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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 (ET_o) and soil moisture deficit (SMD) are vital for understanding the hydrological processes. Precise estimation of ET_o 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 ET_o 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 ET_o using the temperature from meteorological station and WRF derived variables. After estimating the ET_o, 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

39 using the standardised FAO-56 Penman-Monteith model [8] for grasses and given the term
40 reference ETo. ETo can be represented as the sum of water that can be evaporated from the soil
41 surface and transpired from vegetation when the soil water is sufficient to meet the atmospheric
42 demand [8]. Many studies already conducted have documented that ETo fluxes at various scales
43 have direct effect on water balance and hydrological cycle [9]. The regional variations in ETo
44 also influences the soil water content and irrigation water demand [10]. Therefore, accurate
45 estimation of ETo are needed for an improved monitoring of climate, water resources, drought
46 and flood [11,12].

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

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

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

72

73 **2. Materials and Methodology**

74 **2.1 Study area and datasets**

75 The Brue catchment (135.5 Km²) is used as a study area, having an elevation of 105 m
76 above mean sea level, positioned in the south-west of England (51.11 °N and 2.47 °W) (**Figure**
77 **1**). All the measured dataset were provided by the Natural Environment Research Council and

78 the British Atmospheric Data Centre, United Kingdom. For benchmark SMD, a probability
79 distributed model or PDM is employed using the locally measured flow, rainfall and
80 Evapotranspiration. PDM is used in UK for both operational and design purposes and
81 successfully employed in other parts of the world [21,22]. The calibration of the model involves
82 two years of hourly data from 1st February 2009 to 31st January 2011 is used, while for validation
83 one year of data is taken into account for the period 1st February 2011 to 31st January 2012. The
84 SMD obtained during the validation is considered for all the models development. The overall
85 analysis of PDM indicated a satisfactory performance with NSE value of 0.84 and 0.81 during
86 the calibration and validation respectively. The detailed information on PDM calibration,
87 validation, sensitivity and uncertainty analysis over Brue is reported in [20]. The flowchart of the
88 methodology used in present study is depicted through **Figure 2**.

89
90
91 **Figure 1 Geographical location of the study area with WRF domains**

92 **Figure 2 Flowchart of the methodology used in this study**

93 94 95 **2.2 WRF-Noah LSM downscaling of surface temperature**

96 The WRF-Noah Land Surface Model (LSM) based on eta-coordinate modeling system is used
97 for downscaling surface temperature from ERA interim global reanalysis dataset. In total 28
98 terrain following the eta levels in the vertical direction from surface are used following a two-
99 way nesting scheme [23,24]. The WRF physical scheme is shown through **Table.1**. The WRF-
100 Noah LSM includes an explicit canopy resistance design given by Jacquemin and Noilhan in
101 1990 [25] and a surface runoff scheme provided by [26]. A more comprehensive explanation of
102 the WRF-Noah LSM can be found in [27]. The WRF-Noah LSM model is used with three nested
103 provinces having horizontal grid resolutions of 81 km (D1), 27 km (D2) and 9 km (D3). The D1,
104 D2 and D3 consist of 18×18, 19×19, and 22×22 horizontal grids respectively. The area with 9
105 km resolution is used because generally WRF dynamical downscaling improves domain
106 performances [28-30].

107 **Table.1 WRF physical schemes employed in this study**

108 **2.3 Probability Distributed Model and Soil Moisture Deficit**

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

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

where $\frac{E'_i}{E_i}$ is the ratio of actual ET to potential ET; and $(S_{\max} - S(t))$ 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 temperature and 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:

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

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

$$e_s = 6.108 \left(\frac{17.2143}{T + 237.3} \right) \quad (3)$$

146 2.5 Performance analysis

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

$$151 \quad \% \text{Bias} = 100 * [\sum (y_i - x_i) / \sum (x_i)] \quad (4)$$

$$152 \quad NSE = 1 - \frac{\sum_{i=1}^n [y_i - x_i]^2}{\sum_{i=1}^n [x_i - \bar{x}]^2} \quad (5)$$

$$153 \quad RMSE = \sqrt{\left(\frac{1}{n} \sum_{i=1}^n [y_i - x_i]^2 \right)} \quad (6)$$

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

156

157 3. Results and Discussion

158 3.1 Evaluation of hydro-meteorological variables

159 The WRF-Noah LSM downscaled temperature data is evaluated by utilising the observed
160 temperature measured at the meteorological station. The trends in the WRF and observed
161 temperature are represented through **Figure 3a**, while the association between the SMD and
162 rainfall are indicated in **Figure 3b**. Both the plots are used to understand the relationship
163 between the SMD behavior and the hydro-meteorological parameters (rainfall and temperature).
164 A direct appraisal of the temperatures from WRF with the other hydro-meteorological variables
165 showed that these results are comparable to those obtained in the past and with the other data sets
166 collected in this catchment. In spite of some mismatch in the data, the plot indicates a general
167 covenant between the temporal trend of the WRF and observed temperatures with seasons and
168 the declining trend of the rainfall throughout the observation period. A significant optimistic
169 relationship between the SMD and temperature are also evident in the **Figure 3a-b**. All the plots
170 exhibit a close match with the seasonal changes from winter to autumn. There is a gradual rise in
171 temperature observed, when progressing from the winter to spring and summer seasons, followed
172 by gradual decrease in temperature on arrival of the autumn season. Similar behavior can be seen
173 in the SMD pattern also, as rise in temperature cause an increase in SMD values. Some spikes in
174 the temporal plots can be attributed to some sporadic rainfall or storm events. These short

175 duration storms cause a change in SMD and create spiky fluctuations in temperature. It is also
176 evident from the figure that after a rainfall event, there is some lag time for SMD changes for
177 nearly ~1-2 days. Therefore, in overall, there is significant relationships exist between the
178 temperature and the SMD in the Brue catchment.

179

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

182 The ETo calculated by using the temperature data from WRF and ground based observations are
183 shown using the correlation matrix plots along with the SMD in **Figure 4**. Hydro-meteorological
184 variables used for ETo estimation are temperature, sunshine hour and saturation vapor pressure
185 following the Hamon method. The Hamon model is grounded on coefficient derived from an
186 empirically determined model. The time series of both the observed and WRF ETo are ranges
187 from 0.0005 mm/day to 0.0040 mm/day. There is a no major difference found between the WRF
188 and observed dataset when plotted against SMD. The r and rs correlations indicates a value of
189 0.75 for both WRF and observed ETo, which indicates that the WRF downscaled surface
190 temperature when used with Hamon method can provide an accurate estimates of ETo for
191 various applications. Some lower performances in correlation can be attributed to the high
192 precipitation in the Brue catchment and the influence of temperate maritime climate. Further,
193 slight overestimation of ETo over wet areas indicates that a correction factor is needed in the
194 Hamon model.

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

197 **3.2 Comparison of SMD estimated using different ETo products**

198 For utilization of dataset for hydrological applications, relationship between PDM and ETo
199 based SMD is examined using various linear and nonlinear algorithms. To segregate the data for
200 calibration and validation, the dataset is distributed into two third and one-third parts. The first
201 two third parts are considered for model calibrations while the remaining part is for the models
202 validation. This method has its own significance as it represent the data for all seasons. In total
203 five linear and non-linear models are employed to estimate the relationships for SMD assessment
204 using the perceived and WRF ETo *viz* linear, second and third order polynomial, exponential
205 and logarithmic algorithms (**Figure 5 and 6**). In **Table 2**, the performances of the diverse models
206 in terms of R^2 are indicated by using the ETo derived from WRF and Observed dataset. The
207 model results indicate that the observed ETo and SMD indicate a higher performance in
208 comparison to WRF ETo. Among all the techniques 0.749 is the best NSE obtained with 3rd
209 order polynomial regression technique, implies that the relationship between PDM SMD and
210 observed ETo can be best represented by third order polynomial. Other than this logarithmic and
211 second order polynomial models are also produced satisfactory R^2 values of 0.689 and 0.722
212 respectively. On the other hand, the linear and exponential model does not provide good results

213 as compared to other techniques. The performance statistics between WRF ETo and PDM SMD
214 indicates a marginally lower performance in contrast to the observed ETo (table. 2). As expected,
215 in case of WRF, the R^2 for different regression techniques gives the similar values as observed
216 ones with the highest in case of 3rd order polynomial (0.739) followed by 2nd order polynomial
217 (0.731), logarithmic (0.689), exponential (0.549) and linear (0.616) during the calibration. It
218 is evident from the R^2 statistics that WRF simulated surface temperature data could be used for
219 SMD in absence of ground-based observations. However, an exact accuracy of the dataset is
220 needed for operational applications. The validations of linear and non-linear models for SMD
221 estimation are presented with their performance statistics. The statistical indices such as NSE,
222 RMSE and %Bias test are used to understand the model performance during validation (**Table**
223 **3**), while the behavior of the dataset can be pictured through **Figure 7**. Different algorithms
224 provide different NSE values, which ranges from 0.013 to 0.448. From the results, it is evident
225 that linear regression technique has good NSE (0.448) as compare to all the other models.
226 Herein, the high performance of linear model can be revealed by analyzing the Pearson's and
227 Spearman's correlation statistics between PDM SMD, observed and WRF ETo. From the
228 Spearman's correlation statistics, it is clear that that there is no strong non-linearity exists
229 between the dataset and therefore, the proposed linear model could be used for SMD estimation,
230 because of its simplicity.

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

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

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

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

238 **Table 3 Performance of models during validation**

239

240 **3.3 Performance with growing and non-growing seasons**

241 Many studies indicated that vegetation plays an important role in the differences of soil water
242 content. Authors have reported that the transformation in seasons specially growing and non-
243 growing season have significant impact on SMD. In earlier study, it has been found that growing
244 and non-growing seasons behave differently, so for proper assessment and understanding of
245 SMD inclusion of growing and non-growing seasons are important. During growing season,
246 crops hamper the exact valuation of ETo as they do not have proper correction factor to
247 differentiate the growing and non-growing seasons (Srivastava et al., 2013). For understanding

248 the data in efficient way, the dataset is divided conferring to the growing and non-growing
249 seasons. As per the UK met office, temperature is an important parameter for deciding the
250 growing and non-growing seasons. When the temperature of five consecutive days exceeds 5 °C,
251 there will be onset of growing season, while it ends when the temperatures fall below 5 °C for
252 five consecutive days. The 1971 to 2000 average season length was 280 days (~ 9.3 months)
253 (Source: <http://www.metoffice.gov.uk/climate/uk/averages/ukmapavge.html>). Therefore, in
254 current study the entire season of winter (December-February) is taken as non-growing (average
255 temperature <5°C), while March-November are chosen as growing season (average temperature
256 >5°C).

257 Box plots are used to understand the variations in SMD values during the growing and non-
258 growing seasons as shown in **Figure 8**. In non-growing season, the SMD from WRF ETo is
259 showing good match with benchmark SMD in terms of distribution as it is capturing good
260 variations. The results of WRF ETo based SMD is found comparable with the observed ETo
261 based SMD. The upper and lower minima of WRF and observed dataset based SMD are found
262 on the same levels. Growing season is also providing the similar types of results, which indicates
263 a comparable performance between the WRF and observed dataset based SMD. In non-growing
264 season during December, January and February the range of SMD lies in between 0.017 to
265 0.038m. This is likely to be because of lower temperature, low evaporation and lesser solar
266 radiation that leads to high soil moisture in the non-growing season and hence low SMD. During
267 the growing season from March to November, there is a steady rise in SMD observed with
268 recorded highest value of 0.10 m in the month of June.

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

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

286 The three evaluation statistics are used to assess the influence of growing and non-growing
287 seasons on SMD (**Table 4**). The performance statistics indicates that during the growing season,
288 the SMD estimated using the WRF ETo (RMSE = 0.025, $r = 0.245$) has lower performance than
289 the SMD using the observed ETo (RMSE = 0.024, $r = 0.281$). However, during the non-growing
290 season some lower performances are detected in terms of %Bias and r in the datasets as related
291 to the growing season. On the other hand, a better performance is found during the non-growing
292 season as compared to the growing season with lower value of RMSE in former case than the
293 latter. The performance statistics during the non-growing season reveals a slight lower efficiency
294 of the linear model in case of WRF ETo based SMD (RMSE = 0.012, $r = 0.161$) as compared to
295 observed ETo based SMD (RMSE = 0.011, $r = 0.244$). The PDM and simulated SMD during the
296 growing and non-growing seasons with 1:1 equiline are shown in **Figure 10**. By looking over the
297 %Bias of the model, both the growing and non-growing seasons indicates a similar performance.
298 A high bias is recorded in the dataset from the SMD simulated using the WRF ETo during the
299 non-growing season. Similarly during the growing season an underestimation is recorded in the
300 both the dataset. Even though there is some mismatch between the model performances during
301 the two seasons, by comparing the %Bias the datasets indicates a satisfactory performance.
302 Therefore, the ETo derived from the WRF temperature can be utilised for SMD estimation in
303 absence of ground based information. The analysis reveals that there is profound effect of
304 growing and non-growing season on the SMD simulation. Therefore, separate algorithms are
305 needed to represent the responses of both the seasons.

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

308 **Figure 10 Performance during growing and non-growing seasons**

309 **Table 4 Performance statistics during growing and non-growing season**

310

311 **4. Conclusions**

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

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

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