study area with WRF domains

Figure 2 Flowchart of the methodology used in this study

2.2 WRF-Noah LSM downscaling of surface temperature

The WRF-Noah Land Surface Model (LSM) based on eta-coordinate modeling system is used for downscaling surface temperature from ERA interim global reanalysis dataset. In total 28 terrain following the eta levels in the vertical direction from surface are used following a two-way nesting scheme [23,24]. The WRF physical scheme is shown through **Table.1**. The WRF-Noah LSM includes an explicit canopy resistance design given by Jacquemin and Noilhan in 1990 [25] and a surface runoff scheme provided by [26]. A more comprehensive explanation of the WRF-Noah LSM can be found in [27]. The WRF-Noah LSM model is used with three nested provinces having horizontal grid resolutions of 81 km (D1), 27 km (D2) and 9 km (D3). The D1, D2 and D3 consist of 18×18, 19×19, and 22×22 horizontal grids respectively. The area with 9 km resolution is used because generally WRF dynamical downscaling improves domain performances [28-30].

Table.1 WRF physical schemes employed in this study

2.3 Probability Distributed Model and Soil Moisture Deficit

The Probability Distributed Model (PDM) comes under the category of lumped model for depicting rainfall runoff relationship developed by the Centre of Ecology and Hydrology (CEH) Wallingford. It is employed in this study for SMD simulation using the ground based inputs of rainfall and reference evapotranspiration (ETo) [22]. It has a better representation of soil moisture computation and equipped with appropriate time steps for hydrological modelling. Through this model, the SMD can be estimated using the relationship below [31]:

$$\frac{E_i^{'}}{E_i} = 1 - \left\{\frac{\left(S_{\max} - S(t)\right)}{S_{\max}}\right\}^{b_e} \qquad (1)$$

where $\frac{E_i^{'}}{E_i}$ is the ratio of actual ET to potential ET; and $\left(S_{\max} - S(t)\right)$ is Soil Moisture Deficit; b_e is an exponent in the actual evaporation function; $S_{\max}$ is the total available storage and $S(t)$ is storage at a particular time *t*. The model structure of PDM is further discussed in [31]. Sensitivity analysis (SA) and uncertainty analysis (UA) are considered important to explore the high dimensional parameter spaces, structural uncertainty and also to understand the sources of uncertainty [32,33].

After a rigorous and careful calibration of the PDM following the Generalized Likelihood Uncertainty Estimation (GLUE), the SMD is extracted. The model parameters for PDM calibration are provided in the study conducted by Srivastava et al., in [22].

2.4 Reference Evapotranspiration or ETo

Many studies have confirmed that Hamon provides a stable and reasonable output as compared to the Thornthwaite, Hargreaves and Samani methods [34,35], therefore it is also used in the current study to estimate the ETo,. Hamon [13] proposed an equation to calculate ETo by providing day length and mean air temperature [36]. It shows the relationships among potential evapotranspiration, saturation vapor pressure, and the possible incoming radiant energy by means of the prevailing air temperature. The hours of sunlight can be used as an index for the maximum possible incoming radiant energy, while the absolute humidity at saturation is used for the estimating the moisture-holding capacity of air. It uses the mean daily temperatureand sunshine hours for ETo calculation. The saturation vapor pressure, e_s is then determined directly from the mean air temperature. One atypical feature of this method is that when mean air temperature is lesser than 0°C, the ETo does not drop up to zero; instead, it provides effectively the same as annual total of the Thornthwaite method [4]. In the Hamon technique, ETo (mm/day) is estimated as follows:

$$ETo = 29.8 * L_{day}\left(\frac{e_s}{T + 273.3}\right) \qquad (2)$$

where: T = Temperature (degree centigrade); L_{day} = Day time length (Unitless); e_s Saturation Vapor Pressure (mb) at given T can be computed using:

$$e_s = 6.108_e\left(\frac{17.27T}{T + 237.3}\right) \qquad (3)$$

2.5 Performance analysis

In present study, SMD assessed from the WRF and observed ETo are validated with PDM SMD. The performance statistics Nash Sutcliffe Efficiency (NSE)[37], Root Mean Square Error (RMSE), %Bias and Correlation (r) are used to understand the model performances. The %Bias, NSE and RMSE can be calculated using Eq.4-6.

$$\%Bias = 100*[\sum(y_i - x_i)/\sum(x_i)] \tag{4}$$

$$NSE = 1 - \frac{\sum_{i-1}^{n}\left[y_i - x_i\right]^2}{\sum_{i-1}^{n}\left[x_i - \overline{x}_i\right]^2} \tag{5}$$

$$RMSE = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}\left[y_i - x_i\right]^2\right)} \tag{6}$$

where n is the number of observations; x is the perceived variable and y is the simulated variable.

3. Results and Discussion

3.1 Evaluation of hydro-meteorological variables

The WRF-Noah LSM downscaled temperature data is evaluated by utilising the observed temperature measured at the meteorological station. The trends in the WRF and observed temperature are represented through **Figure 3a**, while the association between the SMD and rainfall are indicated in **Figure 3b**. Both the plots are used to understand the relationship between the SMD behavior and the hydro-meteorological parameters (rainfall and temperature). A direct appraisal of the temperatures from WRF with the other hydro-meteorological variables showed that these results are comparable to those obtained in the past and with the other data sets collected in this catchment. In spite of some mismatch in the data, the plot indicates a general covenant between the temporal trend of the WRF and observed temperatures with seasons and the declining trend of the rainfall throughout the observation period. A significant optimistic relationship between the SMD and temperature are also evident in the **Figure 3a-b**. All the plots exhibit a close match with the seasonal changes from winter to autumn. There is a gradual rise in temperature observed, when progressing from the winter to spring and summer seasons, followed by gradual decrease in temperature on arrival of the autumn season. Similar behavior can be seen in the SMD pattern also, as rise in temperature cause an increase in SMD values. Some spikes in the temporal plots can be attributed to some sporadic rainfall or storm events. These short duration storms cause a change in SMD and create spiky fluctuations in temperature. It is also evident from the figure that after a rainfall event, there is some lag time for SMD changes for nearly ~1-2 days. Therefore, in overall, there is significant relationships exist between the temperature and the SMD in the Brue catchment.

Figure 3 Temporal relationships between hydro-meteorological variables a) WRF and Observed temperature b) Precipitation and SMD

The ETo calculated by using the temperature data from WRF and ground based observations are shown using the correlation matrix plots along with the SMD in **Figure 4**. Hydro-meteorological variables used for ETo estimation are temperature, sunshine hour and saturation vapor pressure following the Hamon method. The Hamon model is grounded on coefficient derived from an empirically determined model. The time series of both the observed and WRF ETo are ranges from 0.0005 mm/day to 0.0040 mm/day. There is a no major difference found between the WRF and observed dataset when plotted against SMD. The *r* and *rs* correlations indicates a value of 0.75 for both WRF and observed ETo, which indicates that the WRF downscaled surface temperature when used with Hamon method can provide an accurate estimates of ETo for various applications. Some lower performances in correlation can be attributed to the high precipitation in the Brue catchment and the influence of temperate maritime climate. Further, slight overestimation of ETo over wet areas indicates that a correction factor is needed in the Hamon model.

Figure 4 Correlation matrix plot between SMD, observed and WRF downscaled temperature based ETo

3.2 Comparison of SMD estimated using different ETo products

For utilization of dataset for hydrological applications, relationship between PDM and ETo based SMD is examined using various linear and nonlinear algorithms. To segregate the data for calibration and validation, the dataset is distributed into two third and one-third parts. The first two third parts are considered for model calibrations while the remaining part is for the models validation. This method has its own significance as it represent the data for all seasons. In total five linear and non-linear models are employed to estimate the relationships for SMD assessment using the perceived and WRF ETo *viz* linear, second and third order polynomial, exponential and logarithmic algorithms (**Figure 5 and 6**). In **Table 2**, the performances of the diverse models in terms of $R^2$are indicated by using the ETo derived from WRF and Observed dataset. The model results indicate that the observed ETo and SMD indicate a higher performance in comparison to WRF ETo. Among all the techniques 0.749 is the best NSE obtained with 3rd order polynomial regression technique, implies that the relationship between PDM SMD and observed ETo can be best represented by third order polynomial. Other than this logarithmic and second order polynomial models are also produced satisfactory R^2 values of 0.689 and 0.722 respectively. On the other hand, the linear and exponential model does not provide good results as compared to other techniques. The performance statistics between WRF ETo and PDM SMD indicates a marginally lower performance in contrast to the observed ETo (table. 2). As expected, in case of WRF, the R^2 for different regression techniques gives the similar values as observed ones with the highest in case of 3rd order polynomial (0.739) followed by 2nd order polynomial (0.731), logarithmic (0.689), exponential (0.549) and linear (0.616) during the calibration. It isevident from the R^2 statistics that WRF simulated surface temperature data could be used for SMD in absence of ground-based observations. However, an exact accuracy of the dataset is needed for operational applications. The validations of linear and non-linear models for SMD estimation are presented with their performance statistics. The statistical indices such as NSE, RMSE and %Bias test are used to understand the model performance during validation (**Table 3**), while the behavior of the dataset can be pictured through **Figure 7**. Different algorithms provide different NSE values, which ranges from 0.013 to 0.448. From the results, it is evident that linear regression technique has good NSE (0.448) as compare to all the other models. Herein, the high performance of linear model can be revealed by analyzing the Pearson's and Spearman's correlation statistics between PDM SMD, observed and WRF ETo. From the Spearman's correlation statistics, it is clear that that there is no strong non-linearity exists between the dataset and therefore, the proposed linear model could be used for SMD estimation, because of its simplicity.

Figure 5 Calibration of different models-a) Linear b) Polynomial 2 c) Polynomial 3 d) Logarithmic e) Exponential using WRF ETo

Figure 6 Calibration of different models -a) Linear b) Polynomial 2 c) Polynomial 3 d) Logarithmic e) Exponential using Observed ETo

Figure 7SMD simulated using WRF and Observed ETo during validation from the models -a) Linear b) Polynomial 2 c) Polynomial 3 d) Logarithmic e) Exponential

Table 2 Different models used for SMD estimation using WRF and Observed ETo

Table 3 Performance of models during validation

3.3 Performance with growing and non-growing seasons

Many studies indicated that vegetation plays an important role in the differences of soil water content. Authors have reported that the transformation in seasons specially growing and non-growing season have significant impact on SMD. In earlier study, it has been found that growing and non-growing seasons behave differently, so for proper assessment and understanding of SMD inclusion of growing and non-growing seasons are important. During growing season, crops hamper the exact valuation of ETo as they do not have proper correction factor to differentiate the growing and non-growing seasons (Srivastava et al., 2013). For understanding the data in efficient way, the dataset is divided conferring to the growing and non-growing seasons. As per the UK met office, temperature is an important parameter for deciding the growing and non-growing seasons. When the temperature of five consecutive days exceeds 5 °C, there will be onset of growing season, while it ends when the temperatures fall below 5 °C for five consecutive days. The 1971 to 2000 average season length was 280 days (~ 9.3 months) (Source: http://www.metoffice.gov.uk/climate/uk/averages/ukmapavge.html). Therefore, in current study the entire season of winter (December-February) is taken as non-growing (average temperature <5°C), while March-November are chosen as growing season (average temperature >5°C).

Box plots are used to understand the variations in SMD values during the growing and non-growing seasons as shown in **Figure 8**. In non-growing season, the SMD from WRF ETo is showing good match with benchmark SMD in terms of distribution as it is capturing good variations. The results of WRF ETo based SMD is found comparable with the observed ETo based SMD. The upper and lower minima of WRF and observed dataset based SMD are found on the same levels. Growing season is also providing the similar types of results, which indicates a comparable performance between the WRF and observed dataset based SMD. In non-growing season during December, January and February the range of SMD lies in between 0.017 to 0.038m. This is likely to be because of lower temperature, low evaporation and lesser solar radiation that leads to high soil moisture in the non-growing season and hence low SMD. During the growing season from March to November, there is a steady rise in SMD observed with recorded highest value of 0.10 m in the month of June.

Figure 8 Box and whisker plots for SMD distribution during growing and non-growing season

Figure 9 is showing seasonality in the PDM, WRF and observed ETo. For pastoral landscape, the demand of water is mostly depends on the exposure of the land and thickness of the grass type. The vegetation covers over the surface of soil reduces the loss of the moisture from the soils because of reduced exposure to the sunlight. The extent of non-growing period is lesser than that of the growing season and the accessibility of environmental variable such as soil moisture is mainly depends on the climate, soil (texture) and vegetation. For the non-growing period (mostly a bare soil or snow covered), the SMD from WRF ETo is slightly overestimated in comparison to PDM SMD. In the growing season, it might be because of the roughness of the soil and high soil moisture variability, there is an overestimation recorded in the months of late February to mid May, whereas an underestimation is found all through the months of mid May to August tailed by the November month (**Figure 9)**. The SMD from WRF ETo matches closely to PDM SMD throughout the year except for the last week of July where it is showing an underestimation when compared with the SMD using the Obs ETo. Further, during the June, although both WRF and observed ETo based SMD follows a close pattern but there is some sharp drops occurred that might be due to some short duration storms in the area.

The three evaluation statistics are used to assess the influence of growing and non-growing seasons on SMD (**Table 4**). The performance statistics indicates that during the growing season, the SMD estimated using the WRF ETo (RMSE = 0.025, r = 0.245) has lower performance than the SMD using the observed ETo (RMSE = 0.024, r = 0.281). However, during the non-growing season some lower performances are detected in terms of %Bias and r in the datasets as related to the growing season. On the other hand, a better performance is found during the non-growing season as compared to the growing season with lower value of RMSE in former case than the latter. The performance statistics during the non-growing season reveals a slight lower efficiency of the linear model in case of WRF ETo based SMD (RMSE = 0.012, r = 0.161)as compared to observed ETo based SMD (RMSE = 0.011, r = 0.244). The PDM and simulated SMD during the growing and non-growing seasons with 1:1 equiline are shown in **Figure 10**. By looking over the %Bias of the model, both the growing and non-growing seasons indicates a similar performance. A high bias is recorded in the dataset from the SMD simulated using the WRF ETo during the non-growing season. Similarly during the growing season an underestimation is recorded in the both the dataset. Even though there is some mismatch between the model performances during the two seasons, by comparing the %Bias the datasets indicates a satisfactory performance. Therefore, the ETo derived from the WRF temperature can be utilised for SMD estimation in absence of ground based information. The analysis reveals that there is profound effect of growing and non-growing season on the SMD simulation. Therefore, separate algorithms are needed to represent the responses of both the seasons.

Figure 9 Temporal behavior of simulated and PDM SMD during growing and non-growing season

Figure 10 Performance during growing and non-growing seasons

Table 4 Performance statistics during growing and non-growing season

4. Conclusions

The mesoscale model-WRF-Noah LSM is a sophisticated model for the numerical weather prediction that can be used for downscaling of global hydro- rological variables into finer spatio-temporal resolutions and thus can be used for ETo estimation. In this work, the Hamon method has been employed to calculate ETo from WRF downscaled surface temperature data and station observations. The trend indicates marginal differences in the WRF and station based ETo when plotted against SMD. Similar results are also reported by correlation statistics between the station and WRF derived ETo for SMD prediction. Among many linear and non-linear techniques used in this study, the best performance is reported by linear model for SMD estimation during the validation.

The changes in ETo are dependent on the climatic and geographical factors, which affects the spatial distribution of ETo. Therefore, more analysis is needed in this direction for different geographical areas to estimate the changes in ETo in terms of spatial and temporal distributions of temperature, precipitation, location and the elevation. This study indicates a reliable relationship between the temporal variability of ETo flux and SMD in the region influenced by temperate maritime climate. The ETo derive in this study can be further improved by providing the physical characteristics of locations (e.g. climate, topography, etc.), so that a modified Hamon model for ETo would be available for different applications. Therefore, future work will focus on providing a correction factor in the Hamon method, which is expected to result to a more accurate ETo estimation suited particularly for hydrological applications.

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