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Impact of Land Surface and Forcing Parameters on the Spin-up Behaviour of Noah Land Surface Model over the Indian Sub-Continent

A. Bhattacharya,[1] A. N. V. Satyanarayana,[1] and M. Mandal[1]

Abstract—In the present study, an attempt is made to understand the influence of land surface parameters (such as soil moisture conditions, soil type and vegetation type) and forcing parameters on the model spin-up behaviour of a land surface model (LSM), namely Noah LSM, over the Indian sub-continent. The work presented here primarily aims to understand the optimum initial conditions to achieve the least spin-up time over the sub-tropical conditions that exist over the region of interest. The study is presented in three major parts. In the first part, a multivariate statistical analysis, namely principle component analysis is employed to investigate how parameters such as precipitation, air temperature, soil moisture, radiation components as well as various parameters that characterize soil and vegetation types influence the model spin-up. The second part deals with the study of the impact of soil and vegetation parameters in different seasons on the model spin-up behaviour. Finally, the third part looks into the influence of initial soil moisture condition and precipitation forcing on the spin-up behaviour of the model in different seasons to obtain the optimum initial conditions for the minimum spin-up time of the model. From the study, it is seen that the soil and vegetation type, as well as the soil moisture content influence the model spin-up significantly. The present study reports that the experiments initialized just before a continuous rainfall event has the least spin-up unless the initial soil is saturated.

Key words: Land surface model, soil moisture, principal component analysis, spin-up.

1. Introduction

The land surface is an integral part of the global climate system. Land–atmosphere interface influences the exchanges of energy and moisture fluxes as well as the biogeochemical cycle between the land surface and lower boundary atmosphere. Therefore, land surface modelling is of interest in numerical weather prediction, hydrological and agricultural research (Avissar and Pielke 1989; Dirmeyer et al. 2000; Pitman 2003). The performance of weather and climate models depends on the accuracy of initial conditions provided by a coupled land surface model (De Rosnay et al. 2009). Correct initialization of soil moisture by a land surface model is of importance to climate and weather prediction models (Kar and Ramanathan 1990; Dirmeyer et al. 2000; Koster and Suarez 2003; Seneviratne et al. 2006).

Studies of land surface models (LSMs) in an offline, uncoupled mode where the LSM is driven by provided atmospheric forcings is important for performance evaluation and subsequent improvement of LSMs (Henderson-Sellers et al. 1995; Barlage et al. 2010). Noah LSM is a popular modern LSM (Chen et al. 1996, 1997; Chen and Dudhia 2001; Ek et al. 2003) that has been extensively evaluated (Mitchell et al. 2004; Schaake et al. 2004; Slater et al. 2007; Chen et al. 2007; Xia et al. 2013). Over the Indian sub-continent, its performance has been tested in the offline mode by some studies (Bhattacharya and Mandal 2015; Patil et al. 2011, 2014).

Most of the performance evaluation studies assume a spin-up period for the model. Model spin-up is the process through which the model is adequately equilibrated to ensure balance between the mass fields and velocity fields. Upon completion of the spin-up process, physically realistic state of equilibrium should exist in the model and the simulation should better reflect observations and respond realistically to atmospheric forcing.

The spin-up process is important for the faithful representation of land surface parameters by a LSM. The spin-up time of the model is influenced by initial

[1] Centre for Oceans, Rivers, Atmosphere and Land Sciences, Indian Institute of Technology Kharagpur, Kharagpur 721 302, India. E-mail: anvsatya@coral.iitkgp.ernet.in; achanta.satya@gmail.com

soil moisture content, surface conditions as well as atmospheric forcing (e.g. Yang et al. 1995; Chen and Mitchell 1999; Cosgrove et al. 2003; Rodell et al. 2005; de Goncalves et al. 2006).

Shrestha and Houser (2010) performed eight different tests with different initial soil moisture values and one test with simulations started in different months. This study, performed over several stations in the Midwestern United States concludes that spin-up runs initialized with spatially heterogeneous land surface states averaged over short period are found to perform better than others. Moreover, their study reported that simulations initialized in summer had lower spin-up than those initialized in winter.

Lim et al. (2012) studied the spin-up behaviour of soil moisture content over East Asia using an offline Noah LSM of the Korea Land Data Assimilation System (KLDAS) and noted that for a Monsoon affected area, the spin-up time reduces to 3 months as compared to a dry area. They ran three simulations initialized with (1) a spatially uniform soil moisture, (2) NCEP GDAS soil moisture data, and (3) ECMWF ERA-Interim soil moisture data. Each run starts either after or before the summer monsoon. They noted that spin-up is significantly reduced if the simulation is initiated just before the onset of monsoon. Another study over 22 river basins in the United States reported least model spin-up for saturated initial conditions (Rahman and Lu 2015).

In the present study, an offline 1-D Noah LSM is used to test the impact of land surface parameters and time of model initialization on the model spin-up in a region influenced by monsoon, that is, the Indian sub-continent. For this purpose, a multivariate analysis is employed to identify parameters significant for LSM spin-up. In the present study, the impact of different soil and vegetation parameters on spin-up is also assessed. Further, a comprehensive analysis of initial soil wetness and precipitation forcing is performed to understand their combined impact on the spin-up of Noah LSM.

2. Methodology

The Noah LSM used in this study to carry out site specific land surface simulations is a stand-alone, uncoupled, 1-D column model (version 3.3). The overview of the model is provided in Table 1. In this traditional 1-D uncoupled mode, the model requires initial condition as well as near-surface atmospheric forcing as input. It simulates soil moisture (both liquid and frozen) and soil temperature at four depths. It also simulates other parameters such as skin temperature, snowpack depth, snowpack water equivalent, canopy water content, and the energy flux and water flux terms of the surface energy and water balance.

A commonly accepted measure of spin-up time is the number of repeated loops taken by the model to give the same output as its previous iteration (Yang et al. 1995). Lim et al. (2012) assessed spin-up as a measure of the time taken for yearly changes in monthly averaged model output to fall below a certain threshold. A study over the Indian sub-continent (Nair and Indu 2016) spun-up the LSM by running the model through seven cycles of 3 years of GLDAS forcing data till the error between successive runs reduced to 5%.

In this study, following Lim et al. 2012, a set of 7-year recursive runs is conducted to assess the spin-up behaviour of the land surface model. Soil moisture is used as the primary land surface state to evaluate the spin-up behaviour. The percent change (P) of daily average of soil moisture is calculated by Eq. (1).

$$P = \frac{D_{n-1} - D_n}{D_n} \times 100 \qquad (1)$$

D_{n-1} and D_n are the daily averages of the model simulated soil moisture of the previous and current year, respectively. In our study, the threshold condition of quasi-equilibrium state of the model is

Table 1

Overview of Noah LSM physics

Multilayer (4) soil model	User specified
Time integration	Kalnay and Kanamitsu, 1988
Soil hydrodynamics	Mahrt and Pan, 1984
Soil thermodynamics	Pan and Mahrtm 1987
Potential evaporation	Mahrt and Ek, 1984
Bare soil evaporation	Betts et al., 1997
Runoff and infiltration	Schaake et al., 1996
Surface turbulence and thermal roughness length	Chen et al., 1997
Thermal conductivity and subsurface heat flux	Peters-Lidard et al., 1997

considered as 1% (Cosgrove et al. 2003; de Goncalves et al. 2006).

3. Numerical Experiments

3.1. Identification of Important Parameters Influencing Model Spin-up

A total of 8073 experiments have been performed to investigate the spin-up behaviour of the model at every grid point of a 31 km × 41 km grid mesh over Indian region (5°–40°N, 64°–106°E). This includes 7731 non-glaciated grids considered for the analysis. A 7-year recursive run has been performed with 2009 as the starting year and using initialization and forcing data derived from the NCEP FNL analysis. The soil type and vegetation type data have been obtained from USGS (United States Geological Survey). The data related to soil and vegetation parameters used in the present study are the default values from USGS that are in-built in Noah LSM as used by Kar et al. (2014). Spin-up time is estimated using Eq. (1). The model is assumed to have spun-up when the percentage error between two recursive runs becomes less than 1% for soil moisture.

Because the various parameters that influence spin-up are changing simultaneously and correlated among them, a multivariate statistical technique called principal component analysis (PCA) is used to identify the influence of the parameters on the model spin-up. The success of PCA in the analysis of spatio-temporal pattern in several hydrological applications (Shine et al. 1995; Gangopadhyay et al. 2001; Bengraine and Marhaba 2003; Ouyang 2005) has encouraged its use in the present study. A set of 19 parameters have been chosen for principal component analysis, as provided in Table 2 (the details of the soil and vegetation parameters are provided in Tables 3, 4, 5 and 6).

In addition, the spin-up behaviour of the model is tested at 71 sites randomly distributed over the domain (Fig. 1). These sites fall under the fifteen-dominant soil and vegetation type of the region (Table 7). The model

Table 2

Parameters considered to explain the variability of spin-up

Serial no.	Parameters considered for PCA
1	Longwave radiation
2	Rainfall
3	Shortwave radiation
4	Soil temperature (0–10 cm)
5	Soil moisture (0–10 cm)
6	Air temperature
7	Terrain
8	BB (soil)
9	DrySMC (soil)
10	QTZ (soil)
11	SATDK (soil)
12	SATDW (soil)
13	WiltSMC (soil)
14	AlbedoMax (veg)
15	AlbedoMin (veg)
16	EmissMax (veg)
17	EmissMin (veg)
18	NRoot (veg)
19	RCA (veg)

Table 3

Soil parameter table (used in Noah LSM)

Soil category	Parameter Soil type	BB	DRYSMC	F11	MAXSMC	REFSMC	SATPSI	SATDK	SATDW	WLTSMC	QTZ
1	Sand	2.79	0.01	−0.472	0.339	0.236	0.069	4.66E−05	6.08E−07	0.01	0.92
2	Loamy sand	4.26	0.028	−1.044	0.421	0.383	0.036	1.41E−05	5.14E−06	0.028	0.82
3	Sandy loam	4.74	0.047	−0.569	0.434	0.383	0.141	5.23E−06	8.05E−06	0.047	0.6
4	Silt loam	5.33	0.084	0.162	0.476	0.36	0.759	2.81E−06	2.39E−05	0.084	0.25
5	Silt	5.33	0.084	0.162	0.476	0.383	0.759	2.81E−06	2.39E−05	0.084	0.1
6	Loam	5.25	0.066	−0.327	0.439	0.329	0.355	3.38E−06	1.43E−05	0.066	0.4
7	Sandy clay loam	6.77	0.067	−1.491	0.404	0.314	0.135	4.45E−06	9.90E−06	0.067	0.6
8	Silty clay loam	8.72	0.12	−1.118	0.464	0.387	0.617	2.03E−06	2.37E−05	0.12	0.1
9	Clay loam	8.17	0.103	−1.297	0.465	0.382	0.263	2.45E−06	1.13E−05	0.103	0.35
10	Sandy clay	10.73	0.1	−3.209	0.406	0.338	0.098	7.22E−06	1.87E−05	0.1	0.52
11	Silty clay	10.39	0.126	−1.916	0.468	0.404	0.324	1.34E−06	9.64E−06	0.126	0.1
12	Clay	11.55	0.138	−2.138	0.468	0.412	0.468	9.74E−07	1.12E−05	0.138	0.25

Table 4

Explanation of soil parameters

These parameter are functions of soil-category index	
BB	B parameter
DRYSMC	Dry soil moisture threshold at which direct evaporation from top soil layer ends [volumetric fraction]
F11	Soil thermal diffusivity/conductivity coefficient
MAXSMC	Saturation soil moisture content (i.e. porosity) [volumetric fraction]
REFSMC	Reference soil moisture (field capacity), where transpiration begins to stress [volumetric fraction]
SATPSI	Saturation soil matric potential
SATDK	Saturation soil conductivity
SATDW	Saturation soil diffusivity
WLTSMC	Wilting point soil moisture [volumetric fraction]
QTZ	Soil quartz content

has been initialized at the beginning of five seasons (as defined by the India Meteorological Department: Winter—December and January; Spring—February and March; Summer—April and May; Monsoon: June, July, August and September; Autumn: October and November) at each of these sites to identify the time of initialization that yields the minimum spin-up.

3.2. Impact of Soil Type and Vegetation Type on Model Spin-up

To analyse the impact of soil and vegetation type on model spin-up, the model has been run with the same forcing (using observation data from the Micrometeorological tower at Kharagpur, India) but with different soil and vegetation types (as shown in Table 8) that exist over India. In each case, the model has been initialized at the beginning of five seasons (Winter, Spring, Summer, Monsoon, Autumn). The resulting spin-up is correlated with various soil and vegetation parameters provided in Table 3, 4, 5 and 6.

3.3. Impact of Soil Wetness and Precipitation Forcing on Model Spin-up

The model has been initialized with different soil moisture, at various seasons and months and different precipitation rates. In this connection, two sets of experiments: SV1, model initialized with actual values of soil temperature and soil moisture; and SV2, model initialized with mean values of soil temperature and soil moisture, are conducted. The model is forced with the observation data from the micrometeorological tower at Kharagpur (22.34°N, 87.23°E), India.

4. Results and Discussion

4.1. Identification of Important Parameters Influencing Model Spin-up

In the model run over the entire domain, no spatial pattern in the variation of the initial and

Table 5

Vegetation parameter table (used in Noah LSM)

Veg category	Parameter Veg type	SHDFAC	NROOT	RS	RGL	HS	LAI Min	LAI Max	EMIN	EMAX	ALB Min	ALB Max	Z0 Min	Z0 Max
1	Urban and built-up land	0.1	1	200	999	999	1	1	0.88	0.88	0.15	0.15	0.5	0.5
2	Dryland cropland and pasture	0.8	3	40	100	36.25	1.56	5.68	0.92	0.985	0.17	0.23	0.05	0.15
3	Irrigated cropland and pasture	0.8	3	40	100	36.25	1.56	5.68	0.93	0.985	0.2	0.25	0.02	0.1
4	Mixed dryland/irrigated Cropland and pasture	0.8	3	40	100	36.25	1	4.5	0.92	0.985	0.18	0.23	0.05	0.15
5	Cropland/grassland mosaic	0.8	3	40	100	36.25	2.29	4.29	0.92	0.98	0.18	0.23	0.05	0.14
6	Cropland/woodland mosaic	0.8	3	70	65	44.14	2	4	0.93	0.985	0.16	0.2	0.2	0.2
7	Grassland	0.8	3	40	100	36.35	0.52	2.9	0.92	0.96	0.19	0.23	0.1	0.12
8	Shrubland	0.7	3	300	100	42	0.5	3.66	0.93	0.93	0.25	0.3	0.01	0.05
9	Mixed shrubland/grassland	0.7	3	170	100	39.18	0.6	2.6	0.93	0.95	0.22	0.3	0.01	0.06
10	Savanna	0.5	3	70	65	54.53	0.5	3.66	0.92	0.92	0.2	0.2	0.15	0.15
11	Deciduous broadleaf forest	0.8	4	100	30	54.53	1.85	3.31	0.93	0.93	0.16	0.17	0.5	0.5
12	Deciduous needleleaf forest	0.7	4	150	30	47.35	1	5.16	0.93	0.94	0.14	0.15	0.5	0.5
13	Evergreen broadleaf forest	0.95	4	150	30	41.69	3.08	6.48	0.95	0.95	0.12	0.12	0.5	0.5
14	Evergreen needleleaf forest	0.7	4	125	30	47.35	5	6.4	0.95	0.95	0.12	0.12	0.5	0.5
15	Mixed forest	0.8	4	125	30	51.93	2.8	5.5	0.93	0.97	0.17	0.25	0.2	0.5

Table 6

Explanation of vegetation parameters

These parameters are functions of land-use category. Fields identified as "background" may be modified by snow-cover effects. The "background" value does not include snow-cover effects	
SHDFAC	Green vegetation fraction [fraction 0.0–1.0]
NROOT	Rooting depth [soil layer index]
RS	Stomatal resistance [s m^{-1}]
RGL	Parameter used in radiation stress function
HS	Parameter used in vapour pressure deficit function
SNUP	Threshold water equivalent snow depth [m] that implies 100% snow cover
MAXALB	Upper bound on maximum albedo over deep snow [%]
LAIMIN	Minimum leaf area index through the year [dimensionless]
LAIMAX	Maximum leaf area index through the year [dimensionless]
EMISSMIN	Minimum background emissivity through the year [fraction 0.0–1.0]
EMISSMAX	Maximum background emissivity through the year [fraction 0.0–1.0]
ALBEDOMIN	Minimum background albedo through the year [fraction 0.0–1.0]
ALBEDOMAX	Maximum background albedo through the year [fraction 0.0–1.0]
Z0MIN	Minimum background roughness length through the year [m]
Z0MAX	Maximum background roughness length through the year [m]

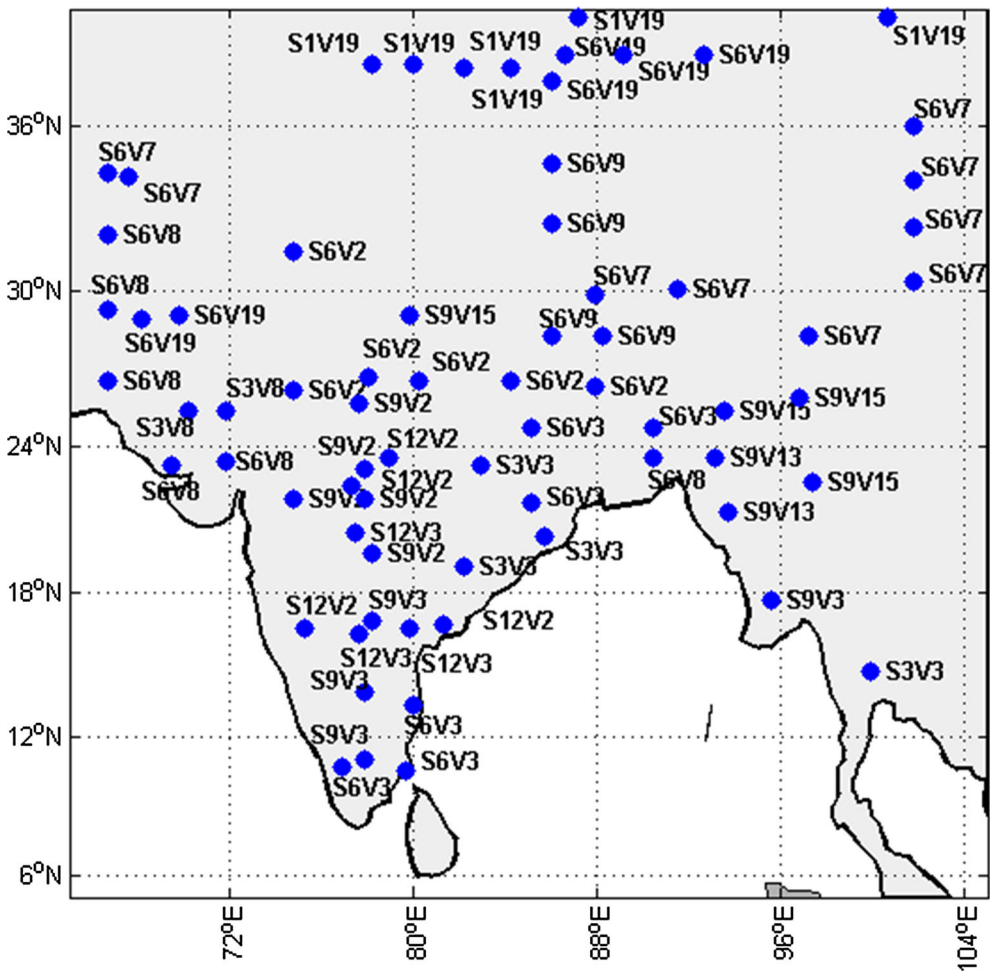

Figure 1
Domain of interest and sites of simulations with dominant soil and vegetation

Table 7

Dominant soil and vegetation over the region of interest

Dominant category	Soil	Vegetation	Percent area covered
S6 V7	Loam	Grassland	15.71
S6 V9	Loam	Mixed shrubland/grassland	8.51
S6 V19	Loam	Barren and sparsely vegetated	8.13
S6 V8	Loam	Shrubland	7.06
S6 V2	Loam	Dryland cropland and pasture	6.6
S6 V3	Loam	Irrigated cropland and pasture	3.71
S9 V3	Clay loam	Irrigated cropland and pasture	3.71
S9 V13	Clay loam	Evergreen broadleaf forest	3.41
S12 V2	Clay	Dryland cropland and pasture	3.07
S1 V19	Sand	Barren and sparsely vegetated	2.6
S9 V2	Clay loam	Dryland cropland and pasture	2.47
S12 V3	Clay	Irrigated cropland and pasture	2.44
S9 V15	Clay loam	Mixed forest	1.84
S3 V3	Sandy loam	Irrigated cropland and pasture	1.79
S3 V8	Sandy loam	Shrubland	1.6

Table 8

Experiment with different soil and vegetation with same forcing

Experiments	Description	
	Soil	Vegetation
S03V02	Sandy loam	Dryland cropland and pasture
S03V03		Irrigated cropland and pasture
S03V05		Grassland/cropland mosaic
S03V07		Grassland
S03V08		Shrubland
S03V09		Mixed shrubland/grassland
S03V13		Evergreen broadleaf forest
S03V15		Mixed forest
S01V05	Sand	Grassland/cropland mosaic
S02V05	Loamy sand	
S03V05	Sandy loam	
S04V05	Silt loam	
S05V05	Silt	
S06V05	Loam	
S07V05	Sandy clay loam	
S08V05	Silty clay loam	
S09V05	Clay loam	
S10V05	Sandy clay	
S11V05	Silty clay	
S12V05	Clay	

parametric field with that of the model spin-up is observed, due to the correlations that exist between the parameters themselves. Principal component analysis (PCA) converts a set of (correlated) variables into a set of values of linearly uncorrelated variables called principal components to reduce the dimensionality of the data space to best explain the variance in the data (Pearson 1901). This procedure uses orthogonal transformation such that the first principal component accounts for the maximum variability in the data with each succeeding component having lesser variance.

It is seen from Fig. 2 that the first three principal components together explain more than 84% of the variability.

Figures 3 and 4 present the PCA biplots. In the figures, the principal components appear as the axes and the parameters as the vectors. The biplot illustrates how each parameter is represented in the principal components and how much each parameter contributes to a principal component. From Fig. 3, it is seen that initial soil temperature, most soil parameters/soil type and the forcing parameters of air temperature, shortwave and longwave radiation and rainfall have a high contribution to the first principal component which explains almost 56% of the variance in spin-up. This could be because the forcing data drives the model, and therefore, their impact on the spin-up of the model is the greatest. Initial values of soil moisture have a dominant contribution to the second principal component which explains more than 18% of the variance. This makes soil moisture particularly interesting for spin-up

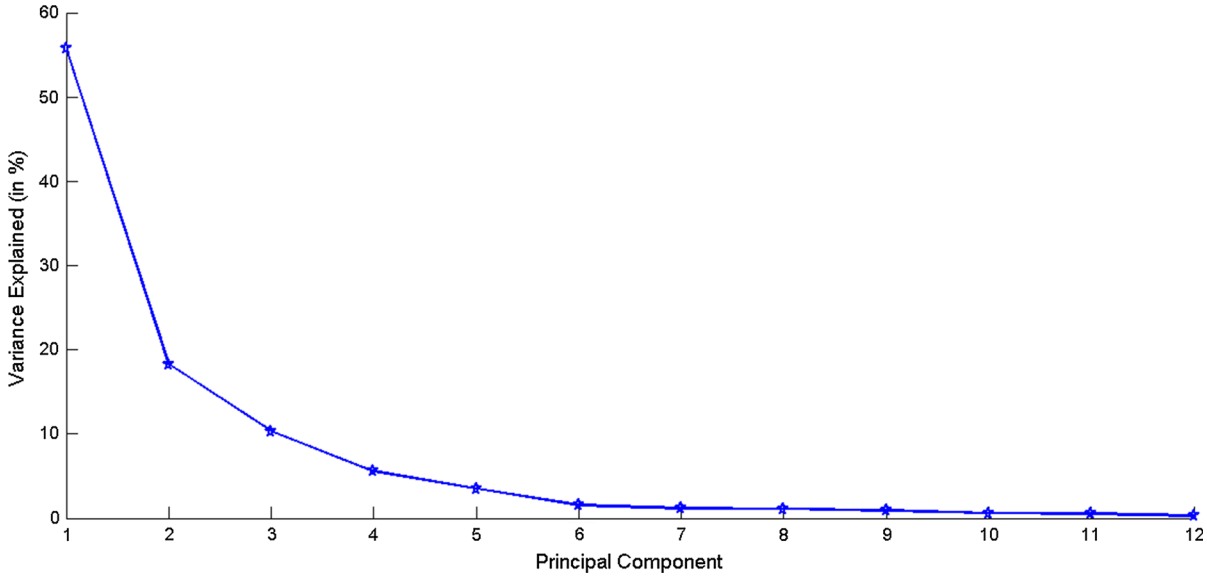

Figure 2
Percentage of variance explained by the principal components

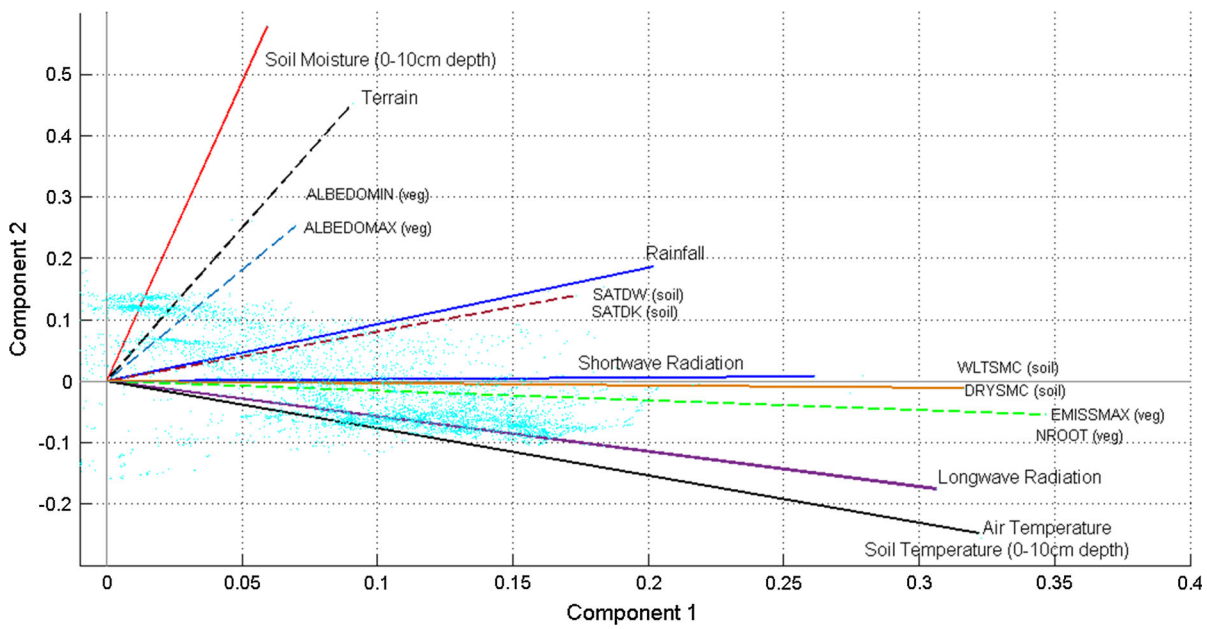

Figure 3
Contribution of each variable to the first and second principal components

studies, even though it does not have a dominant contribution to the first principal component. Given a particular place (fixed soil and vegetation type), it is the variation of initial value of soil moisture that can make a significant impact on the spin-up time. Terrain and certain vegetation parameters/vegetation type also have significant contribution to the second principal component.

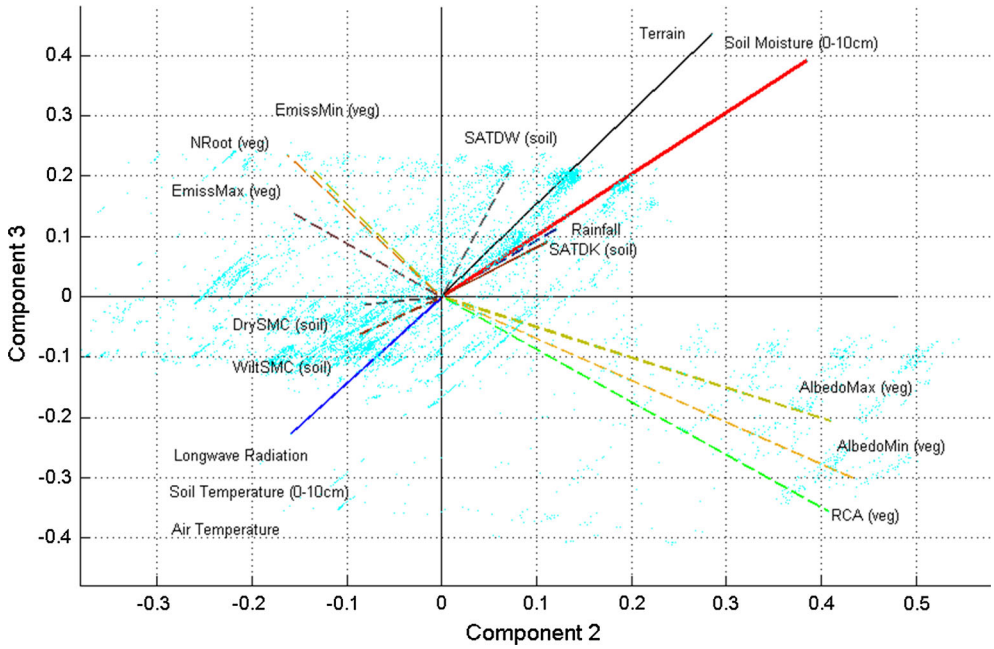

Figure 4
Contribution of each variable to the second and third principal components

Figure 4 shows that terrain and initial soil moisture have majorly contributed to the third component as well, which explain a further 10% of the variability. Vegetation type, longwave radiation and air temperature forcing and initial value to soil temperature also have significant contribution to the third principal component.

4.2. *Impact of Soil Type and Vegetation Type on Model Spin-up*

It is seen that when the model is integrated with the same forcing keeping vegetation unchanged but with different soil types, it is observed that the model has shorter spin-up for soils with high porosity (maxSMC) and higher diffusivity (SatDW). It has longer spin-up for soils which higher conductivity (SatDK) and higher quartz content (QTZ) as shown in Fig. 5a. Similarly, when the model is integrated with same forcing keeping soil type fixed but with different vegetations, it is seen that the model has least spin-up for vegetation having higher roughness length (Z_0) and greater rooting depth (NRoot) (Fig. 5b). It is seen that in general, spin-up is more strongly correlated with the soil parameters than the vegetation parameters.

Figure 6a, b shows the seasonal dependence of the correlation of model spin-up with soil and vegetation, respectively. It is seen that the seasonal variations are much more pronounced in the case of vegetation parameters as compared to the soil parameters. Higher mean correlation of spin-up with vegetation parameters in the wetter seasons indicates that the model spin-up is more sensitive to vegetation is the wetter seasons as compared to the drier seasons.

4.3. *Impact of Soil Wetness and Precipitation Forcing on Model Spin-up*

From the model runs initiated during different seasons, it is seen that model initialized during summer has the least spin-up time (Fig. 7). This agrees with the findings reported by Shrestha and Houser (2010). Further, from the model runs initiated at the beginning of every month (SV1), it can be seen that models initiated at the beginning of June (just before the onset of monsoon) has the least spin-up time (Fig. 8). Lim et al. (2012) reported similar spin-

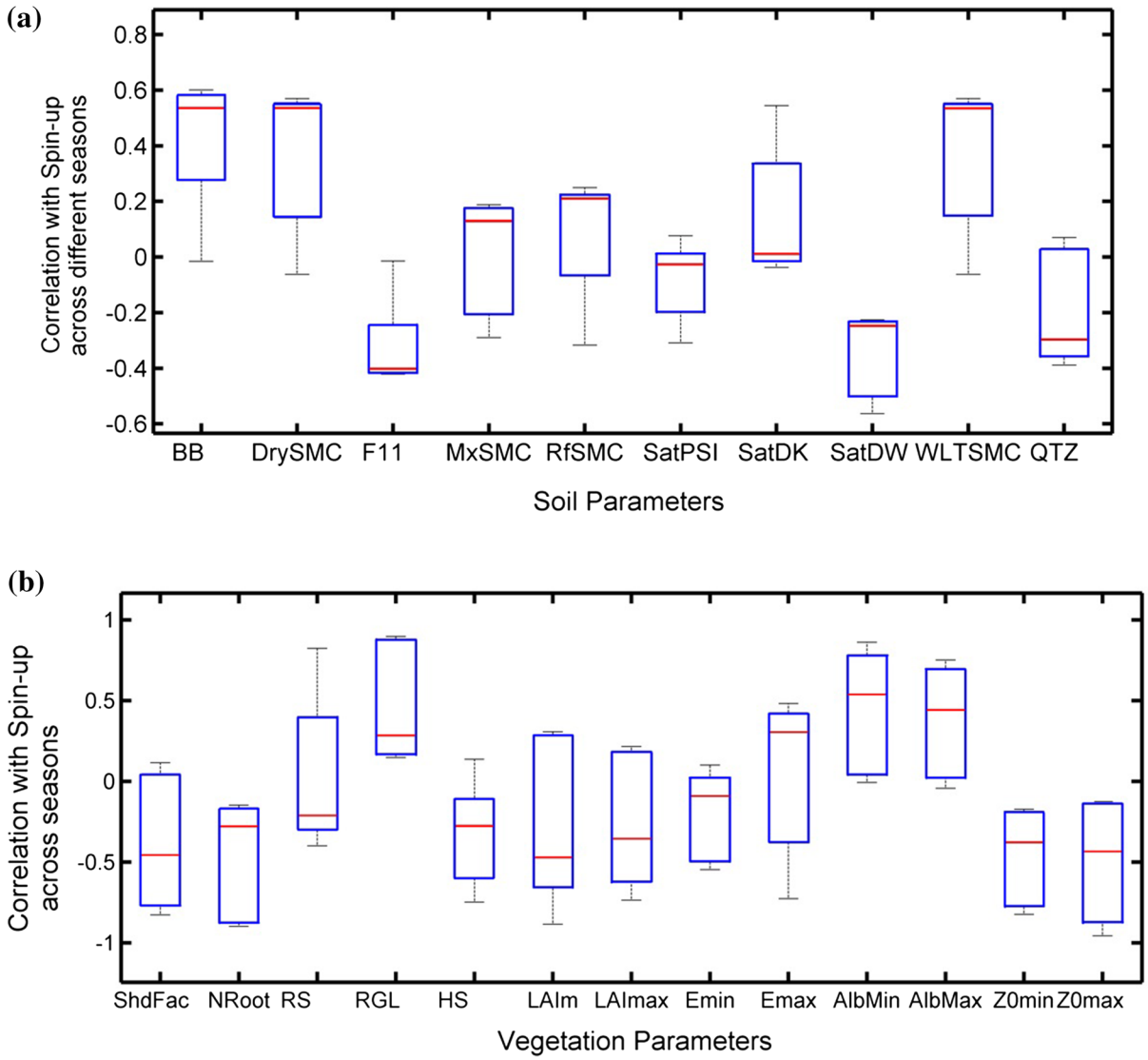

Figure 5
Variation of model spin-up with **a** soil and **b** vegetation parameters

up behaviour of the Korean Land Data Assimilation system.

To investigate the impact of initial soil moisture on model spin-up, experiments SV1 (actual initial SM) and SV2 (mean initial SM) are compared (Fig. 9). It is seen that in general, a wetter soil reaches equilibrium faster. However, in the presence of heavy rainfall (August–October), the wetter soil has a longer spin-up.

To further investigate the impact of the initial value of soil moisture and the time of initialization on the spin-up behaviour, the model has been run with different initial soil wetness conditions (from completely dry to completely saturated) and initialized during a period of no rain (14 January 2009), just before a small rainfall event (22 March 2009) and just before a continuous rainfall event (12 May 2009).

Rahman and Lu (2015) reported that a land surface model has the lowest spin-up time under saturated initial conditions. However, we see from Fig. 10, under saturated initial conditions, a land surface model has a longer spin-up time when it is

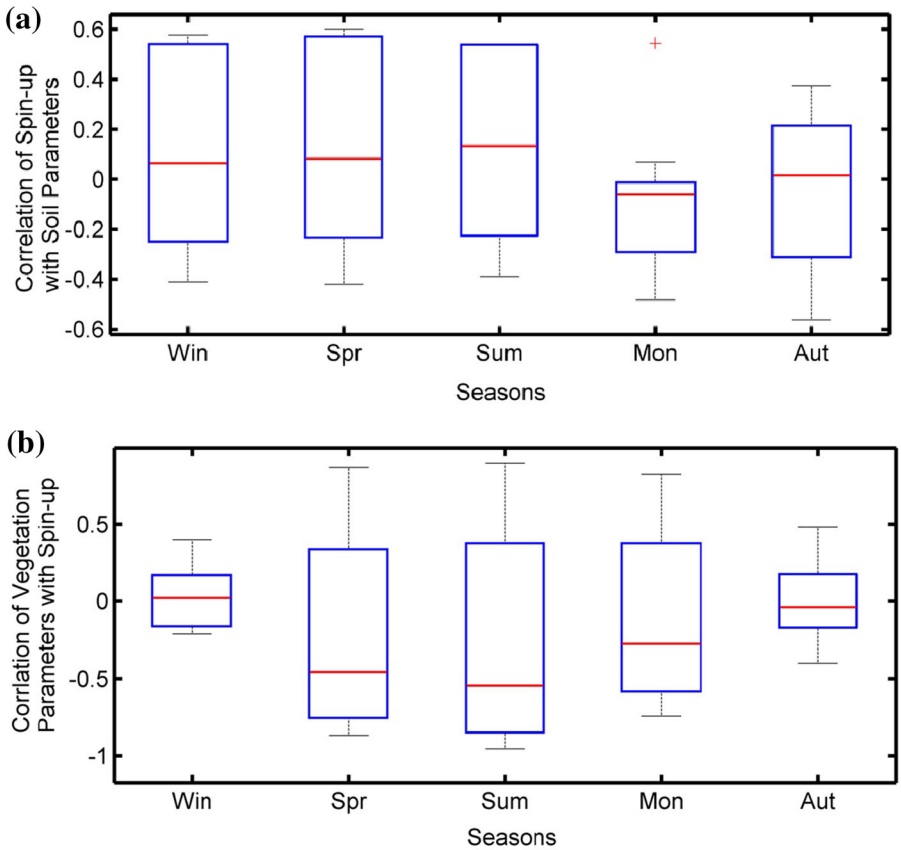

Figure 6
Change in the correlation of the model spin-up with **a** soil and **b** vegetation parameters with model initialized at different seasons

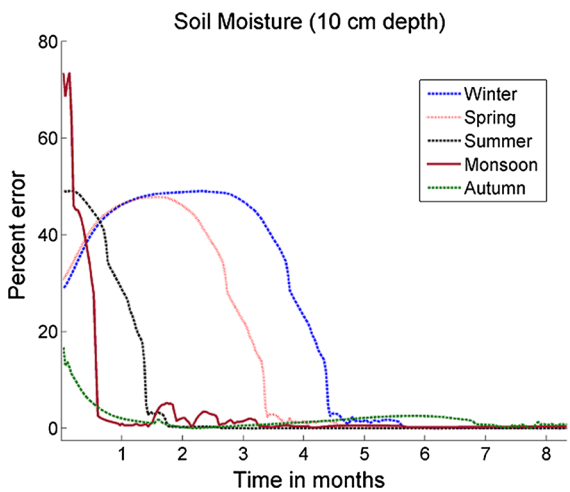

Figure 7
Spin-up of soil moisture for model initialized at different seasons

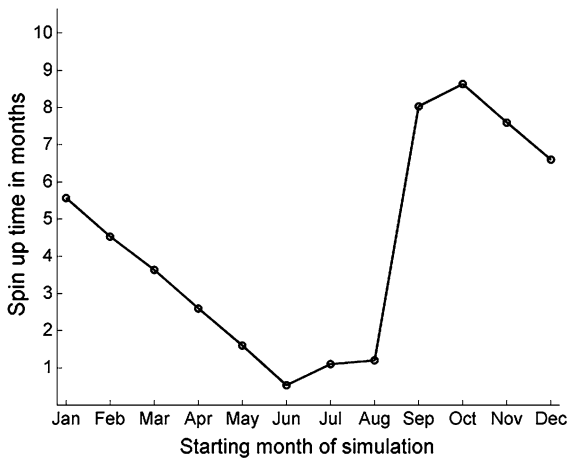

Figure 8
Spin-up of soil moisture for model initialized at the beginning of each month

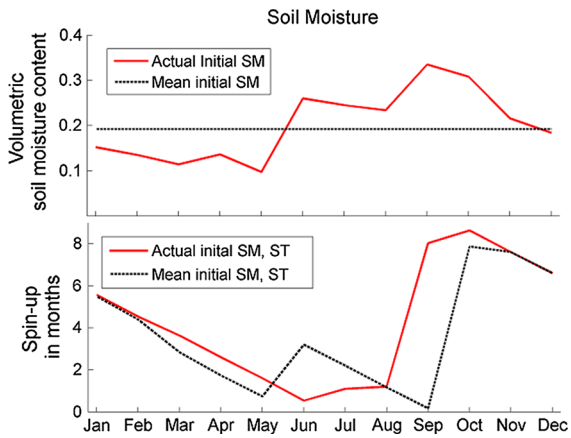

Figure 9
Dependence of spin-up of initial soil moisture and time of initialization

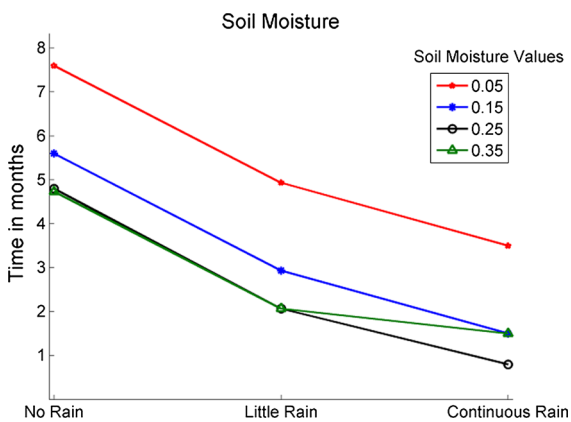

Figure 10
Spin-up of soil moisture for different initial soil moisture values and the model being initialized under different rainfall conditions

initialized just before an episode of continuous rainfall. Further, it is seen from Fig. 11 that in the absence of significant moistening forcing in the form of precipitation (model initiated during a no rain period and just before a small rainfall event), the model spin-up decreases with increasing soil wetness. However, in the case of the model initialized just before a period of continuous rainfall, it is seen that a moderately wet soil has a lesser spin-up time than a drier soil or a wetter soil.

It is seen from our study that the average spin-up time of a land surface model reduces when the model is initialized just before the monsoon season. The above results may be interpreted following Cosgrove et al. (2003). Through the process of spin-up, the

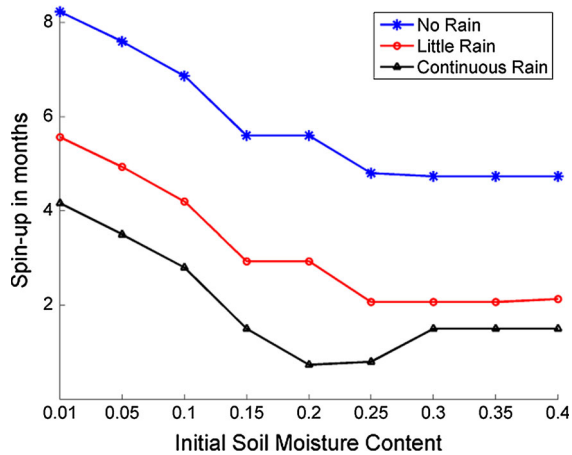

Figure 11
Spin-up under different soil wetness and precipitation conditions

model tries to reach an equilibrium state. In case of a dry initialization, the spin-up process requires the soil column to moisten which can only occur when precipitation forcing is available. In the case of a wet initialization, for the model to reach equilibrium, the soil column needs to lose moisture through evaporation and infiltration which is governed by the model physics. Thus, in general, it is seen that a wet initialization results in a faster (lower) spin-up as reported by Rahman and Lu (2015). However, when the model is initialized just before or during heavy precipitation events, a very wet initial soil condition has a larger spin-up than a moderately wet soil since the readily available excessive moisture acts as a shock to the model physics rather than aid it.

From the study, it is seen that the experiments initialized just before a continuous rainfall event has the least spin-up unless the initial soil is saturated.

5. *Conclusion*

An offline 1-D Noah LSM is used to test the impact of land surface parameters and time of model initialization on the model spin-up. PCA analysis has been performed to identify parameters that explain the spatial variance of spin-up. It is seen that forcing parameters such as longwave and shortwave radiation, air and soil temperature, rainfall and soil type have major contributions to the first principal component which explains more than half of the variance.

Soil moisture is the dominant contributor to the second principal component which explains about one-fifth of the variance. Vegetation type also contributes significantly. Overall, it is seen that soil moisture is a major factor affecting spin-up of the land surface model as it has significant contributions in the first three principal components which together explain more than 80% of the variance.

An investigation of impact of soil and vegetation parameter shows that soil type has a stronger impact on model spin-up than vegetation. However, the seasonal variation of impact is higher for vegetation than soil. It is seen that the model has least spin-up for vegetation having higher roughness length and greater rooting depth. The model has shorter spin-up for porous soil and longer spin-up for soils having higher conductivity and higher quartz content.

It is seen that the average spin-up time of a land surface model reduces when the model is initialized just before the monsoon season. It is also found that wetter soil with continuous precipitation events, especially during monsoon, would lead to longer spin-up time.

The present study will be useful in identifying the optimum initialization conditions for the LSM in different seasons for the least possible spin-up time.

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