Monthly and seasonal scale rainfall and temperature predictions for climate risk management in Agriculture

by

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We deeply acknowledged to our prime collaborator IMD for linking of our developed monthly and seasonal scale rainfall and temperature forecast products among end users and also provided observed and analysis datasets. We thankful to NCMRWF for their support and collaborative R&D work. Our sincere appreciation to IITM Pune for providing their ERPAS monthly forecast products.

We gratefully acknowledge the IRI modeling and prediction group and National Centre for Environmental Prediction (NCEP) for providing the both version of CFS hindcast data sets.
Introduction

- **Agriculture** is an important sector in India and is mainly dependent on the weather and climate, and 80% of variability in the agriculture productivity is mainly due to the variability in local weather conditions.

- **The Indian climate** is highly heterogeneous with time and space. However, the summer monsoon itself contribute around 80% annual rainfall which is an important ingredient to the Kharif crops over India while winter season contribute only 15-20% annual precipitation.

- Although, the less winter precipitation is very important over Northwest India to maintains low temperature and supplements moisture, which is important for the development of Rabi crops such as wheat, barley, peas, gram and mustard.

- Failure of rains and occurrence of natural disasters such as floods and droughts could lead to crop failure, food insecurity, famine, loss of property and life, mass migration and negative national economic growth.

- **The cold conditions** during winter and heat wave conditions in summer affect human comfort, energy, water-management, public utility services, and sometimes cause loss of life over some regions in India.
Significance and Challenges of Monthly and Seasonal forecasts

- An accurate Monthly and seasonal scale forecasts can significantly contribute to food and livelihood security by providing advance information with sufficient lead time to adjust critical agricultural decisions for proper selection of crops, date of crop sowing/planting and crop preventive measures to maximize the crop yields so that they can get benefit from good seasons and minimize the adverse effect of climate extreme for their crops.

- Therefore, the accurate monthly and seasonal forecasts at regional level is very essential to reduce the impacts of hydro meteorological disasters (floods, droughts, heat waves and cold waves) and to attain sustainability especially in food security management for growing population.

- For scientific community, it is a challenging task to predict the monthly and seasonal scale rainfall and temperatures over the small region due to lack of understanding the small scale physical process.

- Small-scale effects (such as topography) important to local climate could be poorly represented in GCMs and there is a growing attention in the dynamical and statistical approaches to downscale GCMs/AOGCMs monthly and seasonal forecasts at regional scale.
Methodology → Forecast products from GCM/AOGCMs → Evaluation & Bias Correction → Multi-Model Ensemble →

- Simple average of bias corrected GCMs output (MME_BC)
- SVD Based Multi-linear Regression (SVDMR)
- Supervised Principal Component Regression (SPCR)
- Canonical Correlation Analysis (CCA)

Combined forecast → Validation in hindcast → Final forecast (ERFS)
### AGCMs & AOGCMs Products used in this study

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Model</th>
<th>Resolution</th>
<th>Ensemble Members</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CCM3v6</td>
<td>(T42)≈ 2.7° x 2.8°</td>
<td>24</td>
<td>2-tier</td>
</tr>
<tr>
<td>2</td>
<td>ECHAM4p5 CA SST</td>
<td>(T42)≈ 2.7° x 2.8°</td>
<td>24</td>
<td>2-tier</td>
</tr>
<tr>
<td>3</td>
<td>ECHAM4p5 CFS SST</td>
<td>(T42)≈ 2.7° x 2.8°</td>
<td>24</td>
<td>Semi-coupled</td>
</tr>
<tr>
<td>4</td>
<td>CFS v2(NCEP)</td>
<td>(T126)≈ 0.9° x 0.9°</td>
<td>24</td>
<td>Fully coupled</td>
</tr>
<tr>
<td>5</td>
<td>COLA-RSMAS-CCSM3</td>
<td>(T106)≈ 1.12° x 1.12°</td>
<td>06</td>
<td>Anomaly-Coupled</td>
</tr>
<tr>
<td>6</td>
<td>GFDL</td>
<td>(T42)≈ 2.7° x 2.8°</td>
<td>10</td>
<td>Fully coupled</td>
</tr>
<tr>
<td>7</td>
<td>GFDL-CM2p5-FLOR-A06 (GFDLA06)</td>
<td>(T42)≈ 2.7° x 2.8°</td>
<td>12</td>
<td>Fully coupled</td>
</tr>
<tr>
<td>8</td>
<td>GFDL-CM2p5-FLOR-B01 (GFDLB01)</td>
<td>(T42)≈ 2.7° x 2.8°</td>
<td>12</td>
<td>Fully coupled</td>
</tr>
<tr>
<td>9</td>
<td>ECMWF</td>
<td>(T159)≈ 0.75° x 0.75°</td>
<td>15</td>
<td>Fully coupled</td>
</tr>
<tr>
<td>10</td>
<td>IMD-SFM</td>
<td>(T42)≈ 2.7° x 2.8°</td>
<td>10</td>
<td>2-tier</td>
</tr>
</tbody>
</table>

**Observed data:** IMD 1-degree rainfall data (Rajeevan et al. 2006)

**Acknowledgement:**

This project outputs are also based on the Indian Global models provided by IMD and IITM (Sahai group)
Climatological mean of JJAS rainfall (mm) with MAY Start

CFSV2
COLA
GFDLA04
GFDLA06
GFDLB01
ECMWF
OBS
IAV of JJAS rainfall (mm) with MAY Start

CFSV2

COLA

GFDLA04

GFDLA06

GFDLB01

ECMWF

OBS
Correlation coefficient in predicting JJAS rainfall with MAY Start

CFSV2

COLA

GFDLA04

GFDLA06

GFDLB01

ECMWF
RMSE in predicting JJAS rainfall (mm) with MAY Start

CFSV2

COLA

GFDLA04

GFDLA06

GFDLB01

ECMWF
Challenge: Climate Model Forecast Use

1) Climate Model Scale - Biased

2) Climate Model Scale - Unbiased

bias-correcting...

then downscaling...
Bias correction methods

- Mean Bias-remove technique (U).
- Multiplicative shift technique (M).
- Standardized-reconstruction technique (Z).
- Regression technique (R).
- Quintile Mapping Method (Q).
- Principal Component Regression (PCR)

## Skill of each techniques on CFSv2 for JJAS All India rainfall

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Obs</th>
<th>Raw</th>
<th>U</th>
<th>M</th>
<th>Z</th>
<th>R</th>
<th>Q</th>
<th>PCR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (mm day-1)</td>
<td>7.63</td>
<td>5.68</td>
<td>7.63</td>
<td>7.63</td>
<td>7.63</td>
<td>7.63</td>
<td>7.61</td>
<td>7.61</td>
</tr>
<tr>
<td>SD (mm day-1)</td>
<td>0.75</td>
<td>0.25</td>
<td>0.25</td>
<td>0.34</td>
<td>0.78</td>
<td>0.34</td>
<td>0.76</td>
<td>0.72</td>
</tr>
<tr>
<td>RMSE (mm day-1)</td>
<td>2.06</td>
<td>0.69</td>
<td>0.44</td>
<td>0.83</td>
<td>0.72</td>
<td>0.80</td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td>Index of agreement (d)</td>
<td>0.37</td>
<td>0.45</td>
<td>0.58</td>
<td>0.65</td>
<td>0.48</td>
<td>0.66</td>
<td>0.60</td>
<td></td>
</tr>
</tbody>
</table>
Interannual variability of All India JJAS rainfall from observation, raw model and six bias correction methods (1982-2008)
Multi-model Ensemble

Experimental Deterministic forecast

Superensemble (M1)
Point by point multiple regression. Use of singular value decomposition is used to estimate weights of different GCMs (Krishnamurti et al. 2000, Yun et al. 2003)

Supervised–PCR (M2)
Stepwise regression of principal components of predictors have been done for each subdivision by screening the models on the basis of correlation.

Canonical Correlation Analysis (M3)
Correlating linear relationships between two multidimensional variables (Model data sets and Observations)

Combine Forecast (M4)
Inter-annual variation for JJAS: MME and Experimental ERFS

<table>
<thead>
<tr>
<th></th>
<th>All India</th>
<th>West UP</th>
<th>Kerala</th>
<th>Gujarat</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MME</td>
<td>ERFS</td>
<td>OB S</td>
<td>MME</td>
</tr>
<tr>
<td>AI</td>
<td>6.6</td>
<td>7.43</td>
<td>7.35</td>
<td>0.27</td>
</tr>
<tr>
<td>West UP</td>
<td>6.3</td>
<td>5.75</td>
<td>5.76</td>
<td>0.33</td>
</tr>
<tr>
<td>Kerala</td>
<td>7.73</td>
<td>15.5</td>
<td>15.7</td>
<td>0.48</td>
</tr>
<tr>
<td>Gujarat</td>
<td>5.7</td>
<td>7.2</td>
<td>7.26</td>
<td>0.5</td>
</tr>
</tbody>
</table>
Real-time assessment of experimental Monthly and seasonal scale Rainfall forecasts (2009-17)
### Summer monsoon (JJAS) Monthly and Seasonal Rainfall

<table>
<thead>
<tr>
<th>Month/Season</th>
<th>No. of subdivisions having the ERFS skill more than 60%</th>
</tr>
</thead>
<tbody>
<tr>
<td>JJAS</td>
<td>31 (91%)</td>
</tr>
<tr>
<td>June</td>
<td>32 (94%)</td>
</tr>
<tr>
<td>July</td>
<td>30 (88%)</td>
</tr>
<tr>
<td>August</td>
<td>26 (76%)</td>
</tr>
<tr>
<td>September</td>
<td>24 (71%)</td>
</tr>
</tbody>
</table>

*Mohanty et al. 2018 (Theoretical and applied Climatology)*
Winter (DJF) Monthly and Seasonal Precipitation

<table>
<thead>
<tr>
<th>Month/Season</th>
<th>No. of subdivisions having the ERFS skill more than 60%</th>
</tr>
</thead>
<tbody>
<tr>
<td>DJF</td>
<td>27 (79%)</td>
</tr>
<tr>
<td>Dec</td>
<td>34 (100%)</td>
</tr>
<tr>
<td>Jan</td>
<td>27 (79%)</td>
</tr>
<tr>
<td>Feb</td>
<td>31 (91%)</td>
</tr>
</tbody>
</table>

Confidence Map shown as % of hits: \((\text{Number of hits} \times 100)/\text{Number of years}\) for each subdivision
<table>
<thead>
<tr>
<th>Month/ Season</th>
<th>No. of subdivisions having the ERFS skill more than 60%</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAM</td>
<td>27 (79%)</td>
</tr>
<tr>
<td>Mar</td>
<td>32 (94%)</td>
</tr>
<tr>
<td>Apr</td>
<td>31 (91%)</td>
</tr>
<tr>
<td>May</td>
<td>31 (91%)</td>
</tr>
</tbody>
</table>
## Post-monsoon (OND) Monthly and Seasonal Rainfall

<table>
<thead>
<tr>
<th>Month/ Season</th>
<th>No. of subdivisions having the ERFS skill more than 60%</th>
</tr>
</thead>
<tbody>
<tr>
<td>OND</td>
<td>29 (85%)</td>
</tr>
<tr>
<td>Oct</td>
<td>30 (88%)</td>
</tr>
<tr>
<td>Nov</td>
<td>32 (94%)</td>
</tr>
<tr>
<td>Dec</td>
<td>33 (97%)</td>
</tr>
</tbody>
</table>
Performance of ERFS at Odisha for JJAS Rainfall with hindcast (1982-2008) and real time (2009-2016)
APPLICATION OF CLIMATE FORECASTS
Linking climate forecasts with Crop Model

- Climate forecasts
  - Daily weather sequences
    - Weather generator
- CRM
  - Decision Support Tool
    - Crop Model
      - Soil Type
      - Variety
      - Sowing time
- Low/Normal/High yield
- Generation of Advisories
Flow of Methodology for linking of Monthly/Seasonal forecast (ERFS) products to crop simulation models

Sequence of observed and forecast weather used as input for crop simulation model

<table>
<thead>
<tr>
<th>Serial number</th>
<th>Monthly/seasonal forecast</th>
<th>Observed sequences</th>
<th>Forecast sequences</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>May start June–September</td>
<td>January–May and October–December</td>
<td>June–September</td>
</tr>
<tr>
<td>2</td>
<td>June start July–September</td>
<td>January–June and October–December</td>
<td>July–September</td>
</tr>
<tr>
<td>3</td>
<td>July start August–September</td>
<td>January–July and October–December</td>
<td>August–September</td>
</tr>
<tr>
<td>4</td>
<td>August start September</td>
<td>January–August and October–December</td>
<td>September</td>
</tr>
</tbody>
</table>
Climate forecasts application at Kharagpur

Experiment details:

1. Data used for crop model (DSSAT)
   - Crop- Rice, Variety: DRRH2
   - Experiment station- Kharagpur
   - Latitude- 23 N Longitude- 83E
   - 3 dates of sowing
     - Early sowing-15\(^{th}\) June
     - Normal sowing-15\(^{th}\) July
     - Late sowing-15\(^{th}\) August

Dhekale et al. 2018 (Theoretical and applied Climatology)
Kharif rice yield at Khargpur simulated by DSSATv4.6 using IMD observed JJAS rainfall and ERFS forecast of JJAS, JAS, AS and Sep rainfall.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>CV</th>
<th>RMS E</th>
<th>MB</th>
<th>Correlation</th>
<th>IOA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>IMD observed</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JJAS</td>
<td>4.45</td>
<td>0.13</td>
<td>2.89</td>
<td></td>
<td></td>
<td>0.31</td>
<td>0.51</td>
</tr>
<tr>
<td>ERFS JJAS</td>
<td>4.50</td>
<td>0.09</td>
<td>1.93</td>
<td>0.20</td>
<td>0.05</td>
<td>0.43</td>
<td>0.60</td>
</tr>
<tr>
<td>ERFS JAS</td>
<td>4.46</td>
<td>0.08</td>
<td>1.89</td>
<td>0.23</td>
<td>0.01</td>
<td>0.65</td>
<td>0.76</td>
</tr>
<tr>
<td>ERFS AS</td>
<td>4.41</td>
<td>0.09</td>
<td>2.07</td>
<td>0.28</td>
<td>0.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERFS September</td>
<td>4.46</td>
<td>0.12</td>
<td>2.67</td>
<td>0.25</td>
<td>0.01</td>
<td>0.88</td>
<td>0.93</td>
</tr>
</tbody>
</table>
Kharif rice yield (kg/hectare) at Kharagpur by DSSATv4.6 using real time ERFS forecasts products for the period 2009-2015

<table>
<thead>
<tr>
<th>Forecast weather sequences</th>
<th>Mean</th>
<th>SD</th>
<th>CV</th>
<th>RMSE</th>
<th>MB</th>
<th>Correlation</th>
<th>IOA</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMD observed JJAS</td>
<td>4.44</td>
<td>0.12</td>
<td>2.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERFS JJAS</td>
<td>4.37</td>
<td>0.05</td>
<td>1.2</td>
<td>0.12</td>
<td>-0.07</td>
<td>0.32</td>
<td>0.55</td>
</tr>
<tr>
<td>ERFS JAS</td>
<td>4.43</td>
<td>0.06</td>
<td>1.3</td>
<td>0.09</td>
<td>-0.01</td>
<td>0.51</td>
<td>0.63</td>
</tr>
<tr>
<td>ERFS AS</td>
<td>4.57</td>
<td>0.17</td>
<td>3.7</td>
<td>0.18</td>
<td>0.13</td>
<td>0.68</td>
<td>0.64</td>
</tr>
<tr>
<td>ERFS September</td>
<td>4.52</td>
<td>0.10</td>
<td>2.2</td>
<td>0.10</td>
<td>0.08</td>
<td>0.81</td>
<td>0.77</td>
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</tbody>
</table>
Simulated grain yields using observed weather and disaggregated seasonal rainfall forecast for June – September, July – September, July – August and September from 1983 to 2007

Ghosh et al. 2015 (Meteorological Applications)
Time series for cross-validated skill in terms of correlation between simulated yields using observed weather and monthly/seasonal rainfall forecast for June – September, July – September, August – September and September.
Goodness-of-fit statistics—correlations, mean bias error (MBE), index of agreement for grain yields, simulated with disaggregated seasonal rainfall forecast for the period 1983–2007

<table>
<thead>
<tr>
<th>Forecast weather sequences</th>
<th>Correlation</th>
<th>MBE (t ha(^{-1}))</th>
<th>Index of agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td>June – September</td>
<td>0.45</td>
<td>−0.01</td>
<td>0.63</td>
</tr>
<tr>
<td>July – September</td>
<td>0.61</td>
<td>0.02</td>
<td>0.73</td>
</tr>
<tr>
<td>August – September</td>
<td>0.73</td>
<td>0.04</td>
<td>0.79</td>
</tr>
<tr>
<td>September</td>
<td>0.78</td>
<td>0.03</td>
<td>0.79</td>
</tr>
</tbody>
</table>
Agromet Advisory for Bundelkhand region using ERFS products for April-2016

अनाव, तिलहन और दास: -
तापमान में बृद्धि की समाप्ति से हो या गहराई का कार्य शीघ्रतापूर्वक पूरा करें। तापमान समाप्ति से ज्यादा रहने को ध्यान में रखते हुए रीमेम्सलीन मुंग की फसल में फिसलां सिंचाई करें। अनेकों दूरसे व लौहसे सतारों में तापमान अधिक रहने के कारण वाष्पीकरण की दर अधिक हो सकती है।
अतः जादुफ पत्ते मुंग, उद्ध व सोयाबीन में 6-7 दिनों के अंतराल पर सिंचाई करें।

फल, पूृा और सब्जियाँ:-
माह के दूरसे सतार में भी तापमान बढ़ने से सिक्के व टमाटर की कस्तूरी मुंग (लीक के) रेंज का प्रकोप बढ़ा जाये हैं इससे तावब हुए किसान भाई। दोहरीसेमेंट 30 ईः, देवास का 2 मिली, लीटर मात्रा प्रति लीटर पानी में धोत बनाकर भिंडिकार करें।

दूरसे तापमान में भी तापमान समाप्ति से 5-6 दिन ज्यादा रहने के कारण संधियाँ उर्मी-कंद, लूकी, टिक्का, केला, तुरुब एवं खरूठ में लाल कीता फल भमे व क्रिया का प्रकोप हो सकता है। अतः किसान भाई फसल का मिश्रण करें तथा पर्याप्त ज्यादा हेतु दुर्जिताचार 40 ईः, 9 दिन, देवास की 2 मिली, लीटर अथवा मेलायमिथाइन 50 ईः, 9 दिन, देवास की 1.0 मिली, प्रति लीटर पानी में भोग बनाकर भिंडिकार करें।

दूरसे तापमान में भी नींदों और फल इंडेक्स की आवश्यकता हो सकता है, किसान भाई फसल का अवलोकन करें तथा पानी के लिए कर्जपान है।, देवास की 10 दिन, देवास की 2 मिली, लीटर मात्रा प्रति लीटर पानी में धोत बनाकर भिंडिकार करें।

दूरसे तापमान में भी फल इंडेक्स की आवश्यकता हो सकता है, किसान भाई फसल का अवलोकन करें तथा पानी के लिए कर्जपान है।, देवास की 10 दिन, देवास की 2 मिली, लीटर मात्रा प्रति लीटर पानी में धोत बनाकर भिंडिकार करें।

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Agromet Advisory for Bundelkhand region using forecast products for March-2016

<table>
<thead>
<tr>
<th>March 2016 Advisory</th>
<th>March 2016 Advisory</th>
</tr>
</thead>
</table>

Anwaj, तिलहन और दास- तालाब में बुध से शनिवार से बचने की जरूरत में पफ़ु, एकर और थाइलिन। हृदय में बुलंद होने से ग्रामीण युवा दरम्यान बुरी शक्ति का साधन बुद्धि हो रही है। तालाब का पानी बढ़ता है। यह स्थिति बालिका और महिला प्रकृति का खतरा है।

<table>
<thead>
<tr>
<th>मुद्रा करने</th>
<th>पफु के अंश</th>
<th>मुद्रा की दोनों</th>
</tr>
</thead>
</table>
Future Scope:
Dynamical-statistical downscaling approach for developing Monthly and Seasonal scale predictions at District Level for Climate Risk Management over Predominantly Rainfed Agriculture Regions
Sub divisions with more than 75% confidence of ERFS real time JJAS rainfall forecast (2009-2016)

Total rainfed districts (220) belongs to predominated rainfall agriculture

[Source IMD, Pune]
Rainfed districts with more than 75% ERFS confidence of ERFS real time JJAS forecast

[128 districts under predominated rainfall for agriculture]

<table>
<thead>
<tr>
<th>S. No.</th>
<th>State/Met-subdivision Name</th>
<th>No. of Rainfed districts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Haryana</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Rajasthan</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>West U.P</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Jharkhand</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>Orissa</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Chhattisgarh</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>Gujarat</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>Maharashtra</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>Andhra Pradesh</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Tamil Nadu</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td><strong>Total</strong></td>
<td><strong>128</strong></td>
</tr>
</tbody>
</table>
Distribution of observed and model simulated precipitation

Tiwari et al. 2016 (Quarterly Journal of the Royal Meteorological Society)
Glimpse of regional climate model efficiency over its parent GCM

Precipitation prediction skill

<table>
<thead>
<tr>
<th></th>
<th>GCM</th>
<th>RCM-DD</th>
<th>Bias Corrected RCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation Coefficient</td>
<td>0.21</td>
<td>0.36</td>
<td>0.44</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.78</td>
<td>0.78</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Tiwari et al. 2016 (Quarterly Journal of the Royal Meteorological Society)
High-Resolution Dynamical-Statistical Downscaling: A schematic view on resolutions for district/cluster of districts level forecast
Publications

**Year-2018**


- Maurya RKS, Sinha P, Mohanty MR, Mohnat UC, 2018: RegCM4 model sensitivity to horizontal resolution and domain size in simulating the Indian Summer Monsoon, Atmospheric Research, 210, 15–33


- Madhusmita Swain, Sujata Pattanayak, UC Mohanty, 2018: Characteristics of occurrence of heavy rainfall events over Odisha during summer monsoon season. Dynamics of Atmospheres and Oceans, DOI: https://doi.org/10.1016/j.dynatmoce.2018.05.004
• MM Nageswararao, UC Mohanty, AP Dimri, Krishna K Osuri, 2018: Probability of occurrence of monthly and seasonal winter precipitation over Northwest India based on antecedent-monthly precipitation. Theoretical and Applied Climatology 132 (3-4), 1247-1259

• MM Nageswararao, UC Mohanty, S Ramakrishna, AP Dimri, 2018: An intercomparison of observational precipitation data sets over Northwest India during winter, Theoretical and Applied Climatology 132 (1-2), 181-207

• MM Nageswararao, BS Dhekale, UC Mohanty, 2018: Impact of climate variability on various Rabi crops over Northwest India. Theoretical and Applied Climatology 131 (1-2), 503-521

Year-2017


• Ankita Singh, Raj Kumar Sahoo, Archana Nair, Mohanty UC, Rai RK, 2017: Assessing the performance of bias correction approaches for correcting monthly precipitation over India through coupled models, Meteorological Applications, Vol. no 24 (3), 326-337.

Year-2016

• Nageswararao MM, Mohanty UC, Ramakrishna SSVS, Archana Nair, Kiran Prasad S, 2016: Characteristics of winter precipitation over Northwest India using high-resolution gridded dataset (1901–2013), Global and Planetary Change, 147, 67–85

• MM Nageswararao, UC Mohanty, SK Prasad, KK Osuri, S Ramakrishna, 2016: Performance evaluation of NCEP climate forecast system for the prediction of winter temperatures over India. Theoretical and applied climatology 126 (3-4), 437-451.

Continued…
• MM Nageswararao, UC Mohanty, KK Osuri, S Ramakrishna, 2016: Prediction of winter precipitation over northwest India using ocean heat fluxes. Climate dynamics 47 (7-8), 2253-2271.

• PR Tiwari, SC Kar, UC Mohanty, S Dey, P Sinha, PVS Raju, MS Shekhar, 2016: On the dynamical downscaling and bias correction of seasonal-scale winter precipitation predictions over North India. Quarterly Journal of the Royal Meteorological Society 142 (699), 2398-2410.

• MM Nageswararao, UC Mohanty, Archana Nair, SSVS Ramakrishna, 2016: Comparative evaluation of performances of two versions of NCEP climate forecast system in predicting winter precipitation over India. Pure and Applied Geophysics 173 (6), 2147-2166.

• PR Tiwari, SC Kar, UC Mohanty, S Dey, S Kumari, P Sinha, 2016: Seasonal prediction skill of winter temperature over North India. Theoretical and applied climatology 124 (1-2), 15-29.


**Year-2015**


Continued…


• Archana Nair, Mohanty UC, Panda TC, 2015: Improving the performance of precipitation outputs from General Circulation Models to predict monthly and seasonal rainfall over the Indian subcontinent, Comptes Rendus Geosciences, 347(2): 53-63, DOI: 10.1016/j.crte.2015.03.004

Year-2014


• Tiwari PR, Kar SC, Mohanty UC, Kumari S, Sinha P, Nair A, Dey S, 2014: Skill of precipitation prediction with GCMs over North India during Winter Season, Int. J. Climatology, DOI :10.1002/joc3921

Year-2013


• Nair A, Mohanty UC, Robertson AW, Panda TC, Jing-Jia Luo, Toshio Yamagata, 2013: An analytical study of hindcasts from General Circulation Models for Indian Summer Monsoon Rainfall, Meteorological Applications, DOI: 10.1002/met.1395


Year-2012


**Year-2011**

• Acharya N, Kar SC, Mohanty UC, Kulkarni MA, Dash SK, 2011: Performance of GCMs for seasonal prediction over India - a case study for 2009 monsoon, Theor Appl Climatol, 105, 3, 505–520..


**Year-2010**


**Year-2009**

Bias Correction of GCMs

Without transformation function
- 1. Mean Bias-remove technique (U)
- 2. Multiplicative shift technique (M)
- 3. Standardized-reconstruction technique (Z)

With transformation function
- 1. Regression technique (R)
- 2. Quantile Mapping Method (QQ)
- 3. Principal Component Regression (PCR)

Evaluation and comparison of bias correction techniques
Mean Bias-remove technique (U)

- Mean bias is defined as the difference between observed climatology $\overline{Y}$ and climatology of ensemble mean $\overline{F_t}$:

$$b_t = \overline{Y} - \overline{F_t}$$

For each year this difference ($b_t$) is calculated in the leave one out cross validation manner and adds this mean bias in the ‘test’ ($t$) year’s model mean

$$U_t = \overline{F_t} + b_t$$

Acharya et. Al 2013
This technique also adjusts the mean of GCM predicted rainfall. Ines and Hansen (2006) applied the method in which initially ratio of climatology is evaluated between observed and the ensemble mean of GCM

\[ m_t = \frac{\bar{Y}}{\bar{F}_t} \]

\[ M_t = \bar{F}_t \times m_t \]

\( \bar{Y} \) - observed climatology

\( \bar{F}_t \) - climatology of ensemble mean

For each year \( m_t \) is calculated in the leave one out cross validation manner and multiple with the ‘test’ (\( t \)) year’s model mean
The standardized anomaly of the ensemble mean is:

\[ z_t = \frac{F_t - \bar{F}}{\sigma_{\bar{F}}} \quad , \quad Z_t = (z_t \times \sigma_Y) + \bar{Y} \]

For each year \( z_t \) is calculated in the leave one out cross validation manner and multiple with the observed standard deviation, and add to the observed climatology

- \( \bar{Y} \) - observed climatology
- \( \bar{F}_t \) - climatology of ensemble mean
- \( \sigma_Y \) - observed standard deviation
- \( \sigma_{\bar{F}} \) - ensemble mean standard deviation
• This technique mainly used for to correct the GCM predicted rainfall distribution by mapping it onto the observed rainfall distribution. The process is also referred to as ‘histogram equalization’ and/or ‘rank matching’. In the quantile mapping method empirical probability distributions of observed and forecasted values are used. In the quantile mapping method the bias is not calculated explicitly. Suppose CDFs, \( F_Y \) for observed data and \( F_F \) for ensemble mean of model forecast are known. For \( \overline{F} \), the bias corrected value \( Q \) will then be as follows:

\[
Q = F_{\text{Obs}}^{-1}(F_{\overline{F}}(\overline{F}))
\]

• Here, \( F^{-1} \) is an inverse of CDF. Thus, the quantile mapping procedure is a transformation between two CDFs. The whole procedure is implemented in the leave one out cross validation way.

*Ines and Hansen, 2006; Wood et al.,2002;Hamlet et al.,2003; Piani et al. 2009; Acharya et. al, 2013;*
Observed Rainfall (mm/day)

\[ Q = F^{-1}_{\text{Obs}} \left( F_{\overline{F}}(\overline{F}) \right) \]
Regression technique (R)

\[ Y = \beta_0 + \beta_1 F_t + \varepsilon \]

Where the coefficient of the regression equation is estimated by the least square estimates that try to minimize the error between observed and predicted rainfall. For simplicity, let us assume that, \( X = \overline{F_t} \)

The estimates are obtained in leave-one-out mode and the estimated value of \( Y \) is compared with the reality. This regression coefficient rescales the forecast to correct systematic errors.

\[
\min \sum e^2 = \sum (Y - \hat{Y})^2 = \sum (Y - \beta_0 - \beta_1 X)^2
\]

\[
\beta_1 = \frac{\sum (XY - n \overline{XY})}{(\sum X - n \overline{X})^2}
\]

\[
\beta_0 = \overline{Y} - \beta_1 \overline{X}
\]
Principal Component Regression (PCR)

• In regression techniques, it may be occurring the multi-co-linearity and the over fitting problems among the predictors, when the number of predictors is not sufficiently less to the total number of years and its affect the estimated coefficient adversely (Fisher, 1922, Gowariker et al. 1989, 1991; Delsole and Shukla 2002). Therefore, instead of all the predictors, it should be required the screening of the predictors based on principal component analysis.

• This method was invented in 1901 by Karl Pearson. It involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components.

• The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

• PCA is mostly used as a tool in exploratory data analysis and for predictive models. It involves the calculation of Eigen value decomposition of a data covariance matrix.
• First principal component is the direction of greatest variability (covariance) in the data.

• Second is the next orthogonal (uncorrelated) direction of greatest variability.
  So first remove all the variability along the first component, and then find the next direction of greatest variability
• Thus each eigenvectors provides the directions of data variances in decreasing order of eigenvalues
Overview of Principal Component Analysis

Original data $X_{m \times n}$

Transformation

Reduced data $Z_{m \times p}$

where $p \leq n$

Correlation matrix $(X^TX)/(n-1)$

Eigenvector matrix $V_{n \times n}$

$Z = X_{m \times n} \times V_{n \times n}$

Nair et al., (2012), TACC.
• For n original dimensions, correlation matrix is n x n, and has up to n eigenvectors. So n PCs can be retained

• Where does dimensionality reduction come from?

• Can ignore the components of lesser significance.

You do lose some information, but if the eigenvalues are small, you don’t lose much
  – n dimensions in original data
  – calculate n eigenvectors and eigenvalues
  – choose only the first p eigenvectors, based on their eigenvalues
  – final data set has only p dimensions
Let $X_i$ be the independent variable and $Y_i$ be the dependent variable. Consider the regression equation below:

$$Y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \ldots + b_p X_{pi} + e_i$$

Instead of using the independent variables directly, if the principal components of these variables are considered as predictor, then the regression is known as principal component regression.
Superensemble (M1)

- For carrying out weighted multi-model ensemble mean, **multiple regression** method has been employed. Singular value decomposition (SVD) has been employed for the computation of the regression coefficients (referred to as SVD scheme in the following text). The advantage of SVD method is it removes the singular matrix problem while calculating covariance among models which can’t be entirely solved with the Gauss-Jordan elimination method.

\[ S_t = \bar{O} + \sum_{i=1}^{N} a_i \left( F_{i,t} - \bar{F}_i \right) \]

Regression coefficient obtained by a minimization procedure during the training period.
Supervised PCR (M2)

INPUT

PREDICTORS (X) (GCM outputs)

Interpolate to Indian grid

FINAL PREDICTORS

PREDICTAND (Y) (IMD rainfall or Temperature)

Correlation (X & Y)

PCR

Z

Stepwise Model construction using R.M.S.E

OUTPUT
CCA based prediction model (M3)

1. GCM outputs at coarser resolution
2. Predictand variable for extended Indian domain
3. Canonical analysis (evaluation of canonical predictor, canonical predictand, canonical correlation)
4. Predicted variable at Indian grid points
5. Final prediction as average over m GCMs