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Probabilistic simulation of surface soil moisture using hydrometeorological inputs

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Soil moisture is an important parameter in hydrometeorological as well as terrestrial geochemical processes. Near surface soil moisture is found to be critical for crop yield, occurrence of drought, soil erosion, regional weather prediction etc. However, in situ measurement of this important variable is difficult because of its high spatial and temporal variability. Variability of soil moisture can be attributed to heterogeneity in soil properties and distribution of hydrometeorological factors like precipitation, temperature, relative humidity etc. In this article, a hydrometeorological approach to probabilistically simulate soil moisture, at the monthly scale using a combined hydrometeorological (CHM) index, is proposed. A principal component analysis (PCA)–based approach is adopted to derive the CHM index from several meteorological variables. The joint probability distribution between CHM index and soil moisture is determined by a bivariate copula function. The proposed model is able to estimate soil moisture along with the quantification of associated uncertainty for a new location having a hydrometeorological data set and information on predominant soil type at that location. Simulated soil moisture is compared with soil moisture simulated by H96 Climate Prediction Center (CPC) model, which is based on the leaky bucket model. Advantages of proposed model for 10 soil moisture–monitoring stations in India are discussed.

Keywords: soil moisture; probabilistic simulation; hydrometeorological variables; PCA; copula

Introduction

Soil moisture is critical in partitioning heat flux between sensible and latent fluxes within the boundary layer of the atmosphere close to the surface. It controls the thermal inertia and albedo of the surface and impacts the temperature–evaporation–precipitation feedback loop (Seneviratne et al. 2010). Thus, soil moisture plays a significant role in crop yield (Bastiaanssen et al. 2000) and numerical weather prediction using climate variables at the regional scale (Panareda et al. 2010). The amount of moisture content in the root zone has significant importance, especially during the critical growth period of the crops (Narasimhan and Srinivasan 2005). Soil moisture also controls the terrestrial water balance by partitioning precipitation among infiltration, runoff and evaporation (Seneviratne et al. 2010). The capillary action that determines the evaporative demand and withdrawal of water through plant roots is driven by soil moisture content (Entekhabi et al. 1996).

Thus, soil moisture is an important factor for drought, flood prediction, erosion caused by surface runoff, ground water recharge etc. (Wei et al. 2007). Soil moisture drought generally occurs as a consequence of meteorological drought and directly affects crops and other vegetation (Vazifedoust 2007). Soil moisture influences temperature, relative humidity and precipitation in the regional scale by controlling the evapotranspiration rate (Panareda et al. 2010). It also controls the development of the atmospheric boundary layer. So, antecedent soil moisture data are considered a critical input to land surface models (LSMs) (Benjamin et al. 2004). Change in spatio-temporal distribution of precipitation due to climate change is adding more complexities to its role in different terrestrial processes. Thus, the United Nations Framework Convention on Climate Change (UNFCCC) has declared soil moisture as an Essential Climate Variable (ECV) and taken initiatives for monitoring soil moisture with high precision, over a long period (2010–15) (GCOS 2010).

Spatio-temporal variability of soil moisture can be attributed to heterogeneity in soil properties and distribution of hydrometeorological factors like precipitation, temperature, relative humidity etc. Wide variations in topography, spatial heterogeneity of soil properties and distribution of rainfall are some of the critical issues towards the estimation of overall soil moisture monitoring for a large area. In addition to this, in situ point measuring techniques of soil moisture are labour intensive and expensive. As a matter of fact, in situ soil moisture data are available, until recently, in only some parts of the world and for short time periods (Robock et al. 2000; Dorigo et al. 2011).

Recently, because of the emerging thrust on climate research in the era of climate change, extensive databases of primary climate variables, such as precipitation, temperature, relative humidity, air pressure, wind speed etc. are available. These are either collection of in situ data as in the Climate Research Unit, University of East Anglia, United Kingdom, database (New et al. 2000) or modelled as in the National Ocean and Atmospheric Administration (NOAA) Reanalysis I database (Kalnay et al. 1996).

The objective of this study is to develop a probability-based soil moisture simulation model by utilising available hydrometeorological data as well as information on local soil properties. The results are compared with the output of

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existing simulation models such as the CPC H96 model (Huang et al. 1996; Fan and van den Dool 2004) soil moisture data to explore its advantages.

Methodology

In this article, a hydrometeorological model is proposed to simulate surface soil moisture, using available hydrometeorological inputs and information of predominant soil type for a particular location on a monthly scale. A flowchart showing the overview of the proposed method of simulation is presented in Figure 1. The methodology is explained here.

Simulation of Soil Moisture

Soil moisture, precipitation and relative humidity at a monthly scale are found to follow a Gamma distribution, whereas the near surface air temperature, near surface air pressure and wind speed at the same scale are found to follow a normal distribution. A principal component analysis (PCA) is carried out between the reduced variate of soil moisture and all the possibly influencing hydrometeorological variables (as mentioned before). The principal component that produces the highest association (in terms of correlation coefficients) is selected as multiplying coefficients to develop the CHM index.

As stated before, the distribution of soil moisture depends on a combination of various hydrometeorological variables as well as soil properties, which is dependent on soil grain size or texture class. Hence, monitoring stations with sufficiently long in situ soil moisture data are clustered into groups based on major Indian soil texture class described by Rao (1998), and separate models are developed for each group. PCA coefficients are found to be similar for all stations belonging to a particular soil group. An average (among different stations belonging to the same soil group) of these coefficients are used to compute the CHM index for the soil group. Derived CHM index was found to approximately follow a normal distribution. A joint distribution function is developed between the CHM index and soil moisture using the best bivariate copula function (Genest et al. 2009; Chowdhary et al. 2011). The best copula function is found to be the Clayton copula function. The conditional CDF of soil moisture conditioned on a CHM index is derived that yields simulated soil moisture values. This is repeated for all the soil groups. For a particular soil group, the obtained average coefficients for computing the CHM index and average joint distribution parameter value are utilised for testing stations belong to the same soil group in order to check its spatial extendability.

Performance Checking

For each soil group, separate models are developed. Then, the developed model is used to simulate soil moisture at another station (testing station) that is located in the same soil group. Simulated values of soil moisture at stations used for model development as well as at testing stations are compared with in situ measured soil moisture data, and their association is checked through statistical measures. The simulated values are also compared with the output of the H96 CPC model data, which is derived using one-layer leaky bucket model (Fan and van den Dool 2004) to check the performance of the proposed model. Correlation coefficients, root mean square error (RMSE) and Nash-Sutcliffe model efficiency coefficient (NSE) values are calculated for both soil moisture simulated using the proposed model and CPC model output data with in situ data to quantify the efficiency of the proposed model.

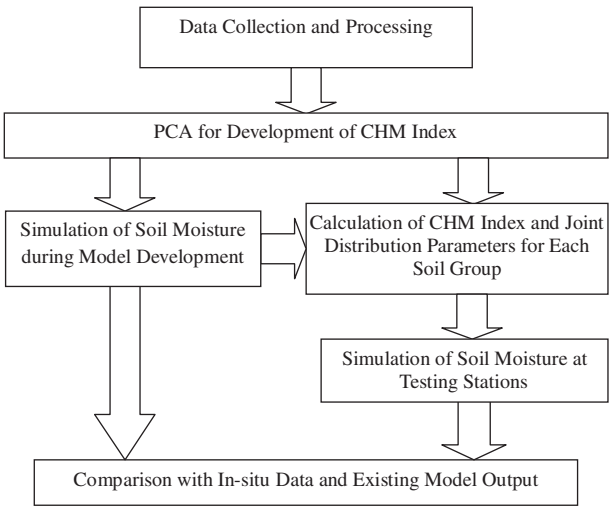

Figure 1. Flowchart summarising the overview of the proposed approach.

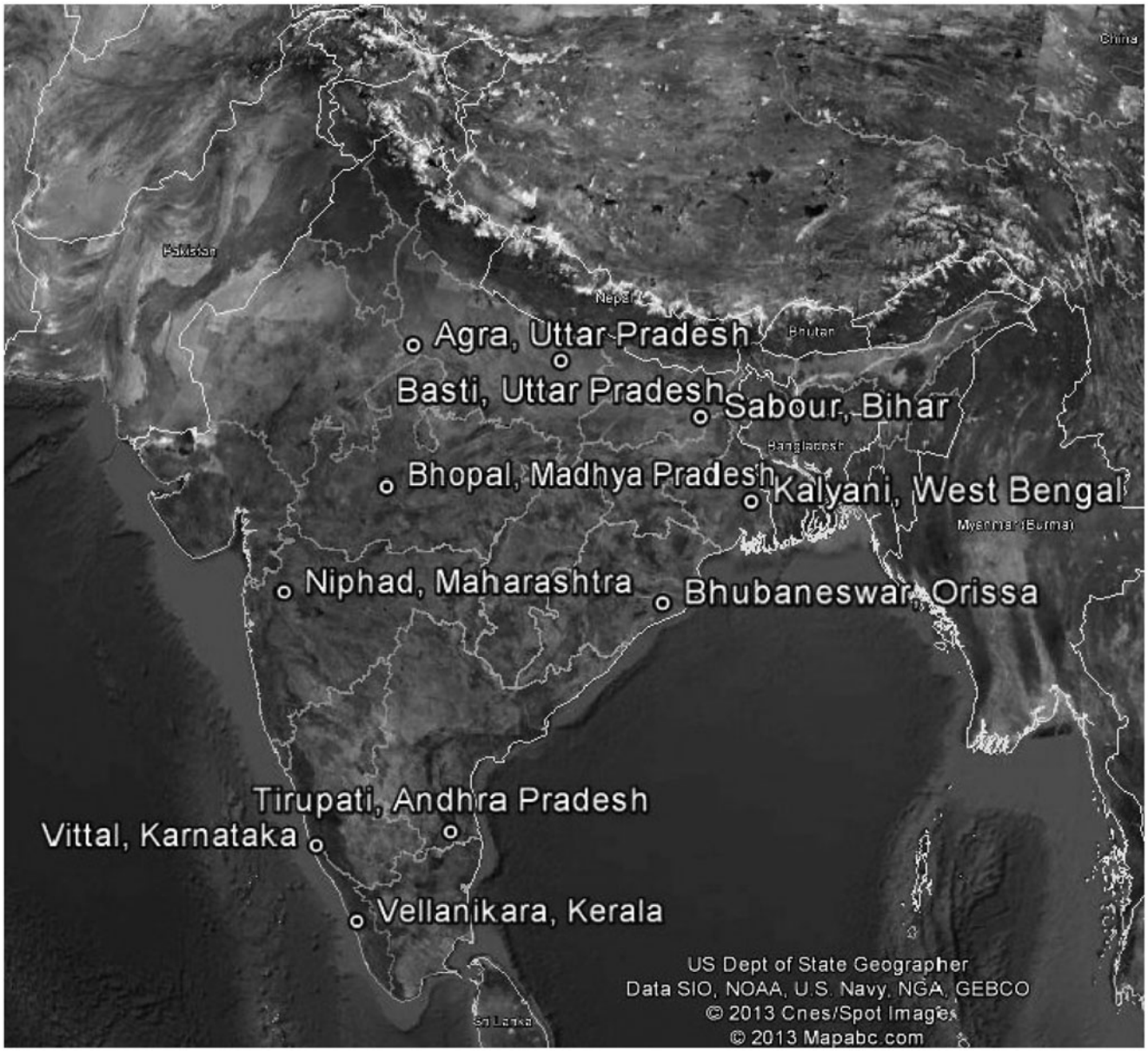

Figure 2. Locations of soil moisture–monitoring stations in India (Google Earth, 2012).

Table 1. Grouping of monitoring stations according to grain size and texture class.

Grain size class	Soil texture	Stations for model development	Stations for testing
Coarse	Loamy sand to sandy loam	Sabour	—
Medium	Sandy loam to loam	Vellanikara, Agra, Basti	Bhubaneswar
Medium to fine	Loam to clay loam	Kalyani, Tirupati	Vittal
Fine	Clay loam	Niphad	Bhopal

Table 2. Results of performance checking: Correlation coefficient, RMSE and NSE of both in situ vs. proposed model data and in situ vs. H96 CPC model data.

	Correlation coefficient		RMSE		NSE	
Testing stations	*In situ vs. proposed model output*	*In situ vs. CPC model output*	*In situ vs. proposed model output*	*In situ vs. CPC model output*	*Proposed model*	*CPC model*
Bhopal	0.604	0.696	71.568	71.817	0.478	0.474
Bhubaneswar	0.363	0.456	27.600	151.050	0.174	−22.928
Vittal	0.164	0.494	104.350	103.010	0.038	−0.026

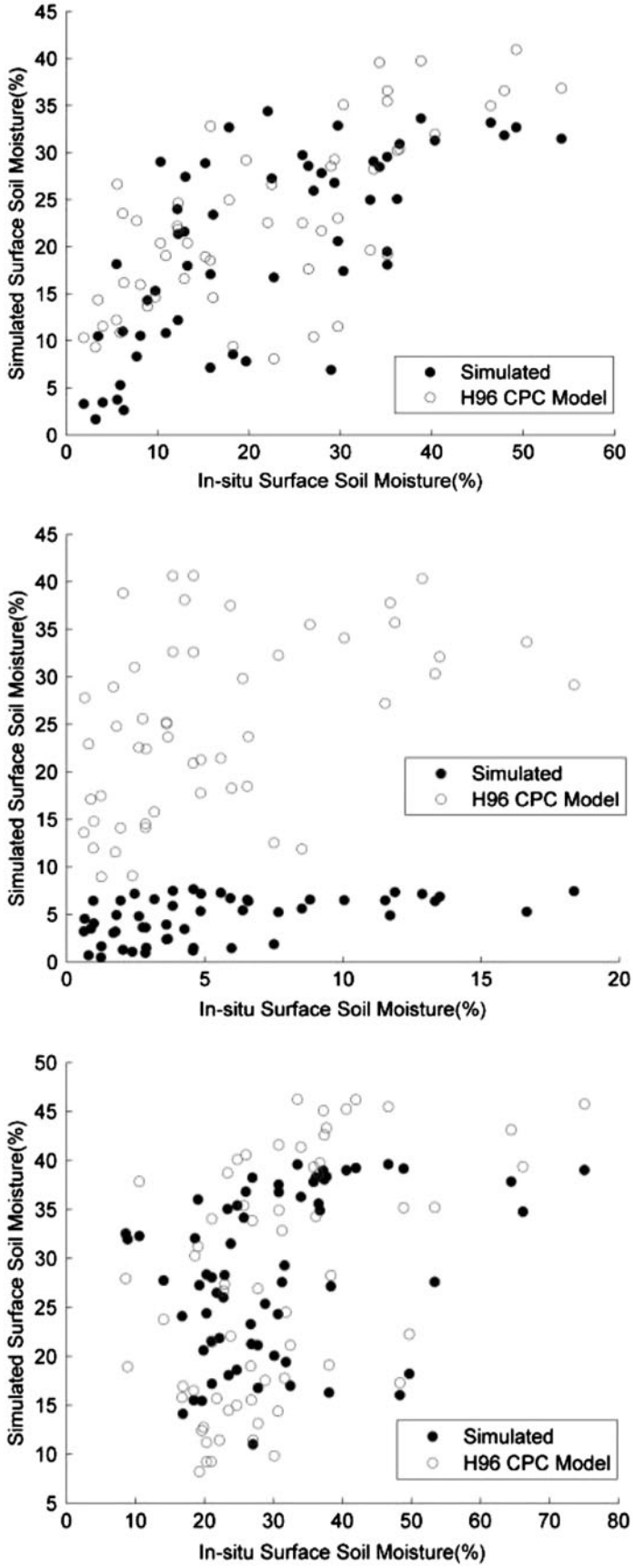

Figure 3. Scatter plots between in situ and simulated (proposed model) & H96 CPC model data at Bhopal, Bhubaneswar and Vittal (top to bottom) respectively.

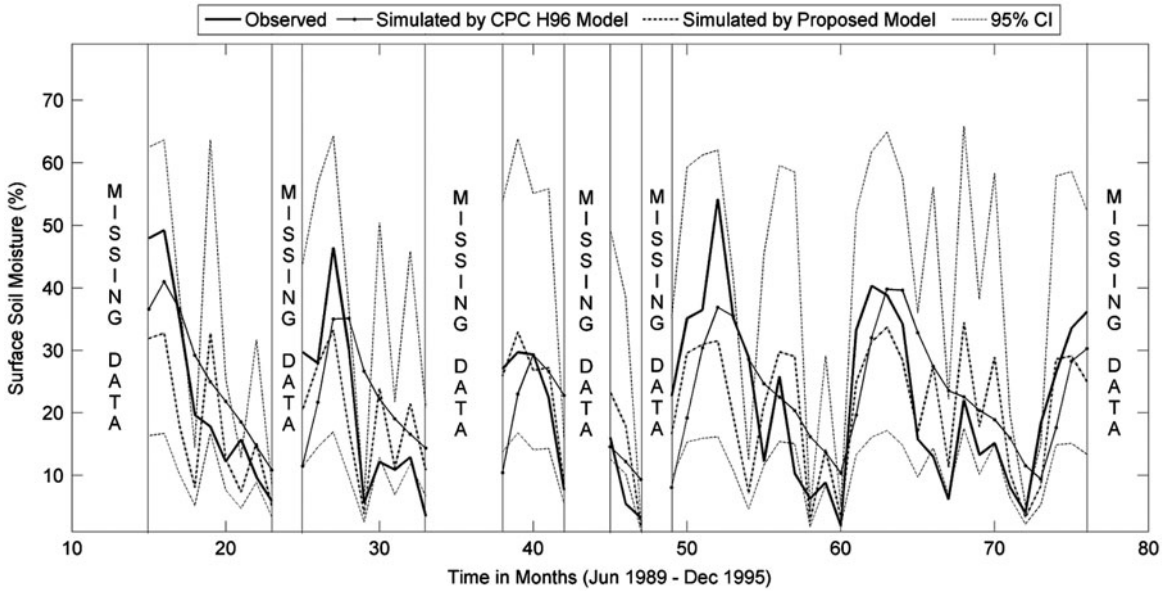

Figure 4. Time series of in situ, simulated with 95% confidence interval and H96 CPC soil moisture series at Bhopal.

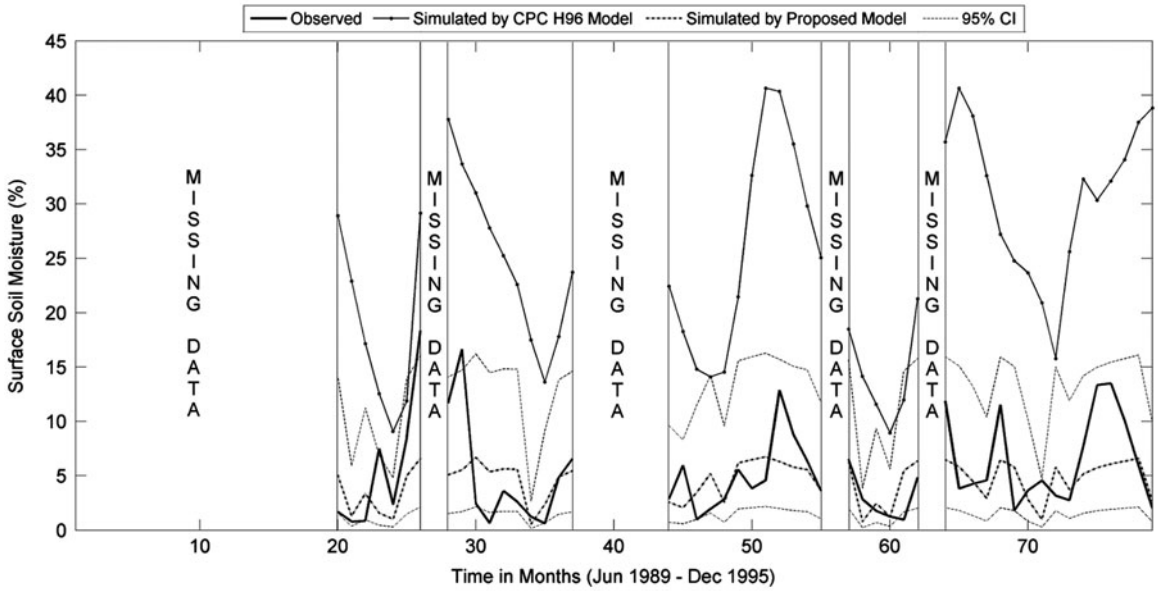

Figure 5. Tme series of in situ, simulated with 95% confidence interval and H96 CPC soil moisture series at Bhubaneswar.

Results and discussion

Data Used

In this study, ten soil moisture monitoring stations in India, located in different climatic regions, having in situ measured soil moisture data for 9 years are used. The locations of the monitoring station across India are shown in Figure 2. The in situ soil moisture data set for depth up to 7.5 cm at a weekly scale for these stations is received from the Global Soil Moisture Data Bank. This weekly data set is converted to a monthly scale for simulation.

The gridded precipitation and temperature data at a monthly scale were collected from the Climate Research Unit, University of East Anglia, database. The gridded data for other hydrometeorological parameters, namely, the near-surface air pressure, relative humidity and wind speed, are downloaded from the Physical Science Division (PSD) database at the Earth System Research Laboratory (ESRL) of NOAA as NOAA/NCAR Reanalysis I data. H96 CPC model data are also downloaded from the NOAA PSD database. These gridded data sets are interpolated using an inverse distance weight (IDW) method proposed by Shepard (1968) based on station coordinates.

Information on the predominant soil texture for these stations is collected from relevant research papers and other published documents (Ghosh and Datta 1974; Ghawana 1997; Rao 1998; Chaitanya and Chandrika 2006; Tessy and

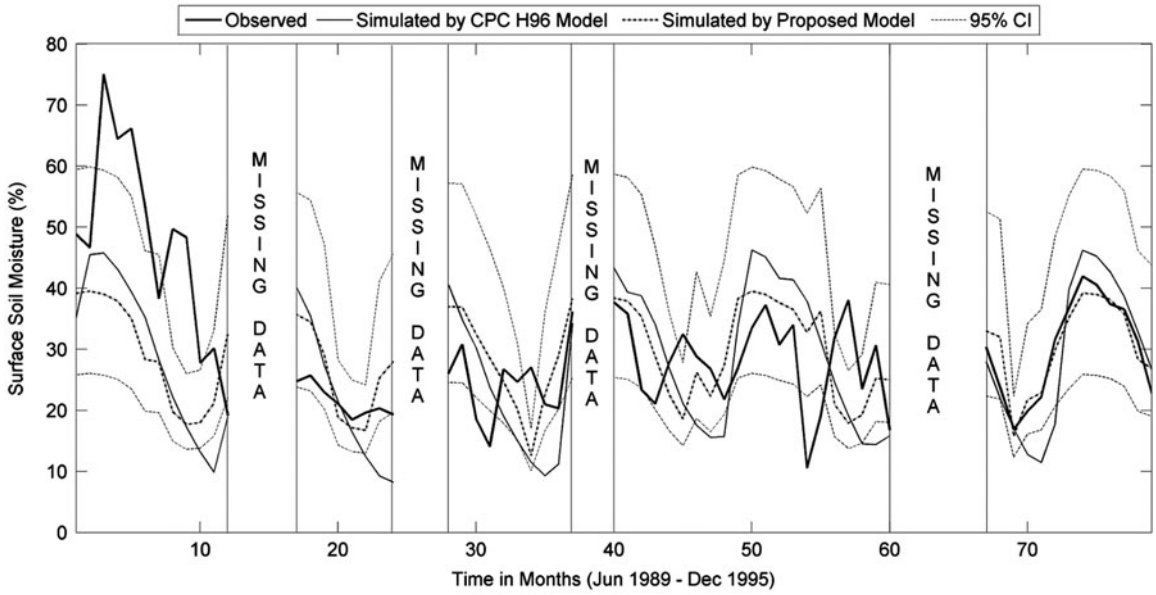

Figure 6. Time series of in situ, simulated with 95% confidence interval and H96 CPC soil moisture series at Vittal.

Renuka 2008; CGWB 2009; BSA 2011). Soil moisture–monitoring stations are clubbed into four groups based on information regarding the predominant soil texture at each station. Among each group of stations, a few stations are used for model development and one is used for testing. In total, 7 stations out of 10 are used for model development and the rest for testing. In Table 1, the groups of soil moisture–monitoring stations are presented according to grain size class and soil texture class of the predominant local soil.

The simulated soil moisture at various stations during model development is compared with the in situ and CPC H96 model output. The correlation coefficient and RMSE between the simulated soil moisture and in situ soil moisture data varies from 0.449 (Niphad) to 0.898 (Vellanikara) and 108.5 (Sabour) to 19.2 (Tirupati) respectively. NSE values are found to be 0.038 (Vittal), 0.097 (Agra), 0.171 (Niphad), 0.174 (Bhubaneswar), 0.249 (Sabour), 0.375 (Basti), 0.444 (Tirupati), 0.478 (Bhopal), 0.538 (Kalyani) and 0.788 (Vellanikara). Although apparently some of these values may appear to be poor, the proposed model is found to perform better (and much better for some stations) than the CPC H96 model. In fact, in terms of NSE, the proposed model performs better than the CPC H96 model at six stations out of the seven used for model development. The same comparison is done for testing stations as well. Table 2 shows the model performance for all three testing stations for three different groups.

The scatter plots for three testing stations, Bhopal, Bhubaneswar and Vittal, are shown in Figure 3. In Figures 4–6, the simulated time series of soil moisture at target stations along with their 95% confidence intervals are plotted against time series of in situ as well as H96 CPC soil moisture data for the same testing stations. Missing data points before June 1989 were left out while plotting.

It is noticed from Table 2 that at Bhubaneswar, although the correlation coefficient is less between simulated and in situ measured soil moisture than the same between CPC data and in situ measured data, the RMSE is much lower (better) as well as the NSE value is much higher (better) for the proposed approach. From Figure 5 (Bhubaneswar), it is observed that the CPC model estimates much higher values than the in situ data, which is reflected in the RMSE and NSE values for this station. Thus, simulated soil moisture data using the proposed hydrometeorological approach also was found to produce much better results compared with the CPC data. These results indicate the superiority of simulated data over the CPC model data for stations like Bhubaneswar.

For other testing stations (i.e. Bhopal and Vittal), results are also found to be better (Table 2). Thus, the hydrometeorological approach provides better results than the H96 CPC model. Moreover, the proposed model provides an estimate of uncertainty associated with the simulated data, which is absent for the CPC data. As a future scope of this study, the proposed model will be extended for simulating the soil moisture for entire India based on hydrometeorological inputs and information on soil texture class.

Conclusions

In this study, a probabilistic hydrometeorological simulation model is proposed that uses the hydrometeorological variables as inputs. Predominant soil type is also considered in the approach. Being probabilistic, the information on uncertainty associated with the simulated soil moisture is also available. The 50th quantile of simulated soil moisture series was found to be better (and comparable for some stations) than the available H96 CPC model data derived by using a one-layer leaky

bucket model. However, information on uncertainty is not available in the CPC data. Moreover, as a result of considering uniform soil porosity for the entire globe, this model may fail at several locations. One such case was found in this study for the soil-monitoring station of Bhubaneswar. CPC data was found to continuously overestimate the actual observed value. On the other hand, the proposed approach shows much closer correspondence with the observed soil moisture data and is able to provide an estimate of associated uncertainty. It is also illustrated that the developed model is able to estimate soil moisture along with the quantification of associated uncertainty for a new location having a hydrometeorological data set and information on predominant soil type at that location.

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