Real-time quantitative rainfall forecasts at hobli-level over Karnataka: evaluation for the winter monsoon 2010

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Advance and accurate forecasts of rainfall can aid many sectors, from agriculture to disaster mitigation. However, given the tremendous spatial variability of rainfall, only forecasts at high resolution can serve users' needs. The skill of a dynamical forecast model depends on the resolution and varies from region to region. While such non-uniqueness poses challenges, they also provide avenues for improving skill; in particular, calibration and customization can improve region-specific skill. Here, we present evaluation of rainfall forecast at hobli-level (a cluster of adjoining villages with average area of the order of 10 square kilometers) over Karnataka for the north-east monsoon (October–December) season of 2010, operationally implemented through collaboration between CSIR Centre for Mathematical Modelling and Computer Simulation (C-MMACS) and Karnataka State Natural Disaster Monitoring Centre (KSNDMC) for interactive evaluation. We have adopted and calibrated the Limited Area Model, called Weather Research and Forecasting (WRF) Model, using principles and methodologies developed at C-MMACS and elsewhere. Statistical evaluation of the forecasts is conducted against observations from the telemetric rain-gauge network established by KSNDMC based on large samples (90 forecasts for each of the 740 hoblis). The results show that forecasts capture the observed spatio-temporal variability well enough to be useful. At the same time, certain areas of systematic bias are identified for further calibration to improve forecast skill. As a pioneering effort in the country to generate real time hobli-level forecasts validated against high-density observations, the results quantify realizable skill for the methodology. The forecasts are also disseminated by KSNDMC to various users on a daily basis.

Keywords: Hobli-level, rainfall, forecast, statistical evaluation, winter monsoon.

THE usefulness of advance and accurate forecasts of rainfall in many sectors, from agriculture to disaster mitigation to crop insurance, has been well recognized. Rainfall is generally considered to be the most difficult variable to correctly simulate because of its convective nature, dependence on orography and complex surface forcing. Therefore, assessing the accuracy of precipitation forecasts is particularly important for evaluating numerical forecast models. The skill of rainfall forecasts depends on spatial resolution and the challenges grow as the resolution of the forecast increases. At the same time, for effective application, forecasts must be at relevant spatial scales; given the tremendous spatial variability of rainfall, only forecasts at high resolution can serve the users' needs. Karnataka is one of the states in southern part of India where high spatio-temporal variability in rainfall is observed; a scrutiny of the spatial variability (not shown here) in rainfall shows that the forecasts should be at least at hobli scale. At the same time, it was realized through interaction with user agencies as well as extreme end-users (farmers), that forecasts can be quite useful even if they are not for exact amount of rainfall, but for categories. Currently, there are no operational forecasts in India at such spatial scales.

To develop a forecast system that meets the requirements of the extreme end-user in terms of accuracy, lead and spatial resolution, the CSIR Centre for Mathematical Modelling and Computer Simulation (C-MMACS), Bangalore and the Karnataka State Natural Disaster Monitoring Centre (KSNDMC), Bangalore have embarked upon an explorative programme for generating and disseminating rainfall forecasts at the hobli level. The basic approach is to combine the meso-scale forecast platform at C-MMACS and the observation network of KSNDMC in an interactive loop to develop an optimum configuration for Karnataka. The data from CSIR Climate Modelling and Observation Network (CSIR COMoN) also provide a means to improve forecasts through techniques like data assimilation.

An experimental forecast system at high resolution using the Weather Research and Forecasting (WRF) model customized for regional forecast applications over Karnataka was tested first to examine the general performance of the model; these forecasts were verified subsequently by KSNDMC using its dedicated telemetric rain-gauge observation network. Based on this exercise, the present initiative on operational real-time rainfall forecast system at the hobli-level was taken up as a logical and necessary follow-up. The forecast skill of some meso-scale models over the Indian region during monsoon season has been evaluated in a few recent studies[1–3]. The present study differs from these earlier works in several aspects. The earlier studies evaluated forecast skill for relatively coarser resolution; moreover, the skill was evaluated against observations at coarse resolution, such as gridded rainfall (~ 100 km) from the India Meteorological Department (IMD) or satellite (~ 25 km) observation; in contrast the observations used for our evaluation are at a resolution comparable to that of the

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Table 1. WRF model configuration used in the present study

Dynamics	Non-hydrostatic
Number of domains	Three nested domains
Horizontal resolutions	36 km (outermost domain), 12 km (inner domain) and 4 km (innermost domain)
Integration time-step	90 s (outermost domain), 30 s (inner domain) and 10 s (innermost domain)
Number of grid points	*x*-direction 206, 325 and 271, *y*-direction 206, 325 and 271 points for outermost, inner and innermost domains respectively
Map projection	Mercator
Horizontal grid	Arakawa C-grid
Vertical coordinate	Terrain following hydrostatic with 38 sigma levels up to 50 hPa
Time integration	Third-order Runge–Kutta
Spatial difference scheme	Sixth-order centred difference
Microphysics	WSM6 scheme[7]
Radiation	RRTM long wave[8] and Dudhia short wave[9]
Cumulus parameterization	New Kain–Fritsch scheme[10]
PBL parameterization	YSU scheme[11]
Land surface parameterization	Thermal diffusion

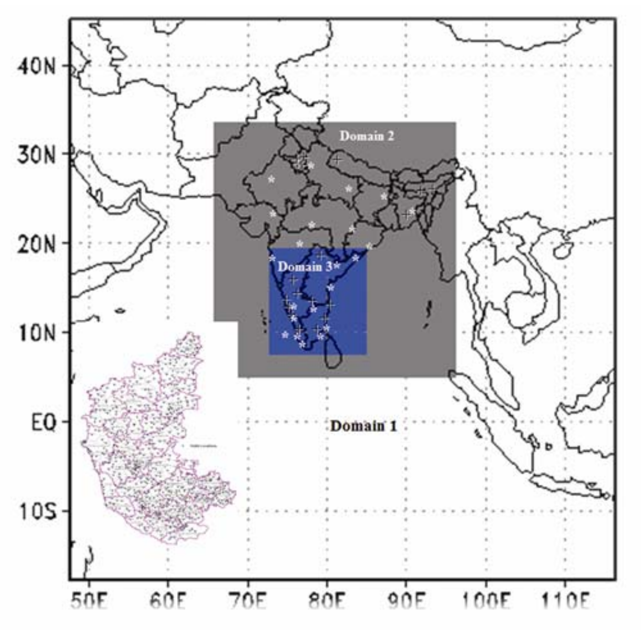

Figure 1. Model domains used for the numerical simulations. The horizontal resolutions of domains 1–3 are 36, 12 and 4 km respectively. Locations of the radiosonde and meteorological towers are marked by * and + respectively. (Inset) Hobli locations where rain gauges are deployed over Karnataka.

forecast. The benefit to the meso-scale modelling community from such an evaluation compared to case studies, is that the large number of forecasts generated provides robust statistical evaluation for the state as a whole. This can help further improvement in forecasts and provide insight into model dynamics. Here we describe the model configuration and evaluation methodology. Then the results are discussed followed by our conclusions.

We have used version 3.1.1 of the state-of-the-art limited area model, called WRF model[4], designed to serve both operational forecasting and atmospheric research, calibrated for meso-scale forecasts over Karnataka. The model configuration (Table 1) used in the present study is based on the results of earlier optimization[3,5]; the focus here is on the forecast skill in hobli-level forecasts. All the forecasts were generated with three nested domains; the outer domain consisting of 206 × 206 (36 km horizontal grid resolution in the *x* and *y* directions), the inner domain consisting of 325 × 325 (12 km horizontal grid resolution in the *x* and *y* directions) and the innermost domain consisting of 271 × 271 (4 km horizontal grid resolution in the *x* and *y* directions) grid points. The number of vertical levels used was 38, with the top of the model atmosphere located at 50 hPa.

The initial conditions for the outer domain were extracted from the three hourly data archived in real-time from the NCEP Global Forecasting System (GFS) at a horizontal resolution of 50 km. Assimilation of local observations (radiosondes, AWS, CSIR network tower data; Figure 1) through an operational implementation of WRF three-dimensional variational assimilation scheme was then carried out to refine the initial conditions. The 10 min (~ 19 km) datasets from the United States Geological Survey (USGS) were used to create the surface boundary conditions for the outer domain, such as model topography, land use, soil types and monthly vegetation fraction. The initial, lower and lateral boundary conditions for the inner domains were obtained by interpolating the fields from the outer domain. The operational set-up of the forecast model is summarized in Table 2. Daily three forecast cycles were initiated. The first forecast (FC1) was for a 36 h period and was initiated from the initial conditions valid at 2330 Indian Standard Time (IST) of the previous day to issue 24 h hobli-level forecast. We have also used two other forecast cycles of longer (36 h and 98 h) leads; however, the focus of the

Table 2. Schedule of meso-scale forecasts

Cycle	Forecast IC*	Forecast IT (h)	Download and pre-processing (h)	Model integration Launch	Model integration Completion	Post-processing	Issue of forecast	Valid till	Purpose
FC1	–23.30	36	3.00	04.00	7.00	8.00	8.30	+11.30	KSNDMC (MF)
FC2	05.30	36	9.00	10.00	13.30	14.00	15.00	+17.30	KSNDMC (AF)
FC3	11.30	78	15.00	16.00	+1.00	+07.00	+09.00	3 days	Forecast Bulletin + web

*The time shown is in Indian Standard Time (IST). – Sign indicates hour of previous day and + sign indicates hour in the following day; a 9 h lag minimum is assured between the hour of IC and download due to the US – India time-lag.

1. A spin-time of 6 h should be used during post-processing. 2. Forecast cycles FC1 and FC2 will generate hobli-level forecasts over Karnataka with three net configurations. 3. Forecast cycle FC3 will generate forecasts over India for the work already contracted by C-MMACS as well as for industrialization, including web dissemination and forecast bulletin.

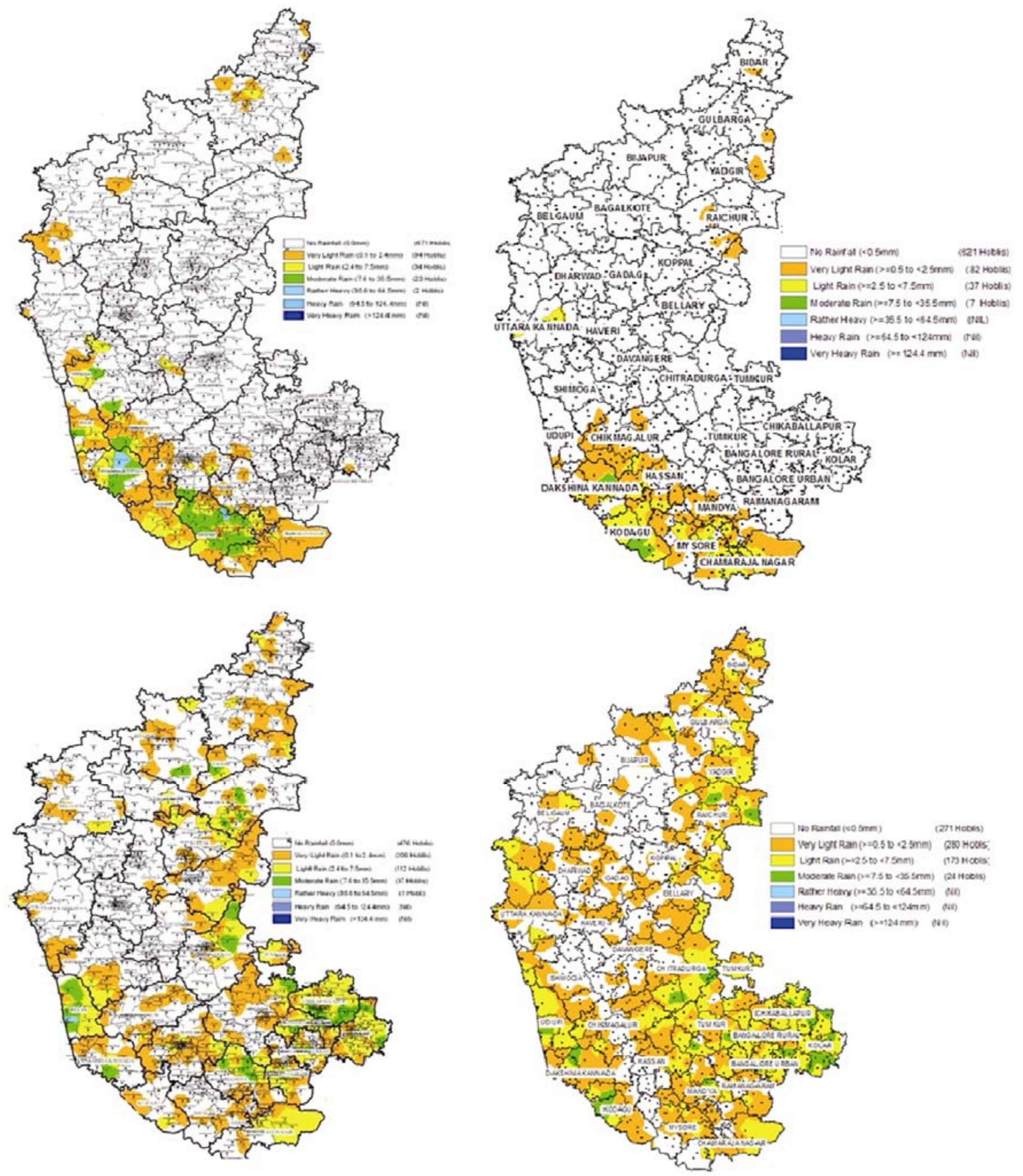

Figure 2. Comparison of 24 h observed accumulated rainfall (left panel) with forecast (right panel) for 12 October 2010 (top panel) and 18 November 2010 (bottom panel).

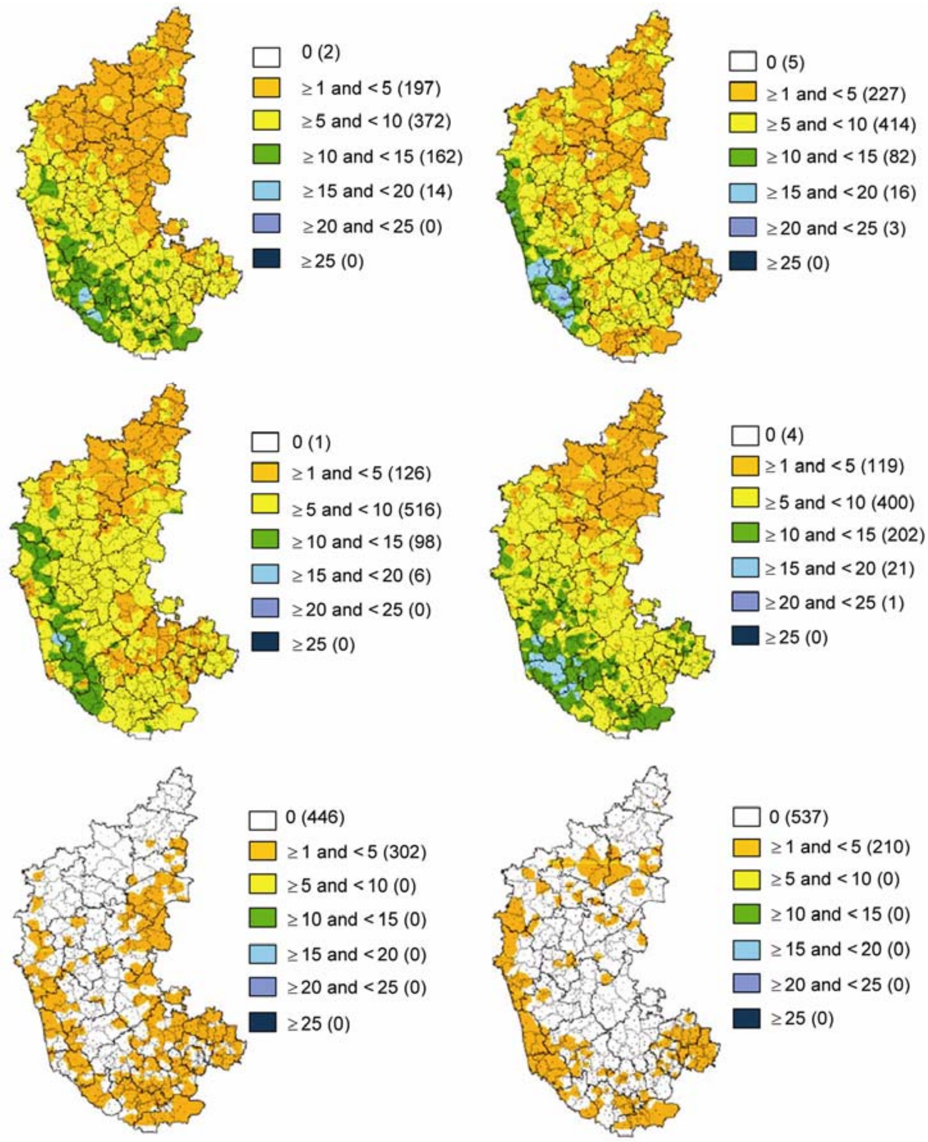

Figure 3. Number of rainy days (days with 24 h accumulated rainfall > 3 mm) from forecast (left panel) and observation (right panel) for October (top panel), November (middle panel) and December (bottom panel) 2010. Numbers in brackets show the hoblis in each range.

Table 3. Number of hoblis with different rainy days (24 h accumulated rainfall > 3 mm)

	Number of hoblis					
	October		November		December	
Number of rainy days	Observation	Forecast	Observation	Forecast	Observation	Forecast
0	5	2	4	1	537	446
≥ 1 and ≤ 5	227	197	119	126	210	302
≥ 5 and ≤ 10	414	372	400	516	0	0
≥ 10 and ≤ 15	82	162	202	98	0	0
≥ 15	19	14	22	6	0	0

present study was on 24 h forecasts from FC1. These forecasts were communicated to KSNDMC for dissemination and evaluation against observations.

Hourly model outputs from domain 3 (innermost high resolution) were considered for validation. Of the 36 h integration time, the initial 9 h was used for spin-up to

Table 4. Number of hoblis with heavy rainfall (24 h accumulated rainfall > 50 mm)

	Number of hoblis					
	October		November		December	
Number of rainy days	Observation	Forecast	Observation	Forecast	Observation	Forecast
0	534	623	436	464	746	746
≥ 1 and ≤ 5	212	124	310	283	1	1
≥ 5 and ≤ 10	1	0	1	0	0	0

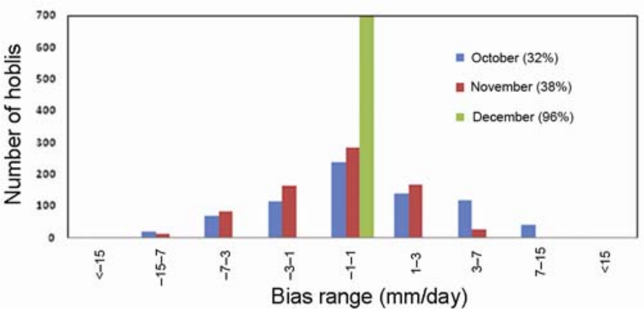

Figure 4. Number of hoblis falling in different bias categories for October–December 2010. Numbers in bracket represent the percentage of hoblis with bias between –3 and +3 mm/day for the respective months.

generate the 24 h forecasts. The model-predicted rainfall was bilinearly interpolated to observation locations for comparison with rain-gauge data. All the validation in this work has been against observations provided by KSNDMC on a daily basis from its telemetric rain-gauge network. For an objective comparison of the forecasts, we considered a number of evaluation parameters[6], as discussed below.

Comparison of sample forecasts issued for two selected days of October and November with the corresponding observed rainfall (Figure 2) shows close agreement between predicted and observed spatial variability in rainfall. In what follows, the monthly diagnostic measures have been computed from daily forecasts compared with the observed 24 h accumulated rainfall (from 0830 IST to 0830 IST of the next day).

The number of rainy days in the forecast (left panels, Figure 3) for the winter monsoon season match the observed (right panels, Figure 3) pattern; the significant rainfall activity over Karnataka, especially in the southern part has been well captured in the forecast. Equally important, the forecasts also show very little rainfall for December (bottom panels, Figure 3) as observed. The number of forecasted rainy days shows reasonably good agreement with observation and the maximum number of hoblis falling in a particular range of rainy days in the forecast matches with the observation for all the three months (Table 3). Even though some of the heavy rain events (24 h accumulated rainfall > 50 mm) observed over the southern part of Karnataka during November have been missed in the forecast, such heavy rain events are generally well predicted by the model (not shown). The number of heavy rain days observed in November (1–5 days of heavy rain was observed over ~ 300 hoblis) has been captured in the forecast (Table 4). Heavy rain events were essentially absent in December, a feature well captured in the forecast (Table 4).

Forecasts for December show most hoblis to be in the lowest rainfall error (< 0.5 mm) category; the average error for the season was also less than 7.5 mm for most hoblis (Table 5). The distribution of hoblis in different rainfall bias bins (forecast–observation) shows that the highest number of hoblis falls in the lowest bias bin (between –1 and 1 mm) for all the three months (not shown). The average bias for the season (October–December 2010) shows slight overprediction over the southern part of Karnataka (not shown). The bias in rainfall prediction for majority of hoblis is in the range ± 3 mm; the distribution of rainfall bias is essentially Gaussian, with marginal positive bias for December (Figure 4).

The root mean square error (RMSE) in forecasts is relatively low (less than 10 mm) over the northern Karnataka compared to somewhat higher (10–20 mm) error over the southern part for both October and November, while RMSE is less than 10 mm for most hoblis during December (Figure 5). The average error for the winter monsoon season also shows that the error is significantly less over northern Karnataka compared to the southern part (Figure 5 *d*). On the whole, the RMSE values are fairly small indicating reasonable skill in rainfall prediction. This aspect of model behaviour is further explored by computing hobli-averaged RMSE in daily rainfall forecast over Karnataka (not shown). As expected, the RMSE in forecast varies from day to day for all the months; the RMSE is highest for November and lowest for December. An estimate of the quality of the forecast pattern was obtained through computing the significance of correlation coefficient (CC) of the model forecast versus observations. The comparatively less number of hoblis (~ 120), where correlation between observed and forecasted rainfall is insignificant (< 60%), for October and November shows that the model is capable of simulating the rainfall pattern at the hobli level (Table 6). A good number of hoblis above 90% confidence level for October and November shows the skill of the model in

Table 5. Number of hoblis in different categories of absolute error

Category of absolute error	Number of hoblis			
	October	November	December	Seasonal average
< 0.5	1	1	536	1
≥ 0.5 and ≤ 2.5	98	98	210	164
≥ 2.5 and ≤ 7.5	376	242	1	487
≥ 7.5 and ≤ 35.5	272	408	0	95

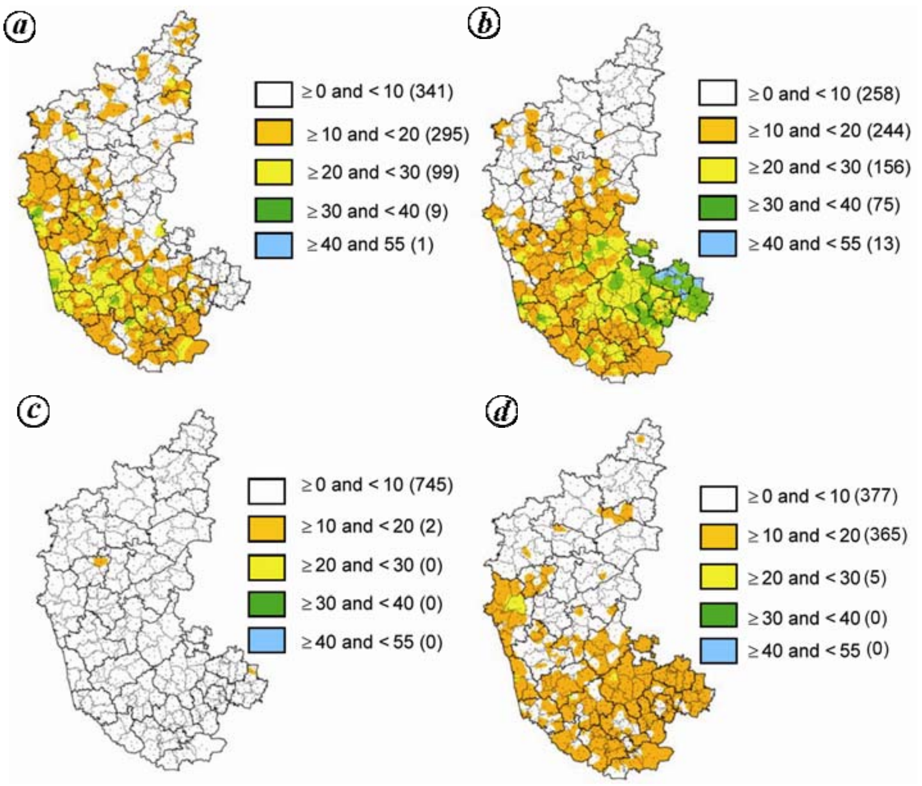

Figure 5. Root mean square error (mm) in forecasts of daily accumulated rainfall for (***a***) October, (***b***) November, (***c***) December and (***d***) average for the winter monsoon season 2010. Numbers in brackets show the hoblis in each error category.

Table 6. Number of hoblis in different categories of significance of correlation

Significance of correlation (%)	October	November	December
<60	127	128	153
60	177	303	259
75	135	123	53
90	62	28	23
95	84	70	34
99	157	93	90

reproducing the rainfall events (Table 6). The poor correlation (low values of significance) of forecasted rainfall pattern with observation over the southeastern part of Karnataka (not shown) is consistent with the higher values of RMSE in rainfall prediction in those areas.

To examine the skill of the model in reproducing the frequency of occurrence of rainfall events at or above a given threshold, we have computed statistical skill scores (such as the bias scores (BSs) and equitable threat scores (ETSs)) for 24 h accumulated rainfall forecasts by comparing with the corresponding observed rainfall from rain gauges at various rainfall thresholds (1 mm, 5 mm, 10 mm and 50 mm). It was found that the model overpredicted the area of occurrence of rainfall events during October for all the thresholds (BS > 1), except the underprediction over some hoblis in the northern part of Karnataka at 10 mm rainfall threshold (not shown). The overprediction of rainfall area in October is largest (BS > 2) over hoblis in the southern tip of Karnataka at all the rainfall thresholds. During November, the model overpredicted rainfall for most hoblis at threshold 1 mm.

Table 7. Number of hoblis in different ranges of bias score for various thresholds

	October			November		
Bias scores	1 mm	5 mm	10 mm	1 mm	5 mm	10 mm
< 0.6	4	78	191	15	7	275
≥ 0.6 and < 0.9	37	77	63	219	116	199
≥ 0.9 and < 1.1	81	115	122	154	175	97
≥ 1.1 and < 1.4	173	93	59	68	205	27
≥ 1.4 and < 2	227	153	76	40	113	28
≥ 2	219	196	156	87	127	44
NA	6	35	80	28	4	77

Table 8. Number of hoblis in different ranges of equitable threat score for various thresholds

	October			November		
Equitable threat score	1 mm	5 mm	10 mm	1 mm	5 mm	10 mm
< 0	35	87	75	73	14	144
≥ 0 and < 0.1	137	228	386	139	139	298
≥ 0.1 and < 0.2	263	171	109	212	231	147
≥ 0.2	292	260	155	215	363	121
NA	0	1	22	8	0	37

Table 9. Summary of error statistics for the northeast monsoon season

Parameter	October	November	December	Average
Observed rainy days count	6	8	0	4.6
Forecasted rainy days count	7	7	1	5
Error in category	1	1	0	1
Days with error > category 1	13	16	5	11
Hoblis with error > category 1	480	475	122	359
Mean absolute error (mm)	6.6	7.7	0.4	4.9
RMSE (mm)	12	16.1	1	9.7
Bias (mm)	0.6	–0.5	0.2	0.1

At 5 and 10 mm thresholds, the model predicted excess area of rainfall over the northern half of Karnataka, whereas rainfall was underpredicted over the southern half (not shown). A significant number of hoblis showed negligible bias in rainfall prediction (BS between 0.9 and 1.1) for October and November (Table 7). The hobli-averaged BSs revealed that the forecasts had a tendency to overpredict rainfall in many days, particularly at low rainfall thresholds (not shown).

It is clear from the monthly averaged ETS that the forecasts show reasonable skill (ETS > 0.2) at low rainfall thresholds; the skill deteriorates at higher thresholds (Table 8). The hobli-averaged ETSs against forecast days at various rainfall thresholds averaged for the winter monsoon season showed majority of days with positive ETS values, particularly at low rainfall thresholds, indicating the forecast to be reasonably skillful. The comparatively small values of ETS, even negative for some days, at high rainfall thresholds indicate the need for improvement in the model for predicting heavy rain events.

The present study illustrates the use of a well-calibrated model customized for operational short-range weather forecasting at the hobli-level over Karnataka. The forecast skill for the season has been evaluated against dedicated high-resolution telemetric rain-gauge observations across the state. An important aspect of the present study is evaluation against daily rainfall over 740 hoblis and thus provide with a sample of 90 forecasts per hobli. A summary of the statistical parameters such as mean absolute error, RMSE and bias (Table 9) indicates that forecasts rarely show error in more than one category. The RMSE in forecast for the season is less than 10 mm for most hoblis. Unlike conventional forecasts, the present forecasts are for categories of rainfall defined by the user (KSNDMC) for creation of advisories. The forecasts show useful skill in predicting hobli-level spatial variability in rainfall.

One of the primary objectives of the present study has been also to identify aspects in rainfall prediction that need improvement. The model overpredicted area of rainfall over the southern part of Karnataka for October, whereas during November it underpredicted the area of rainfall, except light rain. There are some areas over the southern part of Karnataka where forecast errors were large during October and November. Correlation between observation and forecast is significant, especially for October and November, when significant rainfall activities were present. As expected, the model skill is relatively low for heavy rain cases. With the assimilation of more observations such as AWS and CSIR COMoN data, it is expected that the model skill may improve over those areas.

There is a need to improve forecasts in all aspects of accuracy, lead, resolution and scope (variables). The forecast technology is likely to evolve continuously. Thus, as the user demands grow, it will be necessary and possible to improve and upgrade. Further, such forecasts can be more effective if value-added, such as through agro-advisories and communicated in local language. KSNDMC has developed, and is parallelly testing, interface with various agencies to ensure timely and effective dissemination of the forecasts to the end-users.

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Solarization technique: its use in the multiplication of *in vitro* planting materials

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A field experiment was carried out to evaluate the improvement in the quality and quantity of potato (*Solanum tuberosum* L.) seed using the techniques of soil solarization using six potato cultivars. The soil temperatures increased with the use of polyethylene mulch. It was found to be higher by 10.6°C, 9.4°C, 5.5°C and 3.1°C at depths of 0 cm, 5 cm, 10 cm and 15 cm respectively, compared to the unsolarized soil. The technique of soil solarization increased the available nutrients, viz. NO_3–N, P_2O_5 and K_2O by 17.7%, 63.3% and 27.20% at planting and 16.25%, 21.95% and 14.7% at harvesting respectively. The weed populations were also found to be reduced by 94.7% and its fresh weight by 96.8%. The yields of micro-tuber and mini-tuber produce were significantly higher in solarized plots (248.1 q/ha and 425.9 q/ha respectively) compared to unsolarized plots (188.2 q/ha and 369.7 q/ha respectively).

Keywords: Mulching, soil, solarization, potato, weed.

SOIL solarization is a hydrothermal process which brings about thermal and other physical, chemical and biological changes in the moist soil during and even after mulching[1]. The technique has been variously used in the eradication or reduction of soil pathogen population, weed control, increased growth response, and yield and improvement of quality of the produce[2–5]. In India, potato

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