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Optimization of Extreme-Weather Forecasting Systems in Developing Nations

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Abstract

Severe weather events torment the developing world each year crippling their already fragile infrastructure – resulting in innumerable casualties. Advances in numerical modeling have greatly enhanced the capability to accurately forecast weather using personal computers. The recent Uttarakhand cloud-burst of 2013 in India, prompted us to re-evaluate the entire framework of the weather alert systems currently in place in developing nations. We propose an efficient forecast-alert system in developing nations based on advances in mesoscale weather forecasting. With the active involvement of local educational institutions in weather prediction, faster dissemination of alerts can be achieved. This can be made time-effective by optimizing parameters within numerical weather prediction models. Such a strategy extended across the developing world can yield expeditious forecasts ensuring prompt evacuation and thereby saving countless lives

Keywords: Numerical weather prediction, extreme weather, decentralized system, early warning, weather research forecasting model, microphysics parameterization.

Introduction

Owing to advances in numerical weather prediction, hazardous weather can be accurately forecast for any region of the world with sufficient warning time for contingency measures to be put into place. Numerical Weather Prediction models (NWP) models have become increasingly popular with meteorological agencies for issuing not only forecasts 1-2 days in advance, but also extreme weather forecasts for systems like tropical cyclones, tornadoes and other heavy precipitation events. Consequently, these weather systems have also been the focus of many modeling studies including the developing regions of the world.

Studies have been conducted on the effect of precipitation physics of numerical models on hurricane simulations, and the impact of microphysics and planetary boundary layer schemes on extreme rainfall associated with typhoons[1,2]. Numerous other researches conducted globally have demonstrated the extreme weather simulation capabilities of numerical models in different geographical regions, and have assessed the accuracy of these simulations and their response to changes in various parameterizations within these models[3,4,5]. Studies over the Indian region have also tried to detect and monitor severe thunderstorm and heavy rainfall events especially during pre-monsoon and monsoon times using the WRF model[6].

Although substantial advancement has eventuated in mesoscale modeling since they first came into being, they still exhibit uncertainties and often misrepresent the physical processes occurring due to lack of computational precision, resulting in inaccurate forecasts. One of the existing difficulties with respect to regional forecasts is the data insufficiencies and extrapolation needed due to inadequate and inaccurate observational data. Improvements in satellite observations have made it possible to monitor the atmosphere and ocean where in-situ observations aren't feasible. Studies have shown that remote sensing has improved forecasting of mesoscale weather systems[7] yet; results from them are not robust to reach a firm conclusion due to the lack of forecast samples and statistics.

In the Indian-subcontinent, global warming has led to trends of increased destructiveness of cyclonic activities and acute precipitation events[8,9]. On the other hand, advances in numerical modeling have greatly enhanced our capability to accurately forecast weather using personal computers. Although, an extensive system for weather forecasting exists, inconsistent communication between central organizations and the public necessitates the decentralization of weather prediction by the dissemination of forecasts over regional scales through simulations performed at local universities or institutes. It has been shown[10,11] that simulated rainfall patterns are strongly influenced by the choice of convective scheme. The model response to changes in grid spacing or soil moisture[12] is also affected by convective schemes chosen for the simulation. Since no scheme is consistently better than the other[13], accurate prediction of warm season rainfall is extremely challenging, with such extreme sensitivities to one parameterization alone.

This report discusses the methodology to optimize these parameters over the Indo-Himalayan region based on the mid-June 2013 pre-monsoon catastrophe which had left over 100,000 people stranded and 6,000 dead in the northern-Indian state of Uttarakhand, as reported by the BBC and The Hindu. The domain of our study as mentioned above, lies in the primarily mountainous state of Uttarakhand (figure-1), which is traversed by numerous tributaries of the Ganges. This is a region very prone to landslides and floods due to heavy summer rainfall, and improving weather forecasting for such a region is a vital challenge.

Despite reasonably good forecasts, most developing countries lack a robust system to identify and broadcast alerts for extreme weather events. The story of the mid June 2013 catastrophe that struck the state of Uttarakhand in northern India bears an unfortunate familiarity to this situation. Unusually heavy pre-monsoon showers triggered numerous landslides and widespread floods across the mountainous regions of northern India. Uttarkashi and Rudraprayag districts in Uttarakhand were among the most severely affected as reported by the Hindustan Times. Incessant rains of this magnitude not being uncommon in the months of July and August when the South-West Monsoon system engulfs the entire subcontinent, little precautionary measures were taken despite the Indian Meteorological Department (IMD) 'heavy rainfall' forecast 48hrs prior to the disastrous rains. Circumstances were wildly different in June with substantial amounts of snow still on the ground in the high Himalayan regions. Rainfall with snow on the ground is tailor-made to trigger landslide activity (*D. Petley*, Reconstructing the events at Kedarnath using data, images and eye-witness reports; Unpublished Data. A series of events including collapse of a glacial lake, numerous landslides and unremitting rainfall induced floods, spawning the biggest environmental catastrophe in India after the 2004 Tsunami.

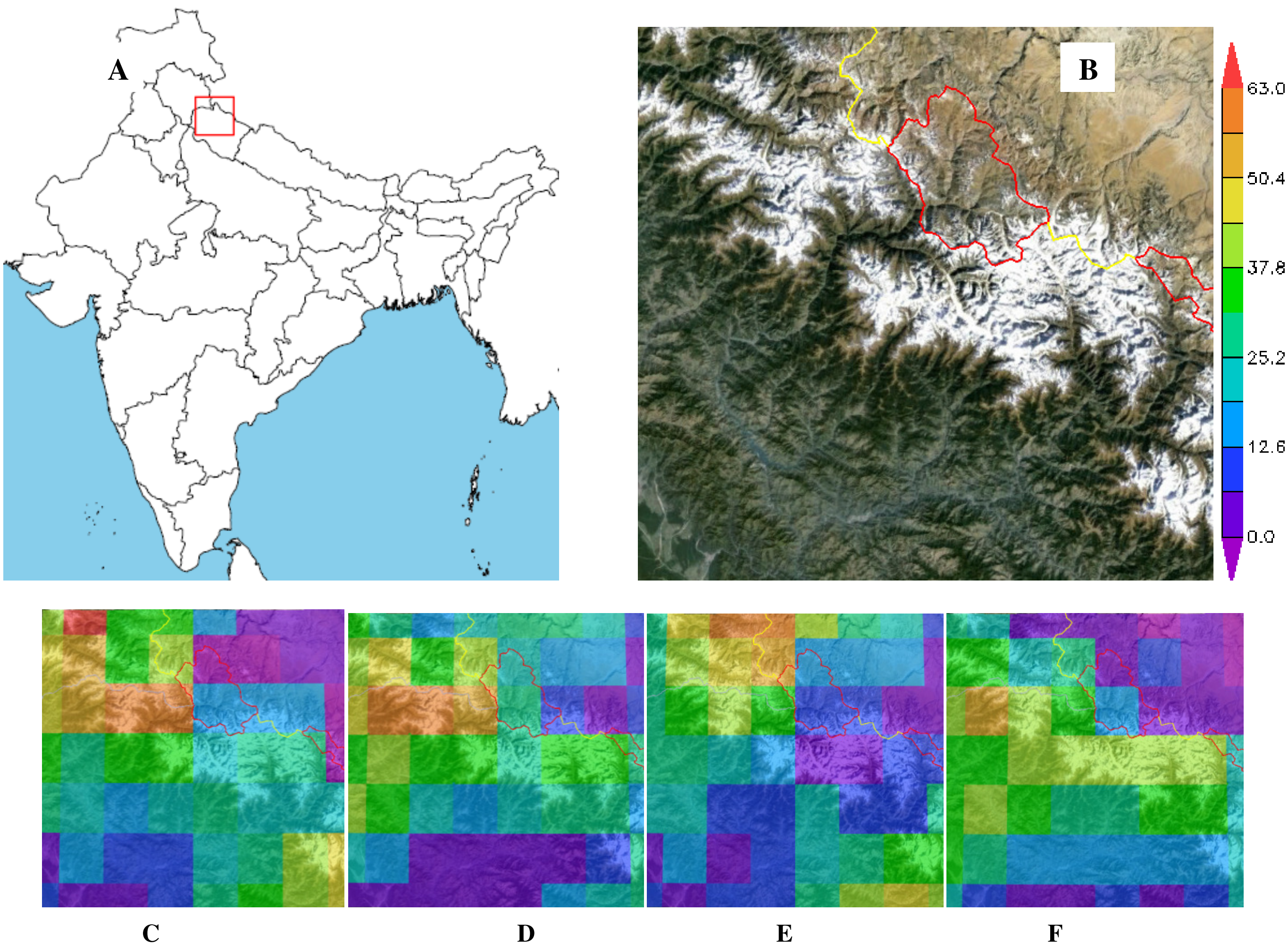


Figure-1
Domain and topography of Uttarakhand (240km x 240km) and TRMM multisatellite precipitation analysis data
(A) The region of the simulation is in Uttarakhand a state in Northern India. (B) Terrain view of the specified domain. (C-F) Actual precipitation (in mm) between 16 June 1200Z to 1500Z (c), 1500Z to 1800Z (d), 1800Z to 2100Z (e), 2100Z to 17 June 0000Z(f)

Methodology

Background and Objectives: Since global weather forecast models are expensive to build and maintain and are conducted only by a few national or multinational governmental organizations, a localized network of forecast stations capable of running real-time forecasts at low computational costs over regional scales need to be developed. Better prediction of Mesoscale Convective System (MCS) rainfall requires the understanding of how numerical weather prediction models respond to changes in physical schemes. MCS consists of thunderstorms that produce a contiguous precipitation area of around 100 km or more in at least one direction[14] and their dynamics is more complex than usual cumulonimbus clouds[15]. Prediction techniques of such systems can be classified into two groups[16], an implicit historical treatment of thunderstorm extrapolation, and the other being explicitly through the use of high resolution numerical weather models. Inadequate modeling capability of sub-grid convection is one of the major impediments associated with poor performance of numerical models[17]. As discussed earlier, numerous studies have demonstrated the variability of simulations of numerical models in response to microphysical schemes, spatial resolutions, and convective schemes. Planetary boundary layer schemes can affect the temperature and moisture profiles in the lower troposphere which could in turn affect other parameterizations to influence simulation of precipitation[18,19]; it is therefore essential to statistically study the impacts of these physical parameterizations on extreme weather forecasts[20, 21]. Our study will use the WRF model to explore these issues. The main objective of this study is to comprehensively investigate the impact of microphysical parameterization and its interaction on MCS rainfall forecasts, based on a known extreme precipitation event, conducted over an area prone to extreme precipitation events in Northern India.

Model Description: The NWP model used in this study is the community WRF[22] (Weather Research and Forecasting) ARW (Advanced Research WRF) model, version 3.3.1, developed primarily at the National Center for Atmospheric Research (NCAR) in collaboration with different agencies like the National Oceanic and Atmospheric Administration (NOAA), the National Center for Environmental Prediction (NCEP), and many others. The WRF is a limited-area, non-hydrostatic, primitive-equation model with multiple options for various physical parameterisation schemes. Use of the WRF model is of particular merit since WRF will be increasingly used to generate ensemble forecasts in the near future[23]. The model was initialized using the GFS (Global Forecast System) dataset (*National Centers for Environmental Prediction/National Weather Service/NOAA/U.S. Department of Commerce*, 2000) initial conditions of 0.5 degree resolution at 1200Z on 16th June 2013. The boundary conditions were updated on a 3 hourly basis from the GFS analysis till 0000Z on 17th June 2013. The WRF model output was compared to the NASA's TRMM (Tropical Rainfall Measuring Mission) Multi Satellite Precipitation Analysis (TMPA) precipitation dataset providing precipitation estimates derived from remote sensing calculations for the domain of our research.

Numerical Experiment: The output data from both the WRF and TMPA were compared spatially and temporally using statistical scores for model validation and verification. Scoring methodology used for statistical validation[24] has been extensively used to assess the performance of a model simulation relative to the observed (validation), or to compare the performance of other model simulations (inter-comparison). The statistical scores were compared using a 2 x 2 contingency table[25] (table-1) where each element (A, B, C, D) holds the number of combination of model prediction and observation in a given statistical population

The bias score (BIAS) determines the tendency of the system to either under predict (BIAS < 1) or over predict (BIAS > 1) events. It cannot be used as a measure of accuracy since it only compares the frequencies of observed and forecasted events. It can be defined as:

$$BIAS = \frac{F}{O} = \frac{A+B}{A+C} \quad (1)$$

Here F is the number of cases where the event was predicted, and O pertains to the number of cases where the event was observed.

The False Alarm Rate (FAR), as the name suggests computes how inaccurate the system is at predicting correct occurrences. FAR can be described as a proportion of falsely predicted events (B) amongst forecasted events (F) ranging between a perfect score of 0 and 1 indicating no skill.

$$FAR = \frac{B}{F} = \frac{B}{A+B} \quad (2)$$

The frequently used Critical Success Index (CSI) and Heidke Skill Score (HSS) were computed as:

$$CSI = \frac{A}{A+B+C} \quad (3)$$

$$HSS = \frac{2(AD-BC)}{(A+C)(C+D)+(A+B)(B+D)} \quad (4)$$

Unlike FAR, CSI is adjusted to describe the skill of the system by accounting for both the false alarms as well as unpredicted events. The scoring scheme for CSI is similar to that of FAR. HSS pertains to how good the system forecasts with respect to a randomly generated forecast. A negative score implies that a forecast influenced by chance is more accurate than the set of predicted events, whereas a perfect forecast would entail a HSS score of 1.

Figure-1 shows the domain of this study (31°40'to 30°N and 78°E to 80°E) which is a 180 km x 180 km area in the Indian state of Uttarakhand. The figure also shows satellite data of accumulated rainfall from TMPA with a temporal resolution of 3 hours from 16th June 2013 1200hrs(Z) to 17th June 2013 0000hrs(Z). The maximum precipitation of over 63 mm in a 3 hour period occurred in the north-western part of the domain. We chose to simulate forecasts for short periods of time to decrease of the magnitude of accumulated errors. They also result in low computational cost, curbing the restraints due to the unavailability of high performance computing facilities in most local institutes in the developing world.

To speed up the process of comparing forecast and real data we decided to compare the data encoded in the output images rather than hard data from all grid points over the domain, which is tedious to obtain. The process of image processing expedited our analysis of the TRMM and model output data and yet, caused very little change in its accuracy of the results which was interesting to note. The accumulated precipitation outputs over the domain were obtained using NCAR Command Language codes. Conversion of the resultant images into rasterized grayscale images further reduced the duration required for statistical analysis (figure-2).

The WRF and TMPA datasets comparison was carried out using MATLAB (R2009b). These images were exported into MATLAB as a 2-D matrix and were compared for the specific rainfall threshold values, and mapped using the given contingency table where each color on the mapped domain represents the different outcomes of forecast verification. Characteristics of the rainfall forecast by the model using the different microphysics options and their variation with changes in grid resolution over the domain when compared to the TRMM data can be seen in figure-5. The optimum microphysics scheme was obtained by comparing the statistical scores namely CSI, HSS, FAR and BIAS, which can be obtained using the contingency table as discussed above (table-1). A comprehensive analysis of these statistical scores over the duration of the simulation was done (figure-5). Spatial structure and distribution of the comparison of TRMM and the model output data as seen in figure-2 also brought out the relative performance of the selected microphysical schemes with respect to the observational data.

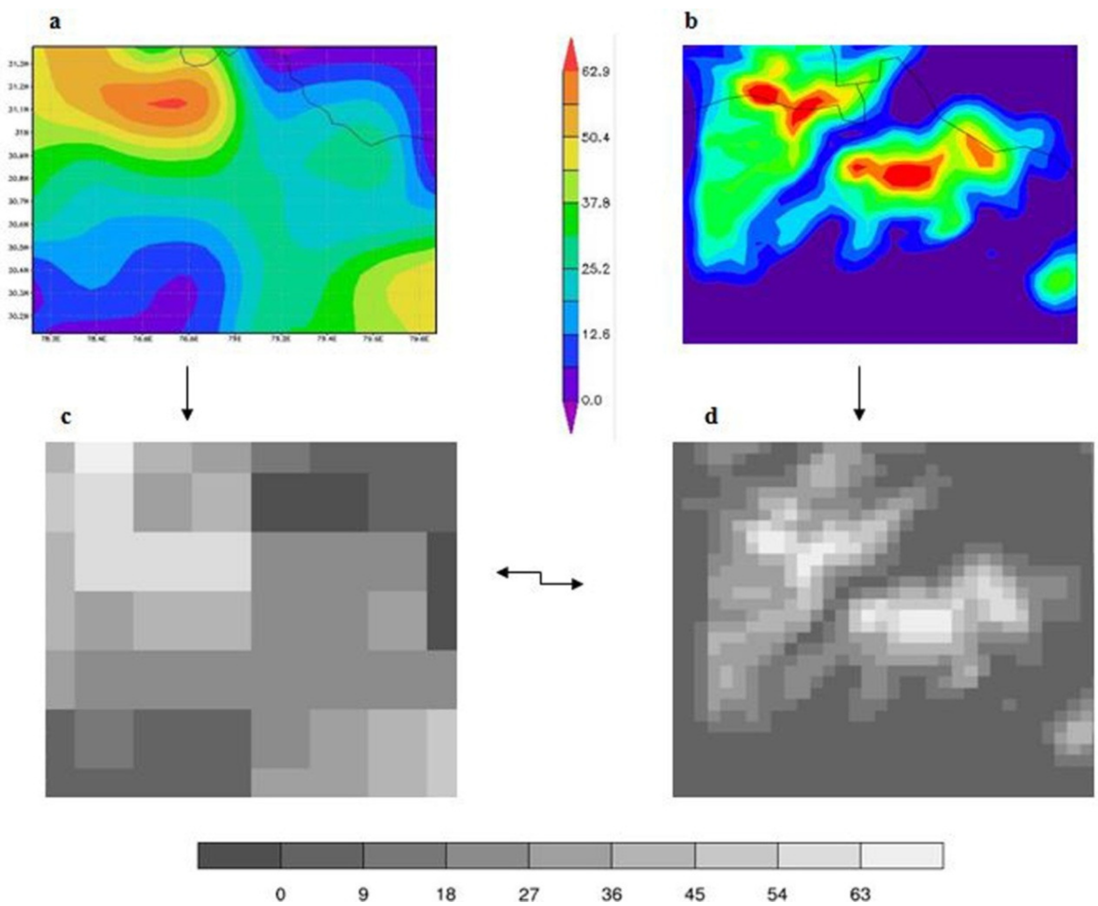


Figure-2
Conversion of colored TRMM and Model output images to rasterized grayscale images for analysis.
TRMM (a) and DM5 (b) precipitation amounts between 16th June 2013 2100(Z) to 17th June 2013 0000(Z) converted to rasterized grayscale form (c,d) for easy readability and quick statistical analysis

Table-1
Contingency Table*

		Observation	
	Event	**Yes**	**No**
WRF	Yes	A	B
	No	C	D

*Frequencies of predicted and observed events. Useful in skill score calculations in Section 2.

Results and Discussion

Our simulations show a great deal of sensitivity to the chosen microphysics – this is not unusual owing to the Himalayan terrain and sustained cold temperatures[26]. The WRF simulation over the domain was executed using input parameters based on mesoscale convective systems and short forecasts. Spatial resolutions of 6 km and 10 km were considered since simulation periods increased rapidly with even higher resolutions. We closely examined the behavior of six different microphysics schemes which included ice processes for each of the spatial resolutions.

Spatial comparisons (figure-5) between forecast and observed data were created using a contingency table[27] (figure-5 m) and mapped over the domain for a critical rainfall threshold of 6mm per hour. The patterns of precipitation of model simulations with observed data were similar in simulating precipitation in the central regions of the domain whereas huge variation was observed in the other regions. This variation in the accuracy of the model with each of the microphysical schemes became apparent with the various statistical scores used in our analysis, namely Critical Success Index (CSI), Heidke Skill Score (HSS) and False Alarm Rate (FAR) scores. Our results show that the DM5 scheme at a spatial resolution of 6kms had the highest CSI and HSS closely followed by DM6 scheme (Figure-5C-F). Brook microphysics shows the lowest CSI and HSS scores regardless of the spatial resolution**.** The other microphysics schemes Lin, Goddard and Milbrandt-Yau followed the same fluctuations as the DM5 and DM6 schemes yet lacked substantially in accuracy. The model simulations in general under-predicted the rainfall as shown by the bias score (BIAS). The DM5 and DM6 had the highest the BIAS scores and the simulated forecasts showed the best correlation with the TRMM data when these two schemes were incorporated in model runs.

With a simulation lead time of twelve hours, all the microphysics severely under-predicted rainfall initially but the CSI improved drastically as the simulation approached an extreme weather event (figure-3). Temporal analysis of the simulations revealed that the simulations correlated better with the actual precipitation nearer to the severe weather event around 0000 Z on 17th June. The DM5 and DM6 consistently had higher scored than the other microphysics options over the 12 hour simulation period. Our research over the Uttarakhand region revealed that the WRF Double Moment scheme (DM5,DM6) performed better than the other schemes spatially and as well as temporally. Moreover, they were able to simulate pre-monsoon rainfall better by strengthening heavier precipitation[28]. As discussed before, since physical schemes are dependent on a variety of parameters it is essential to investigate the performance of these schemes for other microclimatic regions similarly for increased accuracy of numerical models.

Discussions and Perspectives: We conducted these expeditious simulations (table 2) on a commercially available PC. Similarly configured computers are easily available now across the developing world. Table-2 conveys the simulation runtimes associated with each microphysical scheme and its duration of completion, performed within this experiment. For timely and effective evacuation measures to be put into place, forecast time is also an equally important aspect for environmentally sensitive regions such as these. As demonstrated above in the case of the Uttarakhand region in India, the accuracy of the model using DM-5 microphysics at a resolution of 6km performs well even on a minimally configured machine with a BIAS score of a little less than 0.5.

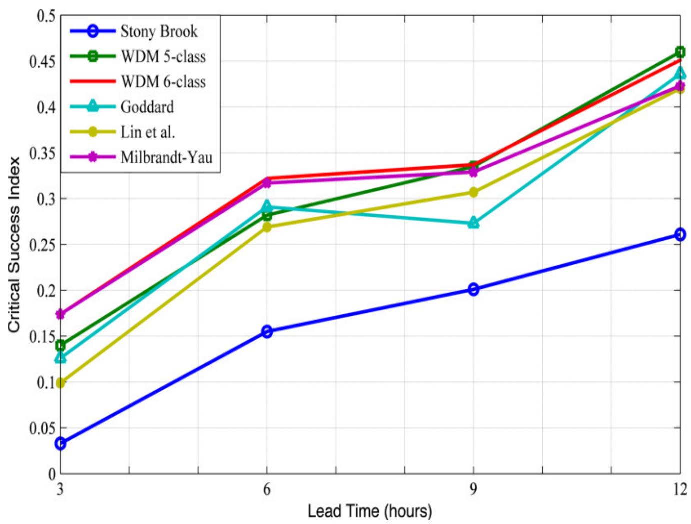


Figure-3
Temporal Comparison of the Critical Success Index Variation of CSI scores across different time-steps. Depicts a steadily increasing trend until the extreme weather event (Lead time: 12 hours)

The results presented in this study are pertinent to anyone carrying out regional weather forecasts using numerical weather prediction models. High resolution in time and space, flexibility and reproducibility are some of the numerous advantages of using NWP models over gridded precipitation products. Hydrological applications like modeling rainfall runoffs, landslides etc. which require not only accumulated precipitation over timescales of months but also daily and hourly precipitation rates, can also be addressed using numerical weather prediction models. Over the Indian, Bhutanese, and Nepalese Himalayas and over the Tibet plateau, we propose that WRF-ARW forecasts with DM-5 microphysics at 6km resolution will easily forewarn most instances of flooding and landslides as well.

Table-2
WRF Simulation Period*

Microphysics	Resolution (km)	Time (minutes)
Stony Brook	6	15
	10	2
WDM 5-Class	6	20
	10	4
WDM 6-Class	6	15
	10	4
Goddard	6	13
	10	3
Purdue Lin (*Lin et. al*, 1983)	6	22
	10	4
Milbrandt-Yau	6	42
	10	9

*Simulations were performed on a Linux Intel PC using a gfortran serial processor (2.5 GHz)

We suggest that local universities and institutes can continuously conduct mesoscale weather forecasts using precise physical parameters associated with their regional climate and topography. The simulation run times on these machines is also miniscule even at high resolutions due to the relatively small size of the domain. As in this case of the Uttarakhand tragedy, these physical parameters can be acquired for varied regions in the world to accurately forecast severe weather. Locally generated weather forecasts will augment the capacity of governmental forecasting centers to detect and monitor an extreme weather event. Once specific physical parameters have been established over every micro-region across the country through meticulous process, they can aid the central agency in stitching together a more robust weather prediction model. Subsequently, this will help in issuing timely alerts and increase disaster preparedness.

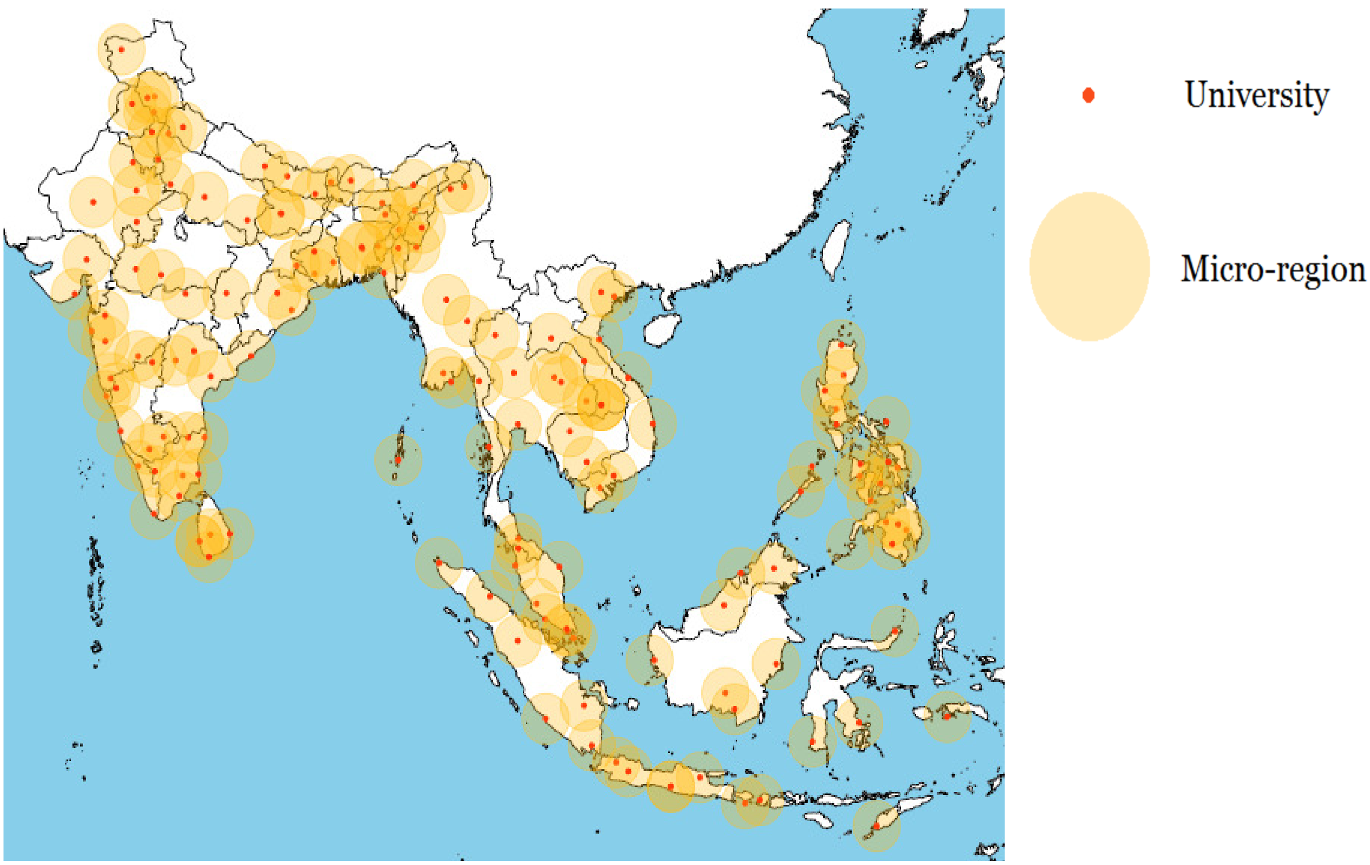
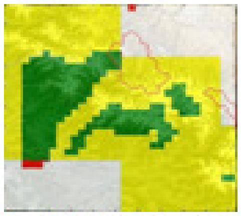


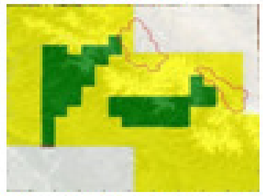
Figure-4
Locations of prospective universities
Micro-forecast coverage across South and South-East Asia with the range of each region extending up to 360 kilometers. The weather prediction zones would span almost the entirety of Philippines, Malaysia and Sri Lanka

A. Brook (6km)



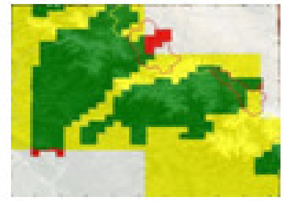
CSI	HSS	FAR	BIAS
0.261	0.151	0.031	0.271

B. Brook (10km)



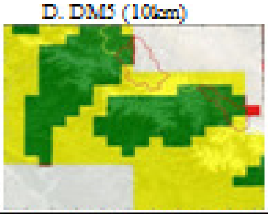
CSI	HSS	FAR	BIAS
0.202	0.119	0.012	0.203

C. DM5 (6km)



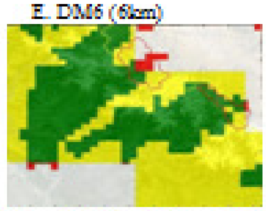
CSI	HSS	FAR	BIAS
0.46	0.298	0.33	0.483

D. DM5 (10km)



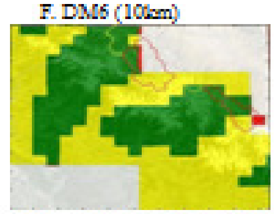
CSI	HSS	FAR	BIAS
0.43	0.298	0.018	0.441

E. DM6 (6km)



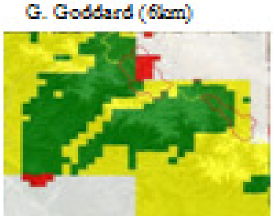
CSI	HSS	FAR	BIAS
0.451	0.287	0.004	0.478

F. DM6 (10km)



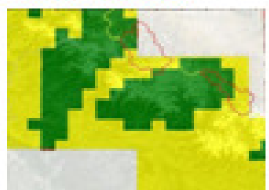
CSI	HSS	FAR	BIAS
0.429	0.282	0.018	0.44

G. Goddard (6km)



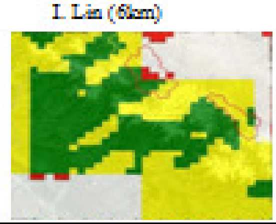
CSI	HSS	FAR	BIAS
0.436	0.267	0.031	0.47

H. Goddard (10km)



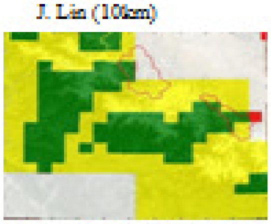
CSI	HSS	FAR	BIAS
0.391	0.237	0.008	0.395

I. Lin (6km)



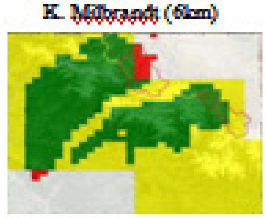
CSI	HSS	FAR	BIAS
0.423	0.259	0.048	0.454

J. Lin (10km)



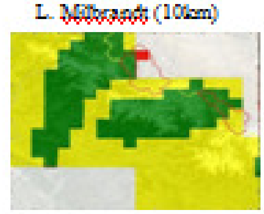
CSI	HSS	FAR	BIAS
0.358	0.224	0.022	0.369

K. Milbrandt (6km)



CSI	HSS	FAR	BIAS
0.42	0.255	0.031	0.453

L. Milbrandt (10km)



CSI	HSS	FAR	BIAS
0.372	0.236	0.019	0.382

M

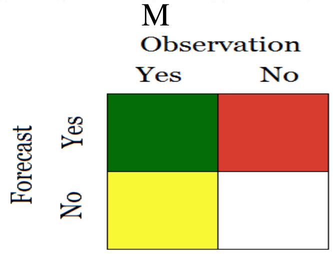


Figure-5
Spatial Comparison of Precipitation Data
(A-L) The regions of consistency between observations and forecasts amongst the various microphysics schemes and resolutions on 17 June 0000Z. (M) The contingency table used to obtain the comparative analyses

Much of South and South-East Asia is tormented by extreme weather. Colleges and Universities in this developing region can perform the role of generating weather forecasts locally. In the event these forecasts reveal a potential for hazardous weather, local institutes would liaise with the central weather forecasting organization to develop an alerting mechanism. Near real-time weather data can be obtained from numerous sources and the central weather agency can also provide the universities with unhindered access to nearby Doppler radars for quicker forecasts. Universities and institutions have a stronger reach within their local community and hence are better enabled to aid governmental authorities in cautioning the public, by involving mobile telephony and social media.

Conclusion

We have identified several major technical universities in major cities in these countries based on their geographical location and potential to conduct geoscientific research (Figure-4). Regional forecasts runs at these institutions with optimized physical parameters could greatly increase the preparedness of these regions against extreme weather events. The immense untapped potential of rigorous mesoscale forecasting using personal computers offline could greatly enhance the capability of governmental weather forecasting institutes and help save countless lives.

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