# The Role of Land Surface Schemes in the Regional Climate Model (RegCM) for Seasonal Scale Simulations over Western Himalaya

P. R. Tiwari[1*], S. C. Kar[2], U.C. Mohanty[3], S. Dey[1], P. Sinha[1], P. V. S. Raju[1] and M.S. Shekhar[4]

[1]Centre for Atmospheric Sciences, Indian Institute of Technology Delhi, India

[2]National Centre for Medium Range Weather Forecasting, Noida, India

[3]School of Earth Ocean and Climate Sciences, IIT Bhubaneswar, India

[4]Snow and Avalanche Study Establishment, Chandigarh, India

*Correspondence
Pushp Raj Tiwari
Centre for Atmospheric Sciences
Indian Institute of Technology, Delhi
Hauz Khas, New Delhi
pushprajiitd@gmail.com

## Abstract

Climate prediction over the Western Himalayas is a challenging task due to its highly variable altitude and orientation of orographic barriers. Surface characteristics also play vital role in the climate simulations and need appropriate representation in the models. In this study, two land surface parameterization schemes (LSPS), the Biosphere-Atmosphere Transfer Scheme (BATS) and the Common Land Model (CLM, version 3.5) in the regional climate model (RegCM, version 4) have been tested over the Himalayan region for nine distinct winter seasons (three years each for excess, normal and deficit) in respect of seasonal precipitation. National Center for Environment Prediction (NCEP)-Department of Energy (DOE) reanalysis-2 data have been used as initial and lateral boundary conditions for the RegCM model. In order to provide land surface boundary conditions in the RegCM model, geophysical parameters (10 min resolution) obtained from United States of Geophysical Survey were used.

The performance of two LSPS (CLM and BATS) coupled with RegCM is evaluated against gridded precipitation and surface temperature data sets from the India Meteorological Department (IMD). It is found that the simulated surface temperature and precipitation are represented better in the CLM scheme than the BATS when compared with the observations. Further, several statistical analysis such as bias, RMSE, spatial correlation coefficient (CC) and skill scores like Equitable Threat Score (ETS), Probability of Detection (POD) are estimated for evaluating the simulations of RegCM using both the LSPS. Results indicate that the RMSE decreases and CC increases with the use of the CLM than the BATS scheme. The ETS and POD also indicate that the performance of the model is better with the CLM than the BATS in simulating seasonal scale precipitation. Overall the results suggest that the performance of RegCM coupled with the CLM scheme improves the model skill in predicting winter precipitation (by 15-25%) and temperature (by 10-20%) over the Western Himalaya.


Key words: Western Himalayas; Land Surface Schemes; Regional Climate Model.

## 1. Introduction

The Western Himalayas region receives substantial amount of precipitation in the form of snow during winter months (December, January and February; DJF). The precipitation over this region shows a large inter-annual variability and is vital for several sectors such as agriculture/horticulture, transportation, tourism, hydropower projects and water resources and management. Excess precipitation over this region causes landslides/avalanches and impact livelihoods and infrastructure. Due to the complex orography, nonlinear interaction of land-atmosphere process and insufficient observed datasets, seasonal-scale prediction of precipitation over such a heterogeneous region is one of the challenging tasks for the meteorologists. Since the heterogeneity of the mountain region plays dominant role in modulating the regional climate (Pielke *et al*., 1990; Dickinson, 1995), advanced land surface parameterization scheme (LSPS) in a model may be able to improve the prediction skill over the mountain region.

Henderson *et al.* (1993) have found in their study that more than 30% of lower boundary condition for the earth surface is provided through land-atmosphere interface in global climate models and in the case of regional climate modeling systems, this percentage can be even more. Since the exchange of momentum and energy between land surface and the atmosphere affects the prognostic variables such as surface temperature, precipitation etc., better representation of surface boundary conditions in a model is very important. Ding *et al.* (1998) have examined the role of different land surface processes and found that the efficiency of regional climate model (RCM) is increased in the simulation of precipitation when an improved land-surface parameterization scheme is used. A few studies on the impact of different land LSPS have been carried out in simulation of upper air circulation associated with precipitation (Pielke *et al.*, 2003, Singh *et al.*, 2007, Dutta *et al.*, 2009, Kar *et al.*, 2014, Tiwari *et al.*, 2014) over the Indian region. It was found that LSPS plays a crucial role in seasonal scale simulation over the Indian region. However most of these studies have been conducted for the Indian summer monsoon seasons and so far there are no such study for the winter seasons (DJF) examining the role of different LSPS in a RCM over the Western Himalayan region.

The main objectives of the present study is to evaluate the performance of two LSPS, i.e. the Biosphere-Atmosphere Transfer Scheme, Dickinson et al., (1993) (hereafter referred to as BATS) and the Common Land Model- version 3.5, Oleson et al., (2008), (hereafter referred to as

CLM) in the Regional Climate Model (RegCM)-version 4, Pal et al., (2007) to simulate winter precipitation and temperature over the Western Himalayas.

The remainder of this paper is organized as follows. A brief description of the model used including simulation specifics and methodology are presented in section 2 and 3 respectively. Section 4 describes the results and discussion of sensitivity experiments with BATS and CLM schemes. Finally salient features of the study are concluded in section 5.

## 2. Model description

The dynamical core of the RegCM (version-4) model is similar to the hydrostatic version of Mesoscale Model MM5 (Grell *et al.,* 1994). The RegCM standard model configuration consists of 18 vertical sigma levels in which five levels (at approximately 40, 110, 310, 730 and 1400 m from surface) are in lower troposphere (within 1.5 km from surface, Giorgi *et al.,* 1989). The radiative transfer package of the NCAR Community Climate Model version 3 (Kiehl *et al.,* 1996), mass flux cumulus cloud scheme of Grell (1993) with Fritch–Chappell closure (Fritch and Chappell, 1980) and nonlocal boundary scheme by Holtslag *et al.* (1999) are used in the RegCM. The Land-surface processes are incorporated via Biosphere-Atmosphere Transfer Scheme or BATS (Dickinson *et al.,* 1993) and Community Land Model or CLM (Oleson *et al.,* 2008) schemes. For this study, the model domain is from 18°N to 45°N and 60°E to 95°E. The model domain and the orography shown in Figure 1 covers all parts of northwest India. The model grid with horizontal resolution of 30 × 30 km is selected to conduct the simulation experiments. As can be seen from the figure, maximum height of the Himalayas represented at this resolution is about 5500m. Most of the sharp gradient in orography in the Himalayas gets smoothed out due to the resolution chosen for the model. Sinha et al (2013) have carried out a detailed study on the role of representation of orography in the RegCM3 simulations. A brief on model configuration used in this study is also given in Table 1. In this study, two sets of numerical experiments are carried out with different land surface models, i.e. the BATS and the CLM.

The BATS land surface parameterization scheme is used to describe the role of soil moisture and vegetation in the model. It calculates the exchanges of momentum, energy, and water vapor associated with surface-atmosphere interaction. It has one vegetation layer, a surface soil layer, a snow layer and 20 vegetation types. The prognostic equations for the soil layer temperatures are solved by using a generalized force-restore method (Dickinson *et al.,* 1993). The

CLM (Oleson *et al.,* 2008) contains one vegetation layer with a canopy photosynthesis-conductance model, ten unevenly spaced soil layers, five snow layers with an additional representation of trace snow and 24 vegetation types. In this scheme, for each layer temperature, ice water and liquid water are solved explicitly. CLM uses a mosaic approach for capturing land surface heterogeneity within a climate model at each grid cell. The main advantages of CLM over BATS are that in CLM there is inclusion of more number of soil layers and vegetation fraction. The CLM has ability to include subgrid ‘‘tiles’’ with a separate water and energy balance conducted for each tile. This approach in the CLM helps the representation of various surface parameters (for e.g. surface temperature, precipitation, fluxes etc.) in a better way compared to the BATS scheme, Steiner *et al.* (2005). A brief comparison of these two land surface parameterization schemes is provided in Table 2.

## 3. Simulation specifics and verification methodology

Seasonal (winter season) precipitation anomalies over the Indian parts of the Western Himalayan region have been computed using 33 years (1975–2008) of observed precipitation data from the India Meteorological Department (IMD) (Rajeevan *et al.,* 2006). For the present study, extreme (excess or deficit) precipitation seasons are considered on the basis of precipitation anomaly departure by one standard deviation or more from its mean. Therefore, among 33 years, there are 3 years in the category of excess precipitation (1990-91, 1994-95, 1997-98; hereafter referred to as excess years), 3 years in the category of deficit precipitation (1996-97, 2000-01, 2004-05; hereafter referred to as deficit years) and 3 years in the category of normal precipitation (1988-89, 1993-94, 2003-04; hereafter referred to as normal years) years. In the present study, these years are considered to conduct the numerical experiments. Composite analyses have been carried out by computing the difference between excess minus normal and deficit minus normal precipitation years.

The RegCM model has been integrated from 1$^{st}$ November to 28 February (29 February for leap year) of each winter season separately. In this study, model integration output for the first month i.e. November is not analyzed as it is considered as the model spin up time. For each year (excess, deficit and normal years), the RegCM model is integrated twice with two different LSPS; first, coupled with BATS and then second, coupled with CLM keeping all the others parameters of the model the same. Initial and lateral boundary conditions (LBCs) for the model integration are provided from NCEP-DOE reanalysis-2 to drive the RegCM model and the LBCs are updated every 6 hourly. The prescribed sea surface temperature in the model is the National Oceanic and Atmospheric Administration Optimum Interpolation SST (NOAA_OI_SST_V2; at 1°×1° resolution). The geophysical parameters are from the United States of Geophysical Survey (USGS; at 10' resolution). The model-simulated results are validated with the IMD gridded (1°×1°) observed precipitation and surface air temperature (hereafter referred to as temperature) data sets. For comparison of model data with observation, model simulated results are interpolated bilinearly to the grid points of the observed data.

Statistical analysis such as spatial Correlation Coefficient (CC), Root Mean Square Error (RMSE), Probability of Detection (POD), Equitable Threat Score (ETS) etc. have been carried out between model and IMD data sets. Probability of Detection (POD) gives that what fraction of the observed "yes" events were correctly forecasted. It is defined as,

$$POD = \frac{H}{H + M} \tag{1}$$

where H and M are hits, misses for each category. POD ranges from 0 to 1 with POD = 1 indicates perfect skill in prediction (i.e. M = 0). Equitable Threat Score (ETS) is a skill metric, which is generally used for Yes/No forecast (Gilbert, 1884, Wilks, 1995). ETS is defined as:

$$ETS = \frac{(H - H_{\lambda})}{(H + M + F - H_{\lambda})} \text{ , where } H_{\lambda} = \frac{(H + M) \times (M + F)}{T} \tag{2}$$

where M, H and F are number of misses, hits and false alarms for each category, hits due to random chance is denoted by $H_{\lambda}$ and T is the total number of events. ETS varies from −0.33 to 1 with ETS = 0 indicating no skill and ETS = 1 indicating perfect skill in prediction. The Student's t-test is used for statistical significant test of anomaly correlation coefficient (CC) and the critical value of CC is 0.27 at 90% confidence level (CL).

## 4. Results and discussion

The composite analyses of observed gridded temperature and precipitation during winter season for excess, deficit and normal precipitation years are presented in Figure 2. It is clearly seen from the figure that temperature is comparatively cooler during the excess years as compared to the normal and deficit years over Jammu and Kashmir. It is seen that the seasonal mean temperature is warmer by 1-2 °C during the deficit years than the excess years over the Western Himalayan region. The range of seasonal mean precipitation during the excess years is about 4.5 to 6.5 mm day$^{-1}$ with maximum of 6.5 mm day$^{-1}$ over Jammu and Kashmir; whereas during the deficits year the seasonal precipitation range is about 1.5 to 2.5 mm day$^{-1}$ with maximum 2.5 mm day$^{-1}$ over the same region. Therefore, it is noticed that the excess precipitation years are comparatively cooler than the deficit precipitation years over the Indian part of the Western Himalayan region. In the following three sub-sections, the results obtained from the simulation of RegCM model with two different LSPS are analyzed.

**4.1 Spatial distribution of surface air temperature**

The simulated seasonal average (DJF) temperature from experiments with BATS and CLM in RegCM for nine distinct precipitation years (three excess, three deficit and three normal) have been examined. It is noticed that the model is able to bring out the mean temperature distribution over the northwest India for the composite excess, composite deficit and composite normal years reasonably well when either of the land surface schemes (BATS and CLM) are used (figure not shown). However, the simulated temperature in terms of distribution and magnitude is better in the CLM experiment than the BATS when results are compared against the observed surface temperature data sets.

In order to understand the variation of seasonal average winter temperature in distinct years, composite differences between the excess and normal as well as the deficit and normal years are computed and shown in Figure 3. It is seen from the figure that the temperature is lesser in the observation as well as in both the RegCM simulation experiments in the excess years than the normal years. Figure 3 (left panel) illustrates that the RegCM model with the BATS simulates a warmer surface by about 1-2°C as compared to the CLM in the difference between composite excess and composite normal precipitation years. On the other hand, it is found that the area with colder temperature is more over the Western Himalaya in the CLM than the BATS. It is also noticed that the magnitude and distribution of temperature difference between deficit and normal year with the CLM scheme is better than that of the BATS when compared with the observed patterns figure 3 (right panel). Analysis reveals an improvement of 10-20% in the predictions of seasonal mean winter temperature with the use of the CLM over the BATS experiment. So, the result suggests that the model-simulated mean as well as variation in temperature (in terms of spatial distribution and magnitude) during the nine distinct years are represented well with the use of the CLM than the BATS land surface scheme.

**4.2 Spatial distribution of precipitation**

The response of the BATS and CLM schemes in the RegCM model is examined in terms of precipitation simulations in nine distinct years described earlier. Results indicate that the model is able to bring out the seasonal mean precipitation distribution for the composites of excess, composite deficit and composite normal years reasonably well with both the land surface schemes (figure not shown). However, the model simulated precipitation in terms of distribution and intensity with the use of the CLM scheme is closer to observations. To understand the RegCM model efficiency in simulating precipitation during nine distinct years, the seasonal mean (DJF) composite precipitation differences between the excess and normal as well as the deficit and normal years are computed. The precipitation differences are shown in Figure 4. In the precipitation difference between excess and composite normal years (figure 4 left panel), it is seen that the representation of precipitation in terms of intensity and distribution is better with the CLM than that with BATS scheme when compared with the observed differences. The precipitation differences between deficit and normal years (figure 4 right panel) are captured well in both the LSPS (CLM and BATS) over the northwest India, however, the variation in precipitation is closer to the observations with CLM scheme than the BATS scheme. The qualitative description of seasonal precipitation suggests that the efficiency of RegCM model is higher with the CLM than the BATS scheme.

Area average of monthly as well as seasonal composite precipitation obtained from the IMD observations and the RegCM (with the BATS and CLM schemes) simulations have been computed and shown in Figure 5. It is seen that the area-averaged precipitation is underestimated in both the LSPS during all the years (composite of excess, composite of deficit and composite of normal years respectively) at monthly as well as seasonal scale. However, the RegCM simulations with the CLM are closer to the observations. An improvement in precipitation magnitude by about 15-25% is noticed with the CLM over BATS schemes in the seasonal mean simulations. It may be noted that the improvement varies from year to year. During all the months and seasons, the efficiency of the RegCM model is higher when run with the CLM than the BATS; though the rate of improvement is more in the month of January than in other months.

Probably one of the reasons for better simulation of precipitation with the CLM may be due to the inclusion of more number of soil layers and better representation of vegetation cover as compared to the BATS as described below.

The vegetation cover over the region of interest as used by the two LSPS (BATS and CLM) is shown in Figure 6. It is seen from the diagram that vegetation cover in the RegCM-CLM simulations has greater spatial coverage over the Indian part of Western Himalayas than the RegCM-BATS. This increased vegetation cover in RegCM-CLM enhances precipitation as found in Zheng et al 2002.

Soil moisture from NCEP-DOE reanalysis-2 and RegCM simulations (with BATS/CLM LSPs) are shown in Figure 7, for composite of excess and normal and deficit and normal precipitation year. The observation shows positive soil moisture over Northern India, which is well brought out by both the LSPS. However, the spatial extent is less in RegCM-BATS simulation for the composite of excess minus normal year. In case of composite difference between deficit and normal precipitation year the spatial extent and intensity is closer to observation in the case of RegCM-CLM compared to RegCM-BATS simulation. This difference in model simulation is due to difference in the soil description and moisture representations between these two LSPS. Therefore, better representation of this soil moisture may be the reason of better precipitation representation in the RegCM-CLM simulation.

Sensible heat flux from NCEP-DOE reanalysis-2 and RegCM simulations (with BATS/CLM LSPS) are depicted in Figure 8, for composite of excess minus normal and deficit minus normal precipitation year. Composite analysis between excess minus normal precipitation years depicts that both the LSPS shows almost similar spatial extent of precipitation over the eastern parts of J&K. However over western part of J&K, the RegCM-CLM simulation produces more wet zones compare to RegCM-BATS combination. In the case of composite difference between deficit and normal precipitation year, simulations with both the land surface schemes are mostly similar.

### 4.3 Statistical evaluation of precipitation

The performance of the RegCM model with the BATS and CLM land surface schemes have been evaluated by computing various statistical skill scores. Some of the important evaluation strategies are to estimate Root Mean Square Error (RMSE), Correlation Coefficient

(CC) etc. The model skill scores are estimated against observed gridded precipitation data from the IMD over the Indian part of the Western Himalayas. The model results are bi-linearly interpolated to the grid points of the IMD observed data for statistical evaluation. The RMSE and spatial CC are calculated for both set of runs using the CLM and BATS scheme. These are presented in Table 3. It is seen that the CC is statistically significant (the threshold value is 0.27 at 90% confidence level) in the precipitation simulation with the CLM scheme during excess, deficit and normal precipitation years. The CC is higher with the CLM experiment (0.39, 0.35 and 0.37 respectively) than the BATS experiment for all the years for which simulation experiments are carried out in this study. The RMSE values of the RegCM model are lesser when the CLM scheme is used than that of the BATS. This suggests that the spatial distribution of precipitation and its intensity is simulated better in the RegCM with the CLM than the BATS scheme.

Several other skill metrics such as probability of detection (POD), accuracy, equitable threat score (ETS), and bias have been estimated for the distinct precipitation years and presented in Table 4. When the observed precipitation is more than or equal to 1 mm/day, that day is considered as a wet day. It is seen from the statistical analysis that POD values are higher in the CLM experiment (0.75, 0.70 and 0.88 for the excess, deficit and normal years, respectively) than the BATS in all the three distinct years. It is found that the number of wet days simulated in the CLM experiment is closer to the observation. Furthermore, the accuracy of precipitation simulation is higher with the CLM than the BATS over the Western Himalaya. Computed model bias indicates that the precipitation intensity and distribution is brought out better with the CLM (bias is closer to 1). However, the model-simulated precipitation is underestimated with respect to observations with both the schemes. Table 4 indicates that the ETS is more in case of the CLM simulations during all the years, which indicates that the precipitation events are captured better with the CLM land surface scheme.

Thus, the statistical analysis (forecast errors and skill scores) also reveals that the RegCM model with the CLM parameterization scheme performs better in simulating precipitation for extreme years with reasonable accuracy over the Western Himalayan region as compared to RegCM with the BATS scheme.

## 5. Conclusion

In the present study, we compare the two different land surface parameterization schemes i.e. BATS and CLM in RegCM to simulate nine distinct winter precipitation years over the Western Himalayas. During the winter months, a notable difference between the BATS and CLM experiments is observed in the simulation of temperature and precipitation amount. The performance of the RegCM with both LSPS is reasonable in reproducing the mean features of seasonal temperature and precipitation, however the skill of the model is higher with the CLM scheme. Furthermore, the temperature and precipitation during extreme winter seasons are also captured better with the CLM than the BATS scheme when compared with the observations. As mentioned earlier, most of the sharp gradient in orography in the Himalayas gets smoothed out due to the resolution chosen for the model. Similarly, the surface characteristics (soil type, soil wetness, vegetation cover etc) does not get properly represented in the model due to the chosen resolution as there is sharp gradient in these parameters over the Himalayan region. This study suggests that even at this resolution, the RegCM model with CLM and BATS schemes is able to reproduce some of the salient features of the distinct years examined.

Forecast errors and skill scores indicate that performance of the RegCM model is better when the CLM scheme is used than the BATS. Further, improvements by about 10-20% in temperature and 15-25% in precipitation predictions are observed with the use of the CLM than the BATS scheme. In sum, the study indicates that the RegCM model with the CLM scheme can be more informative in simulating wintertime temperature and precipitation over the Western Himalayan region.

## Acknowledgements

The authors acknowledge the fund supported by Snow and Avalanche Study Establishment (SASE) to carry out this study. The RegCM4 installed at IIT Delhi was developed at the Abdus Salam ICTP, Trieste, Italy and is duly acknowledged. The authors acknowledge the India Meteorological Department for providing valuable data sets for accomplishing this work. The authors also duly acknowledge NCEP, USA for reanalysis-2 data and the NOAA for optimum interpolated SST version-2 (NOAA_OI_SST_V2) data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at http://www.esrl.noaa.gov/psd/. Authors also wish to thank the anonymous reviewers for their constructive suggestions that improved the manuscript significantly.

## References

Dickinson R. E., A. Henderson-Sellers and P. J. Kennedy, 1993. Biosphere-Atmosphere Transfer Scheme (BATS) version 1e as coupled to the NCAR Community Climate Model. NCAR Technical Note NCAR=TN-387 þSTR, 72 pp.

Dickinson R. E., 1995. Land-atmosphere interaction. *Rev. Geophys.* **33**, 917–922.

Ding Y., J. Zhang and Z. Zhao, 1998. An improved land-surface processes model and its simulation experiment. 2. Land-surface process model (LPM-ZD) and its coupled simulation experiment with regional climate model. *Acta. Meteorol. Sin.* **56**, 385–400.

Dutta S. K., S. Das, S. C. Kar, U. C. Mohanty and P. C. Joshi, 2009. Impact of vegetation on the simulation of seasonal monsoon rainfall over the Indian subcontinent using a regional model. *J. Earth Syst. Sci.* **118**, 413–440.

Fritsch, J.M. and C.F. Chappell, 1980. Numerical prediction of convectively driven mesoscale pressure systems, part 1: Convective parameterization. *J. Atmos. Sci.* **37**, 1722–1733.

Gilbert G.K., 1884. Finley's tornado predictions. *Am. Meteorol. J.* **1**, 166–172.

Giorgi F. and G. T. Bates, 1989. On the climatological skill of a regional model over complex terrain. *Mon. Wea. Rev.* **117,** 2325–2347.

Grell G. A., 1993. Prognostic evaluation of assumptions used by cumulus parameterization. *Mon. Wea. Rev.* **121,** 764–787.

Grell, G.A., J. Dudhia, and D.R. Stauffer, 1994. Description of the fifth generation Penn State/NCAR Mesoscale Model (MM5). *Tech Rep* TN-398+STR, NCAR, Boulder, Colorado, pp.1-121.

Henderson-Sellers A. and R. E. Dickinson, 1993. Atmospheric-land surface fluxes. John Wiley and Sons, pp 387–405.

Holtslag A. A. M., E. I. F. De Bruijn and H. L. Pan, 1999. A high resolution air mass transformation model for short-range weather forecasting. *Mon. Wea. Rev*. **118,** 1561–1575.

Kar S.C., P. Mali, and A. Routray, 2014. Impact of Land Surface Processes on the South Asian Monsoon Simulations Using WRF Modeling System. Pure Appl. Geophys., **171**, 9, 2461-2484.

Kiehl J. T., J. J. Hack, G. B. Bonan, B. A. Boville, B. P. Briegleb, D. L. Williamson and P. J. Rasch, 1996. Description of the NCAR Community Climate Model (CCM3). NCAR Tech. Note NCAR/TN- 420+STR, 152 pp.

Oleson K. W., G. Y. Niu, Z. L. Yang, D. M. Lawrence, P. E. Thornton, P. J. Lawrence, R. Stöckli, R. E. Dickinson, G. B. Bonan, S. Levis, A. Dai and T. Qian, 2008. Improvements to the Community Land Model and their impact on the hydrological cycle. *J. Geophys. Res.* **113,** 1021-1026.

Pal J. S., F. Giorgi, X. Bi, N. Elguindi, F. Solmon, X. Gao, S. A. Rauscher, R. Francisco, A. Zakey, J. Winter, M. Ashfaq, F. Syed, S. Faisal. J. L. Bell, N. S. Diffenbaugh, J. Karmacharaya, A. Konare, D. Martinez, R. P. Da Rocha, L. C. Sloan and A. L. Steiner, 2007. Regional climate modeling for the developing world: The ICTP RegCM3 and RegCNET, *Bull. Amer. Meteor. Soc.* **88,** 1395–1409.

Pielke Sr* R. A., D. D. S. Niyogi, T. N. Chase and J. L. Eastman, 2003. A new perspective on climate change and variability: A focus of India. *Proc. Indian Nat. Acad. Sci.* **69,** 585–602.

Pielke R. and R. Avissar, 1990. Influence of landscape structure on local and regional climate, *Landscape Ecol.* **4,** 133–155.

Rajeevan M., J. Bhate, J. Kale and B. Lal, 2006. High resolution daily gridded rainfall data for the Indian region: analysis of break and active monsoon spells. *Curr. Sci.* **91,** 296-306.

Singh A. P., U. C. Mohanty, P. Sinha and M. Mandal, 2007. Influence of different land surface processes on Indian summer monsoon circulation. *Nat. Hazards* **42,** 423-438.

Sinha P., U. C. Mohanty, S. C. Kar, and S. Kumari, 2013. Role of the Himalayan orography in simulation of the Indian summer monsoon using RegCM3. Pure Appl. Geophys., DOI: 10.1007/s00024-013-0675-9.

Steiner A. L., J. S. Pal, F. Giorgi, R. E. Dickinson and W. L. Chameides, 2005. A coupling of common land model (CLM0) to a regional climate model (RegCM). *Theor. Appl. Climatol.* **82,** 225-243.

Tiwari P. R., S. C. Kar, U. C. Mohanty, S. Dey, P. Sinha, P.V.S. Raju and M. S. Shekhar, 2014. Dynamical downscaling approach for wintertime seasonal scale simulation over the Western Himalayas. *Acta Geophysica.* **62** (4), 930-952.

Wilks, D.S., 1995. Statistical Methods in the Atmospheric Sciences. Academic Press: San Diego, CA, 467 pp.

Zheng Y., Yongfu Qian, Manqian Miao, Ge Yu, Yushou Kong and Donghua Zhang, 2002. The effects of vegetation change on regional climate I: Simulation results; *Acta Meteorologica Sinica* **60,** 1–16.

**List of Tables**



**List of Figures**

Figure 6. Vegetation cover in (a) BATS and (b) CLM land surface schemes.

Figure 7. Seasonal (DJF) soil moisture (kg/kg) difference (composite excess – composite normal and composite deficit – composite normal precipitation year) obtained from observed (a & d) and RegCM4 model simulation with BATS (b & e) and CLM (c & f).

Figure 8. Seasonal (DJF) sensible heat flux (w/m$^2$) difference (composite excess – composite normal and composite deficit – composite normal precipitation year) obtained from observed (a & d) and RegCM4 model simulation with BATS (b & e) and CLM (c & f).

Table 1. Configuration of RegCM4 used in the present study

| | |
|---|---|
| Dynamics | Hydrostatic |
| Main Prognostic Variables | u,v t,q and p |
| Model domain | 18˚N - 45˚N; 60˚E – 95˚E; Res.=30 km |
| Map projection | Lambert Conformal Mapping |
| Vertical co-ordinate | Terrain-following sigma co-ordinate<br>Total 18 sigma levels (5 levels in PBL). |
| Cumulus parameterization | Grell with Fritch & Chappell closure |
| Land Surface Models | Biosphere-Atmosphere Transfer Scheme (BATS) &<br>Community Land Model (CLM) |
| Radiation parameterization | NCAR/CCM3 radiation scheme |
| PBL parameterization | Holtslag |

Table 2. A brief comparison between two land surface parameterization schemes i.e. BATS and CLM

| Category | BATS | CLM |
|---|---|---|
| Land Cover/ Vegetation classes | 20 vegetation types | 24 vegetation types |
| Surface representation | One vegetation layer, a surface soil layer, a snow layer | One vegetation layer with a canopy photosynthesis-conductance model, ten unevenly spaced soil layers, five snow layers with an additional representation of trace snow. |
| Soil temperatures calculation | Uses a two-layer force-restore model | Soil temperature is calculated explicitly by ten-layer soil model |
| Treatment of vegetation canopy | Treats all vegetation within the canopy in the same manner | The canopy is divided into sunlit and shaded fractions as a function of LAI |
| Calculation of stomatal conductance and photosynthesis rate | No individual calculation is made for sunlit and shaded fractions. It does not compute photosynthetic rates. | Stomatal conductance is calculated for sunlit and shaded fractions. Calculation of photosynthetic rates is done in this scheme |
| Treatment of heat and roughness length | Heat and water vapor roughness lengths are constant. | Updates these values over bare soil and snow with values from the stability functions |
| Albedo treatment | Uses prescribed values for vegetation albedo for both short- and longwave components | Uses a modified two stream approach that reduces the complexity of a full two-stream albedo treatment |

Table 3. Root mean square error (RMSE) and correlation for excess, deficit and normal precipitation year

| | | Excess | Deficit | Normal |
|---|---|---|---|---|
| | BATS | 3.448 | 1.587 | 2.778 |
| | CLM | 3.312 | 1.385 | 2.529 |
| | BATS | 0.359 | 0.313 | 0.351 |
| | CLM | 0.385 | 0.352 | 0.374 |

Table 4. Skill score for excess, deficit and normal precipitation years for (>1 mm rainfall category)

| Year | Land Surface Scheme | POD (1) (0 to 1) | Accuracy (1) (0 to 1) | Bias (1) (0 to infinite) | ETS (1) (-1/3 to 1) |
|---|---|---|---|---|---|
| | BATS | 0.715 | 0.589 | 1.502 | 0.113 |
| | CLM | 0.747 | 0.596 | 1.642 | 0.182 |
| | BATS | 0.693 | 0.633 | 1.952 | 0.071 |
| | CLM | 0.697 | 0.711 | 1.381 | 0.167 |
| | BATS | 0.852 | 0.656 | 1.458 | 0.179 |
| | CLM | 0.876 | 0.683 | 1.229 | 0.187 |

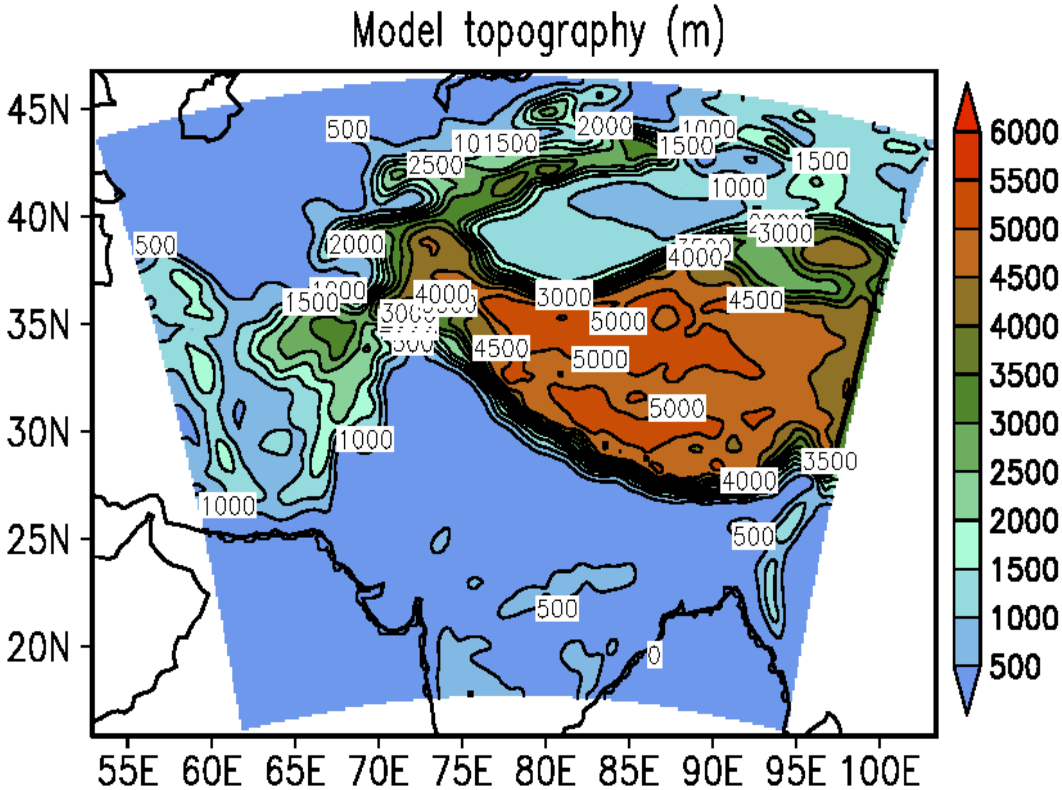


Figure 1. RegCM model domain used in the present study.

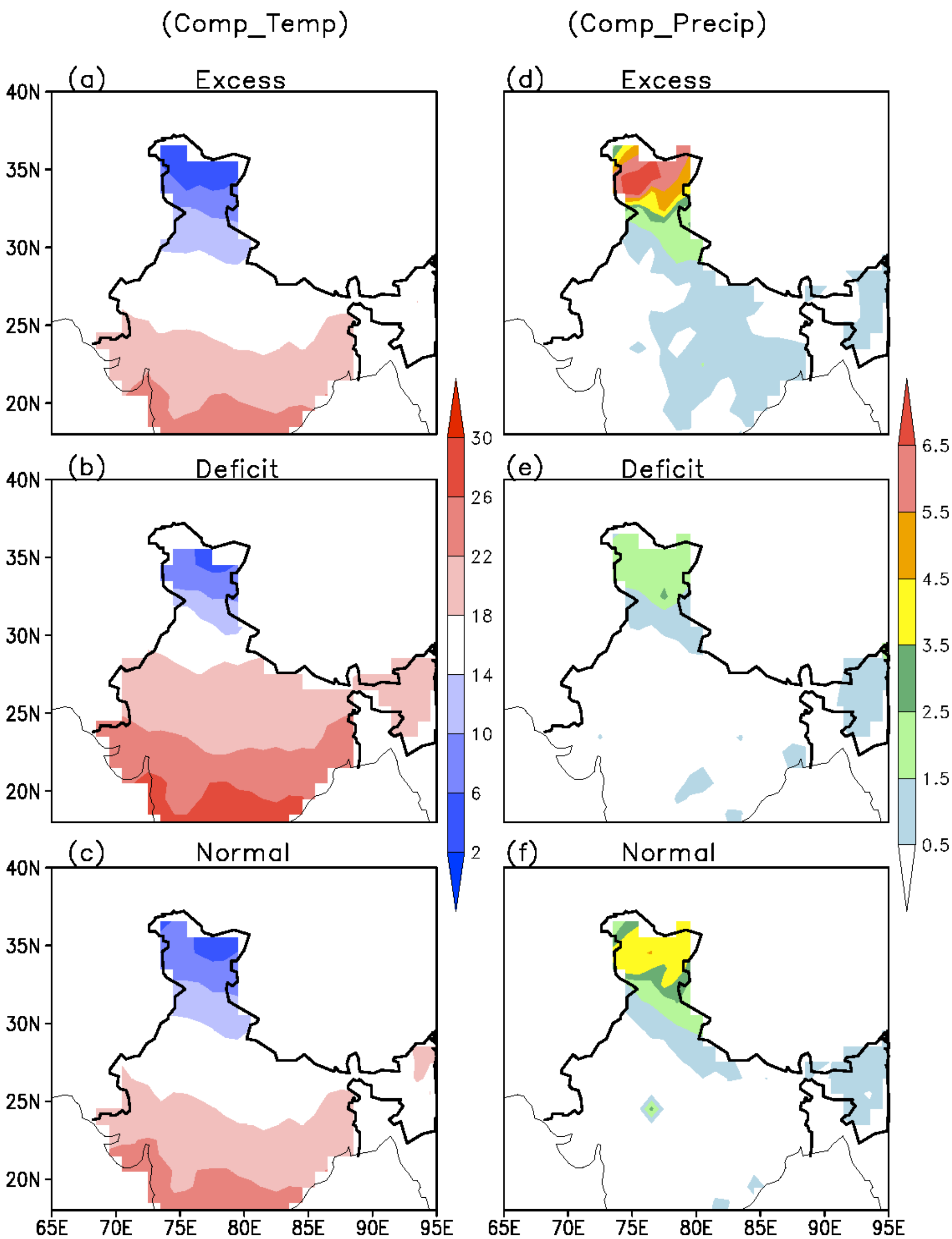


Figure 2. Seasonal (DJF) average of IMD gridded temperature (in $^{0}$C) and precipitation (in mm day$^{-1}$) for composite excess (a & d), composite deficit (b & e) and composite normal (c & f)) precipitation years.

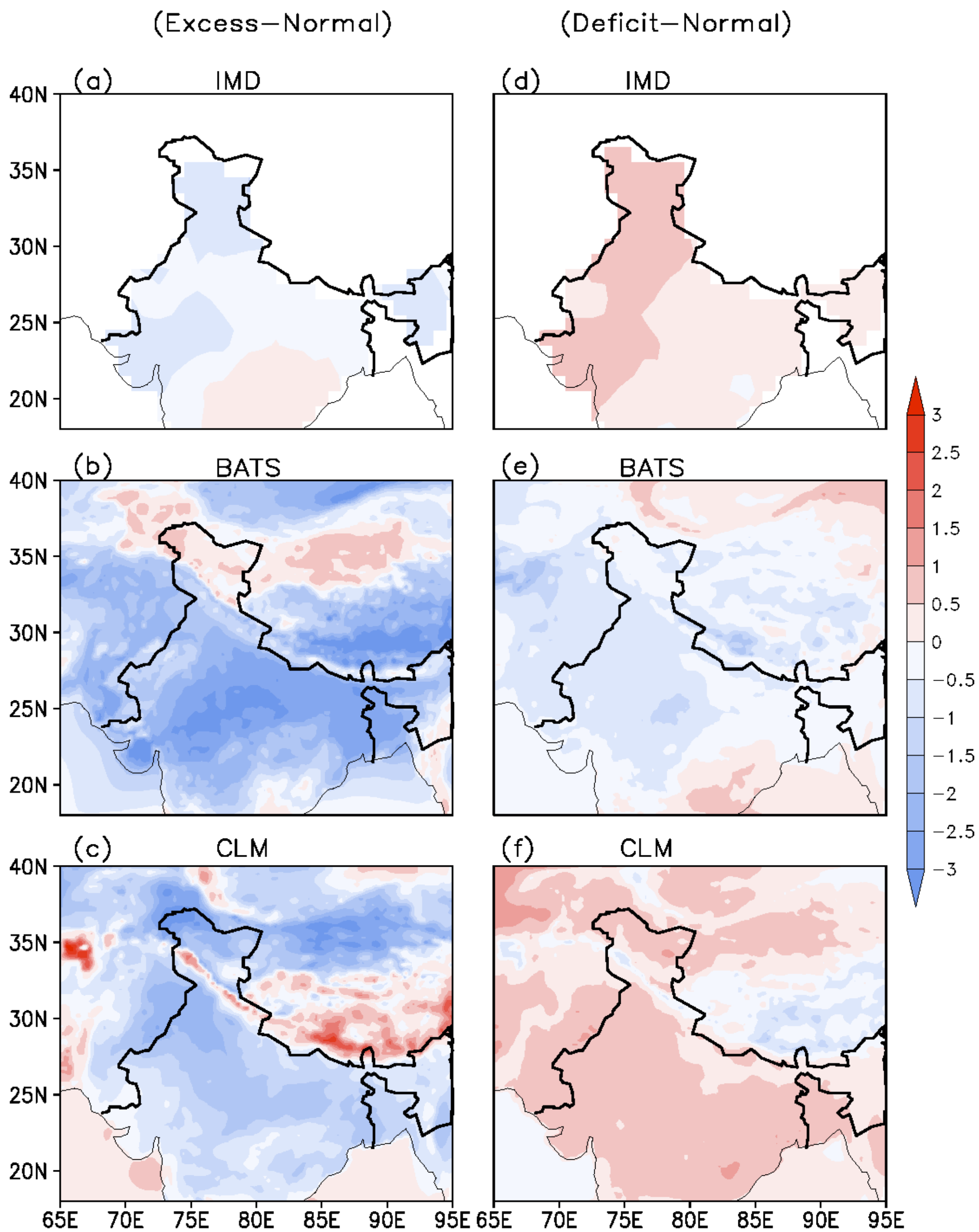


Figure 3. Seasonal (DJF) average surface air temperature difference (composite excess – composite normal and composite deficit – composite normal precipitation year) obtained from observed (a & d) and RegCM4 model simulation with BATS (b & e) and CLM (c & f).

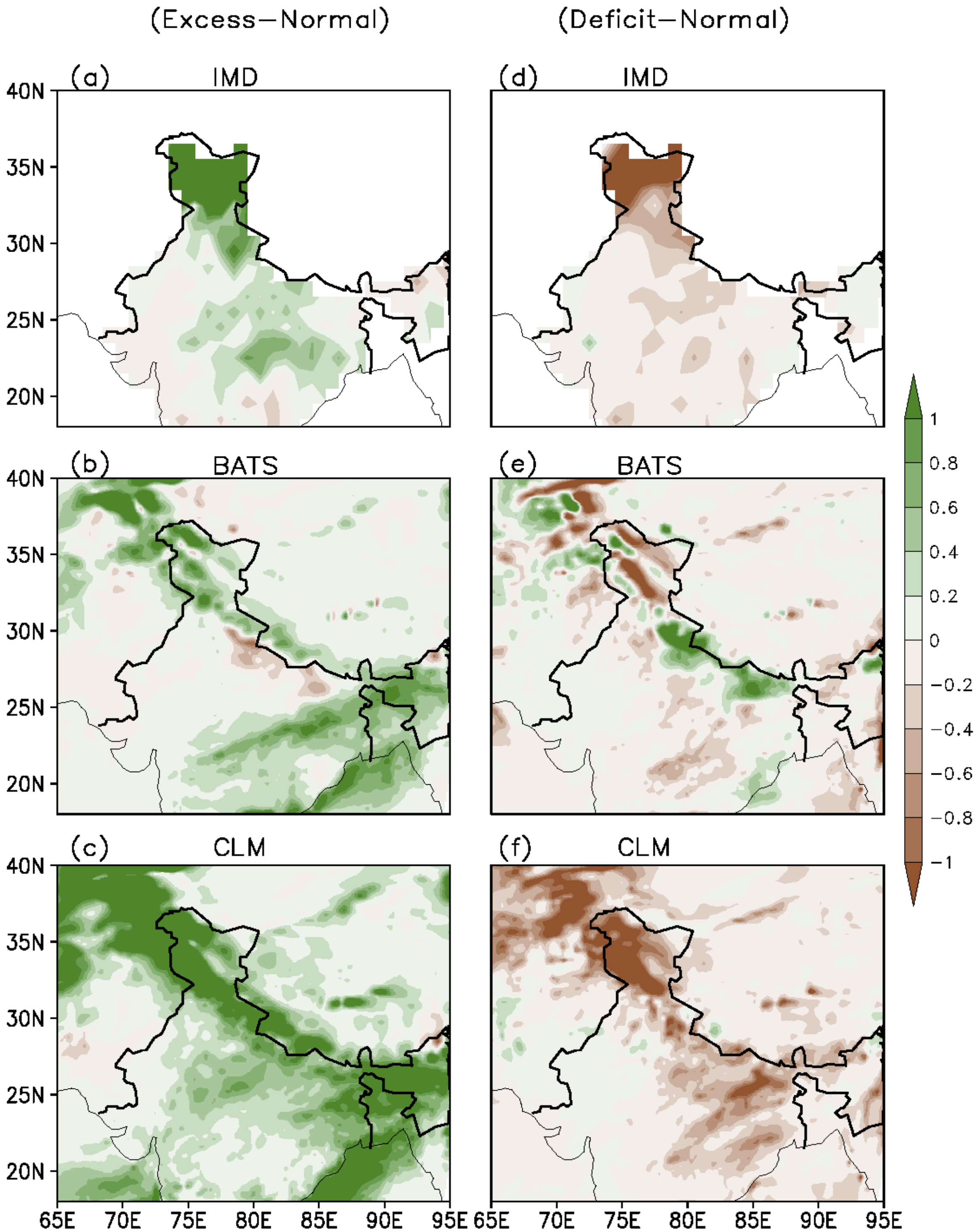


Figure 4. Seasonal (DJF) average precipitation difference (composite excess – composite normal and composite deficit – composite normal precipitation year) obtained from observed (a & d) and RegCM4 model simulation with BATS (b & e) and CLM (c & f).

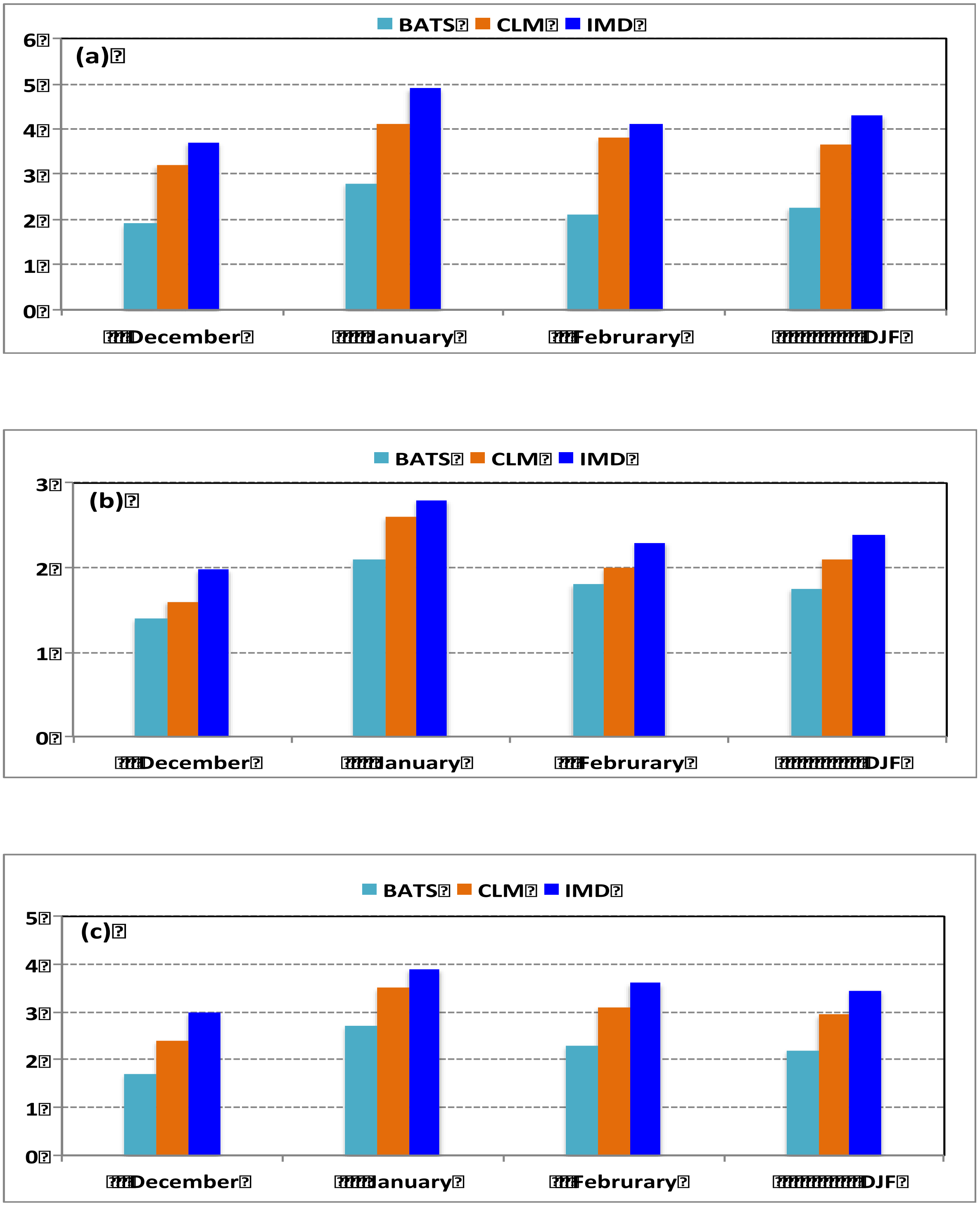


Figure 5. Monthly and seasonal average precipitation (mm day$^{-1}$) from IMD gridded precipitation, RegCM4 model simulation with BATS and CLM for (a) composite excess, (b) composite deficit and (c) composite normal precipitation year.

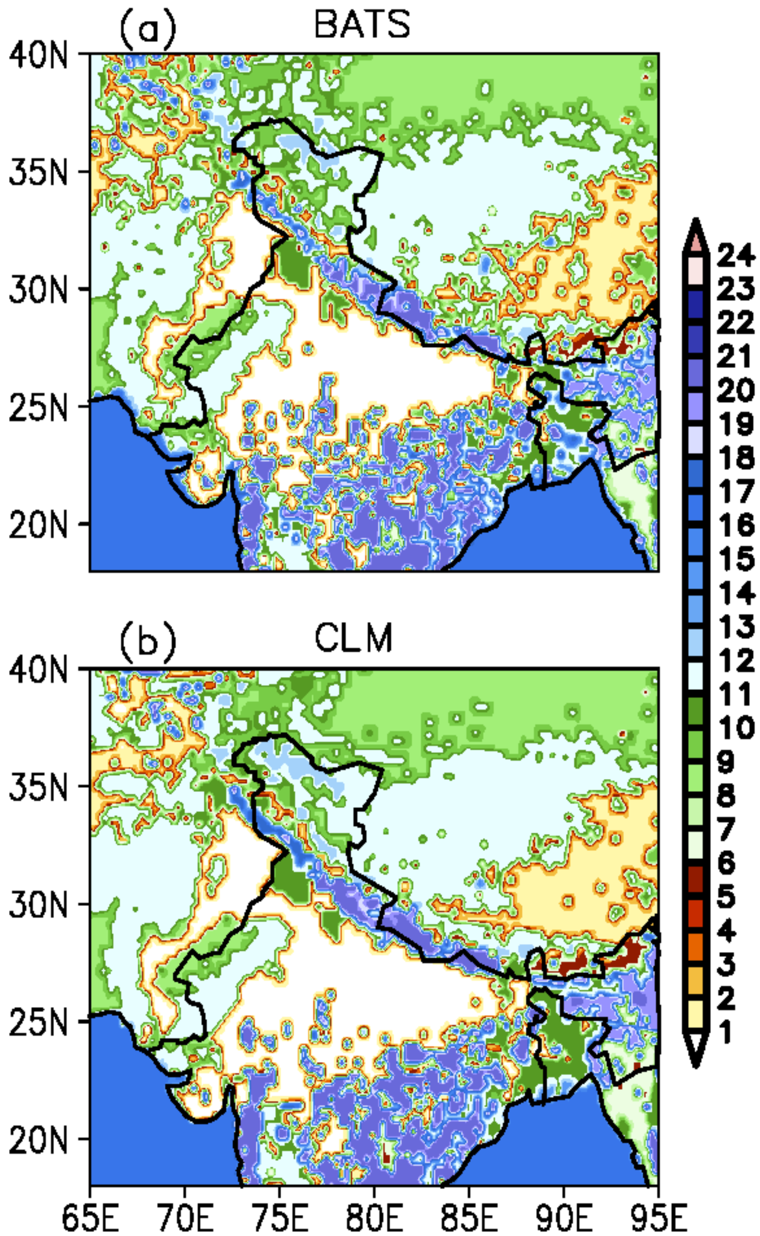


Figure 6. Vegetation cover in (a) BATS and (b) CLM land surface schemes.

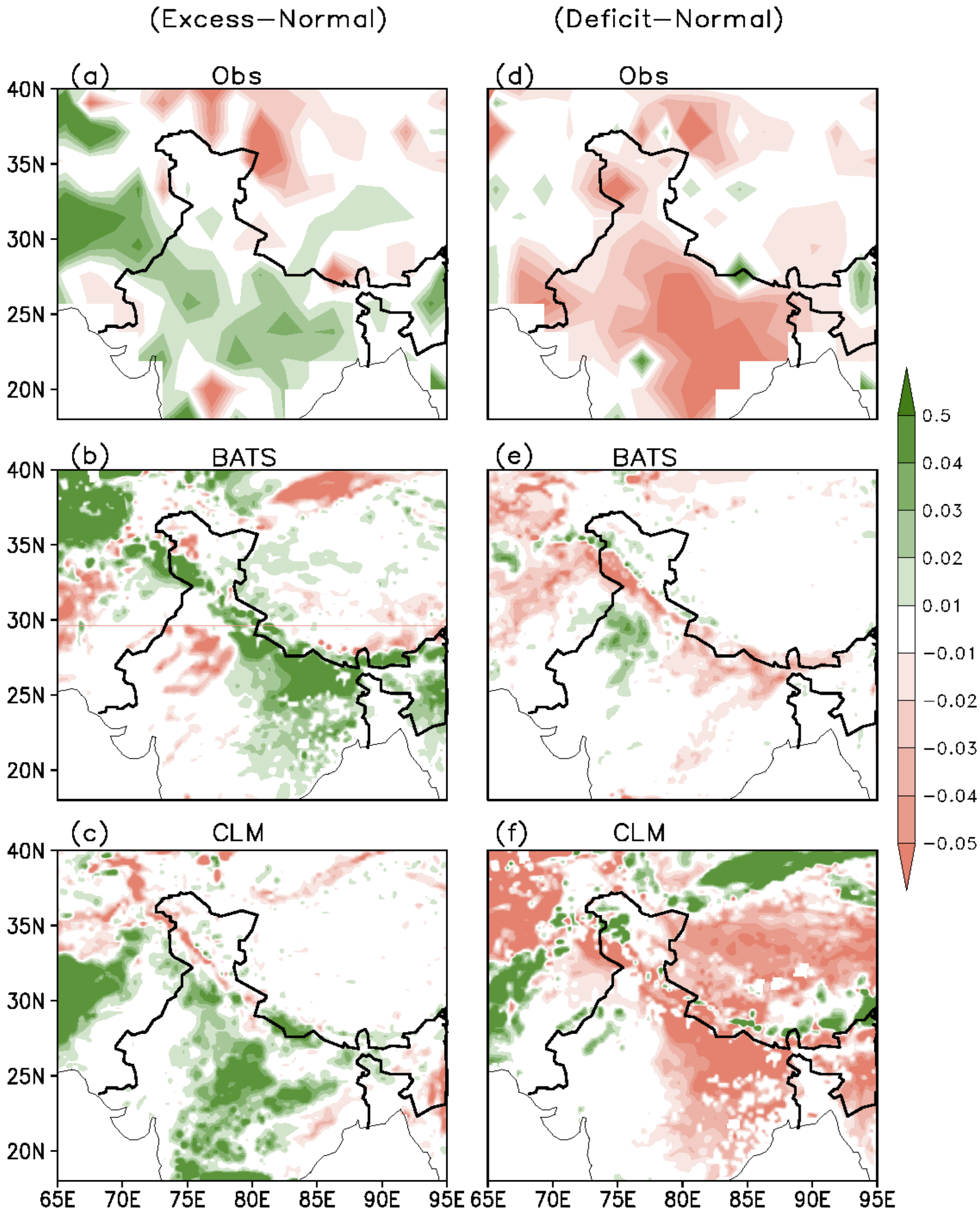


Figure 7. Seasonal (DJF) soil moisture (kg/kg) difference (composite excess – composite normal and composite deficit – composite normal precipitation year) obtained from observed (a & d) and RegCM4 model simulation with BATS (b & e) and CLM (c & f).

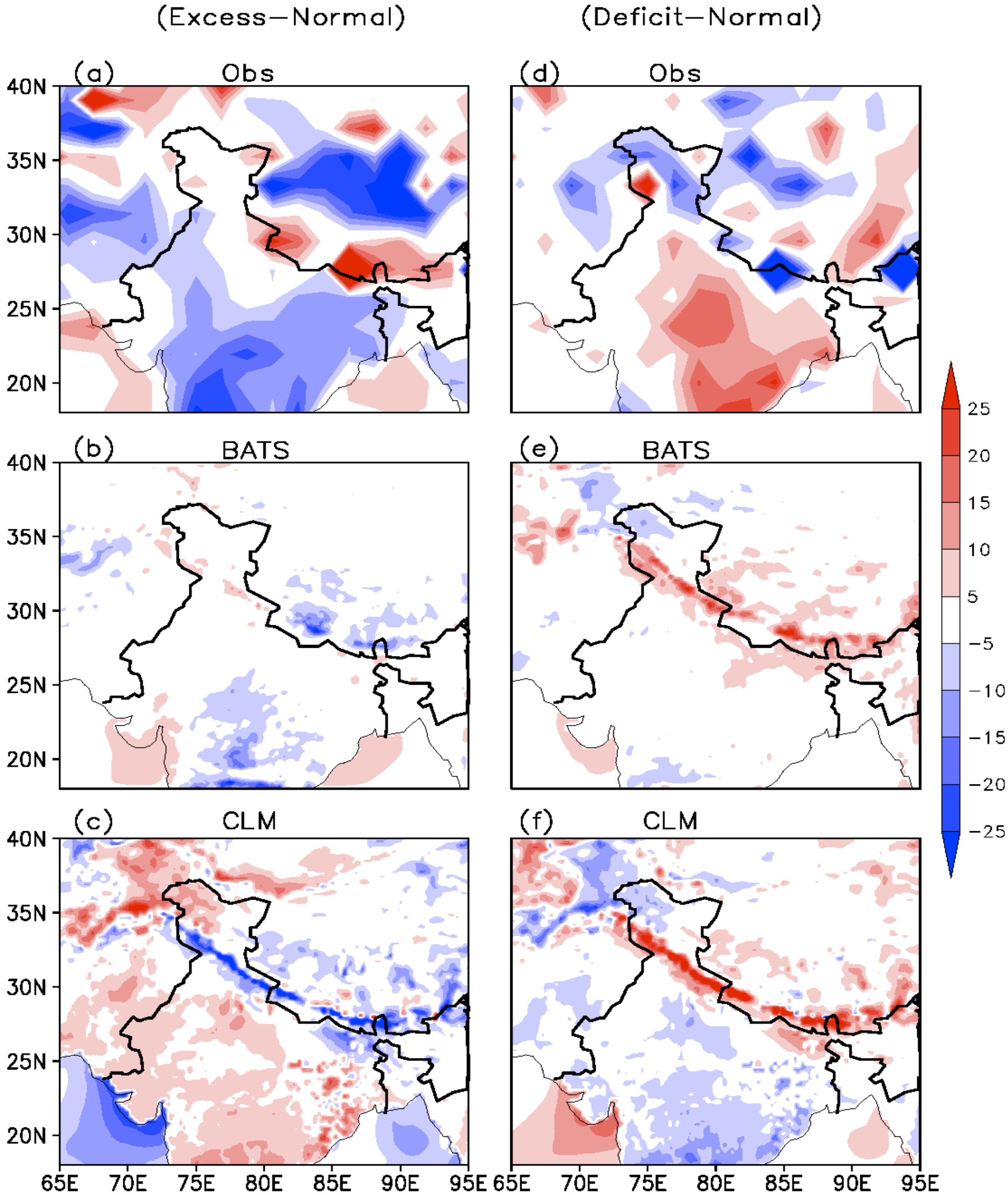


Figure 8. Seasonal (DJF) sensible heat flux (w/m$^2$) difference (composite excess – composite normal and composite deficit – composite normal precipitation year) obtained from observed (a & d) and RegCM4 model simulation with BATS (b & e) and CLM (c & f).