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The application of generalized additive models (GAMs) for assessing the teleconnection of ENSO and IOD with monsoon rainfall variability over Krishna river basin, India

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ABSTRACT

The present study examines the teleconnection of ENSO andIOD with monsoon rainfall (MN) and low, moderate and heavy rainfall events (LREs, MREs and HREs) over the Krishna river basin, using generalized additive models (GAMs) with suitable distribution. The outputs of GAMs indicate that, Poisson distribution is superior to the other distributions in assessing the teleconnection of ENSO-MN-IOD in the study area. Further, study resultsshowed that ENSO and IOD has significant ($p < 0.001$) non-linear responses to theLREs, MREs,HREs and MN. The influence of IOD on MN, LREs, MREs and HREs found positive on some parts, while negative on the other parts of the study area (i.e. heterogeneous in nature). While, ENSO has consistent negative influence on MN, LREs, MREs and HREsin the study area. Furthermore, La Niña and El Niño had positive and negative influenceon the MN, LREs, MREs and HREs respectively. The study outcomes will help the hydro-meteorologist and water related policy makers in modeling the impact of monsoon rainfall system on water, agriculture and allied sectors.

Keywords: Monsoon rainfall, generalized additive models (GAMs), ENSO, IOD.

The monsoon rainfall (MN) is the main source of water for the agriculture, domestic and industrial related activities in the Indian subcontinent. Therefore, under the rapidly growing population, information about variability of MN is vital for planning and management of available water resource and agriculture related operations (Bal *et al.,* 2004). Past studies showed that the Indian Ocean dipole mode (IOD) and El Niño Southern Oscillation (ENSO) had significant role in inter annual variability of monsoon rainfall and also on behavior of extreme events of monsoon rainfall in the Indian subcontinent (Sikka, 1980; Singh *et al.,* 2005; Rajegowda *et al*., 2009; Krishnaswamy *et al*., 2015;Bothale and Katpatal, 2015).

Most of the studies used either correlation techniques, traditional regression and/or composite techniques to analyze the ENSO-MN-IOD teleconnection in the Indian subcontinent. These techniques followed the assumption of the linearity in modelling of the ENSO-MN-IOD teleconnection. While, due to constant dynamism over time and space domain, climate phenomena are highly nonlinear in nature (Box *et al*., 2015). Therefore, analyses of the ENSO-MN-IOD relationship with use of traditional regression methods and composite technique needs to be very cautious or else it misleads the results. Hence it is required to model potential non-linearity under constant dynamism climate to understand the phenomena precisely. Generalized Additive Models (GAMs) is one of the advanced tools that have capability to detect nonlinear relationship between dependent variable and explanatory variables. GAMs are popularizing in recent decades in the field of statistics due to its wide variety of application (Hastie and Tibshirani, 1990). Therefore, present study is attempted to use the GAMs in assessing the non-linear influence of ENSO and IOD on the MN and rain events in the Krishna river basin.

Krishnaswamy *et al*. (2015) have used GAM to detect non-linear influence of IOD and ENSO on Indian summer monsoon rainfall (ISMR) / extreme rainfall events (EREs). In their study, Gaussian distribution has been used for the ISMR and Poisson distribution was used for the EREs.

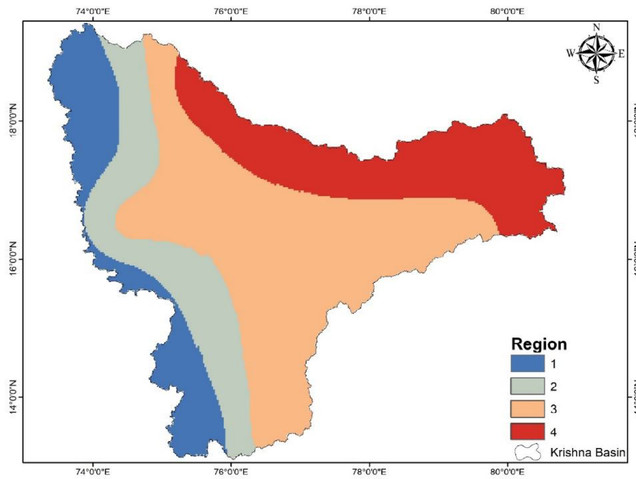

Fig. 1: Regional map of the Krishna river basin

Further, Gao *et al*. (2017) also used Poisson distribution in GAMs to assessing extreme events in climate parameters. However, none of the past studies have recommended which distribution is best suitable tostudy the teleconnection of monsoon season rainfall with oceanic circulations ENSO and IOD. Therefore, this aspect has been examined in the current study, prior to the use of GAMs to assess the relationship between ENSO-MN-IOD, GAMs fitted with Gamma, inverse-Gaussian, Quassi, Quassi-Poisson, Gaussian and Poisson distributions and compared the model's output. Based on the p-value and deviation explained, the best distribution was selected to detect non-linear association of IOD and ENSO with the monsoon rainfall and rainfall events at different thresholds in the study area.

MATERIALS AND METHODS

Study area

Krishna is a major river basin of peninsular India extends over Karnataka (43.8%), Andhra Pradesh (29.4%) and Maharashtra (26.8%), having a total geographical area of 2,58,948 Sq.km. The basin lies between 13°10' to 19°22' N latitudes and 73°17' to 81°9' E longitudes and bounded by the Western Ghats on the west, Eastern Ghats on the east and the south, and Balaghat range on the north. The South West Monsoon (June-September) is the principal season of receiving rainfall and about 90% of annual rainfall is receivedduring this season in the Krishna basin.

Data and methodology

The data sets used in the present study are daily gridded rainfall data, Oceanic index Niño-3.4 and Indian Ocean dipole mode index. Daily gridded rainfall data sets at 1° lat. × 1° long resolution for the period *1951-2007*was collected from the Indian Meteorological Department (IMD), Pune. According to IMD daily gridded rainfall datasets, about 22 grids comes underthe Krishna River basin. K-means cluster analysis has been carried out to reduce the 22 grids into K clusters for which each observation belongs to the cluster with the same imprint of spatial variation in the study area was taken. Total four cluster zones have been observed in the cluster analysis (Fig. 1) and further investigation has been carried out in these four cluster regions.

Oceanic index Niño-3.4 which is the mean sea surface temperature anomaly over regions in between 120°-170°W and 5°S-5°N, which obtained from the National Oceanographic and Atmospheric Administration. Indian ocean dipole mode index (IOD or DMI) which has difference in sea surface temperature anomalies between the western region (50°E-70° E, 10° S - 10° N) and the eastern region (90°E- 110°E, 10°S - 0°N) of Indian ocean, which obtained from the Japan Agency for Marine-Earth Science and Technology (JAMEST). As per the JAMEST, Indian Ocean dipole mode indexabove +0.4 °C considered as positive IOD phase (pIOD), and values below -0.4 °C as negative IOD phase (nIOD).

The present study was carried for the monsoon season (June to September) in which Krishna river basin receivesthe maximum rainfall. The study also includes rain events at different thresholds which occurred in the monsoon season.Classification of rain events considered in the present study as per the IMD rainfall event classification. IMD categorized rain event into Low rainfall events (LREs), Moderate rainfall events (MREs), and Heavy rainfall events (HREs) if rainfall received is < 15.5 mm/day, 15.6 - 64.4 mm/day and > 64.5 mm/day, respectively.

Generalized additive models

In the GAMs, monsoon rainfall / rainfall events has been used as dependent variable and Niño-3.4 and IOD as explanatory variables. The general form of GAM model is represented as:

$$g(E(Y_t)) = \beta_0 + f_1(X_{1t}) + f_2(X_{2t}) \qquad (1)$$

Where, g(.) is the link function which was assumed according to the selected distribution in the model. Generally, link function assumed as identity, inverse, 1/mu^2, log, identity and log for the Gaussian, Gamma, inverse-Gaussian, Poisson, Quassi and Quassi-Poisson distributions respectively. The function f_i are the non-parametric smooth function of

Table 1: P – Values (Significance of smooth terms) of GAMs with different distribution

Distribution type	Significance of smooth terms (P-Value) in GAMs									
	IOD					ENSO				
	R1	R2	R3	R4	WB	R1	R2	R3	R4	WB
Low rain events (LREs)										
Gaussian	0.414	0.398	0.350	0.460	0.361	0.227	0.170	0.272	0.110	0.029
Gamma	0.404	0.631	0.285	0.471	0.279	0.239	0.149	0.249	0.109	0.025
Inverse.gaussian	0.404	0.598	0.266	0.459	0.260	0.246	0.137	0.260	0.110	0.023
Poisson	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Quasi	0.407	0.394	0.312	0.471	0.315	0.233	0.165	0.259	0.109	0.027
Quasi-poisson	0.414	0.398	0.350	0.460	0.361	0.227	0.170	0.272	0.110	0.029
Moderate rain events (MREs)										
Gaussian	0.466	0.609	0.931	0.252	0.970	0.058	0.958	0.293	0.008	0.078
Gamma	0.481	0.002	0.165	0.106	0.638	0.053	0.046	0.246	0.000	0.112
Inverse.gaussian	0.509	0.420	0.882	0.392	0.941	0.053	0.551	0.310	0.002	0.125
Poisson	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Quasi	0.470	0.004	0.542	0.121	0.691	0.054	0.048	0.488	0.003	0.080
Quasi-poisson	0.466	0.609	0.931	0.252	0.970	0.058	0.958	0.293	0.008	0.078
Heavy rain events (HREs)										
Gaussian	0.460	0.260	0.648	0.439	0.511	0.458	0.395	0.895	0.285	0.451
Gamma	0.527	0.631	0.285	0.471	0.565	0.491	0.046	0.246	0.000	0.477
Inverse.gaussian	0.623	0.598	0.266	0.459	0.609	0.537	0.551	0.310	0.002	0.516
Poisson	0.000	0.256	0.999	0.004	0.000	0.000	0.220	0.996	0.043	0.000
Quasi	0.479	0.000	0.000	0.206	0.515	0.463	0.000	0.000	0.204	0.454
Quasi-poisson	0.460	0.260	0.648	0.439	0.511	0.458	0.395	0.895	0.285	0.451
Monsoon Rainfall										
Gaussian	0.170	0.439	0.844	0.053	0.348	0.056	0.418	0.137	0.001	0.039
Gamma	0.180	0.233	0.406	0.027	0.207	0.053	0.364	0.117	0.001	0.029
Inverse.gaussian	0.188	0.139	0.311	0.024	0.179	0.054	0.349	0.111	0.001	0.027
Poisson	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Quasi	0.174	0.490	0.509	0.036	0.263	0.054	0.448	0.134	0.001	0.033
Quasi-poisson	0.170	0.439	0.844	0.053	0.348	0.056	0.418	0.137	0.001	0.039

Bold values in the table indicating significance at $p < 0.001$

explanatory variables X_i which have ability to capture non-linearity's in these variables. In the above equation, monsoon rainfall / rainfall events used as Y_t and ENSO and IOD indices used as X_{1t} and X_{2t}, respectively. β_0 is the intercept of the model.

With parameters of GAM model using link function and back-transformation, fitted values can be obtained. These fitted values and standard error bands plotted against the explanatory variables, which enables visual interpretation of uncertainty in the fitted model for the response variable in the original units. For the GAMs, we used library *mgcv* in R statistical software. Further, deviance explained is the one of the output parameters of the GAMs and similar to the usual R^2 written as a percentage. It is the measure of the discrepancy between the observations and the fitted values of model. The deviance explained (D) in the

GAMs is estimated by using following equation.

$$D = 2\left[l\left(\hat{\beta}_{max}\right) - l\left(\hat{\beta}\right)\right]\phi \qquad (2)$$

Where, $l(\hat{\beta})$ and $l\left(\hat{\beta}_{max}\right)$ is the maximized likelihood of the fitted model and saturated model respectively. ϕ is the scale parameter used in the fitting of GAMs.

RESULTS AND DISCUSSION

The study results (Table 1) indicated that,both ENSO and IOD has displayed significant ($p < 0.001$) non-linear responses to the LREs, MREs, HREs and MN at regional scale as well as at basin scale except for HREs at Region-4. Study outcomes in Table-1 showed Poisson distribution found significant and superior than the other distributions in modelling of non-linear relationship between ENSO and IOD with the MN, LREs and MREs.While for HREs, Poisson distribution was found significant at Region-1 as well at basin scale, Quasi distribution in case of Region-2, Region-3 and Gamma distribution at Region-4was found significant. These change in significance of different distributions for HREs within the river basin might be because of its poor correlation with ENSO and IOD.

Deviance explained by GAMs with different distribution for the LREs, MREs, HREs and MN at regional scale as well as at basin scale is showed in Fig. 2(a-d). Deviance explained by different distribution was found in the range of 0-34 %, 0-55 %, 0-99 % and 0-51 % for LREs, MREs, HREs and MN respectively. In general, the rank of deviance explained by distribution in modelling the ENSO-IOD with LREs, MREs and MNwas found as: Poisson, Inverse-Gaussian, Gamma, Quasi, Gaussian and Quasi-Poisson distribution. The similar rank of distribution was observed for HREs except at Region-3. In general study results (Fig. 2 (a-d) and Table 1) clearly indicated that, Poisson distribution was superior than the other distributions in assessing the teleconnection of ENSO-MN-IOD at regional basis as well as at basin scale.

Deviance explained by GAMs with Poisson distribution observed for the LREs, MREs, HREs and MN about 7-31, 14-46, 7-95 and 11-39 % respectively (Fig. 2 (a-d)). For LREs and MN, the IOD has explained more deviance than the ENSO phenomenon at regional basis as well as at basin scale. However, for the MREs both IOD and ENSO has explained more or similar deviance in the Region-1, Region-4 and at the whole basin scale. But IOD had more influence than the ENSO on MREs at Region-2 and Region-3. Further, ENSO had substantial influence than the IOD at Region-2, Region-3 and Region-4 for HREs.Both IOD and ENSO had similar influence on HREs at Region-1 and at basin scale.

In general, IOD had more influence than the ENSO on LREs, MREs and MN across the study area. While, ENSO had more influence than the IOD on the HREs. In addition, the covariates ENSO and IOD explained deviance lesser than 20% by individually, while together they explain the deviance of dependent variables (MN, LREs and MREs) around 30% except for HREs (Fig.2).

Non-linear response of LREs, MREs, HREs and MN with DMI (IOD) and ENSO using GAMs with Poisson distribution at basin scale is showed in Fig.3 (a-h). At basin scale, ENSO effect consistently changes from negative to positive from El Niño to La Niña phase on LREs, MREs, HREs and MN (Fig.3 (b,d, f and h)).Further, results reveal that influence of IOD (pIOD and nIOD) has heterogenous effect on LREs, MREs, HREs and MN (Fig.3(a, c, e and g)). In other words, pIOD and nIOD has positive influence in some parts and negative influence in other partsof the study area.

Non-linear response of MN with ENSO and DMI (IOD) using GAMs with Poisson distribution at regional scale is showed in Fig.4 (a-h). Similar to basin scale, the homogenous uniform effect of ENSO has been observed across the different regions; its effect changes from positive to negative from La Niña to El Niño for weak to moderate phases. While in case of IOD, the effect of pIOD and nIODwas observed to be regional specific.

Overall, results showed that ENSO had uniform negative effect and IOD influence was regional specific. But both ENSO and IOD has clear non-linear relationship with the LREs, MREs, HREs and MN (Fig.3&4). Further, if we use the Gaussian distribution with link function 'identity' as used in the study Krishnaswamy*et al*. (2015), resultsdepicting the linear relationship between MN with IOD and ENSO at regional scale (Fig.5(a-h)).In addition, uncertainty in the GAMs with Gaussian distribution in explaining the teleconnection of ENSO-IOD-MN was higher as compare to GAMs with Poisson distribution (Fig.4&5).Further, GAMs with Gaussian distribution fail to capture the non-linear effect of ENSO and IOD on MN and shown more uncertainty in the relationship at regional scale. Therefore, outcome of this study suggested that, GAMs with Poisson distribution has advantage over the other distributions in assessing the

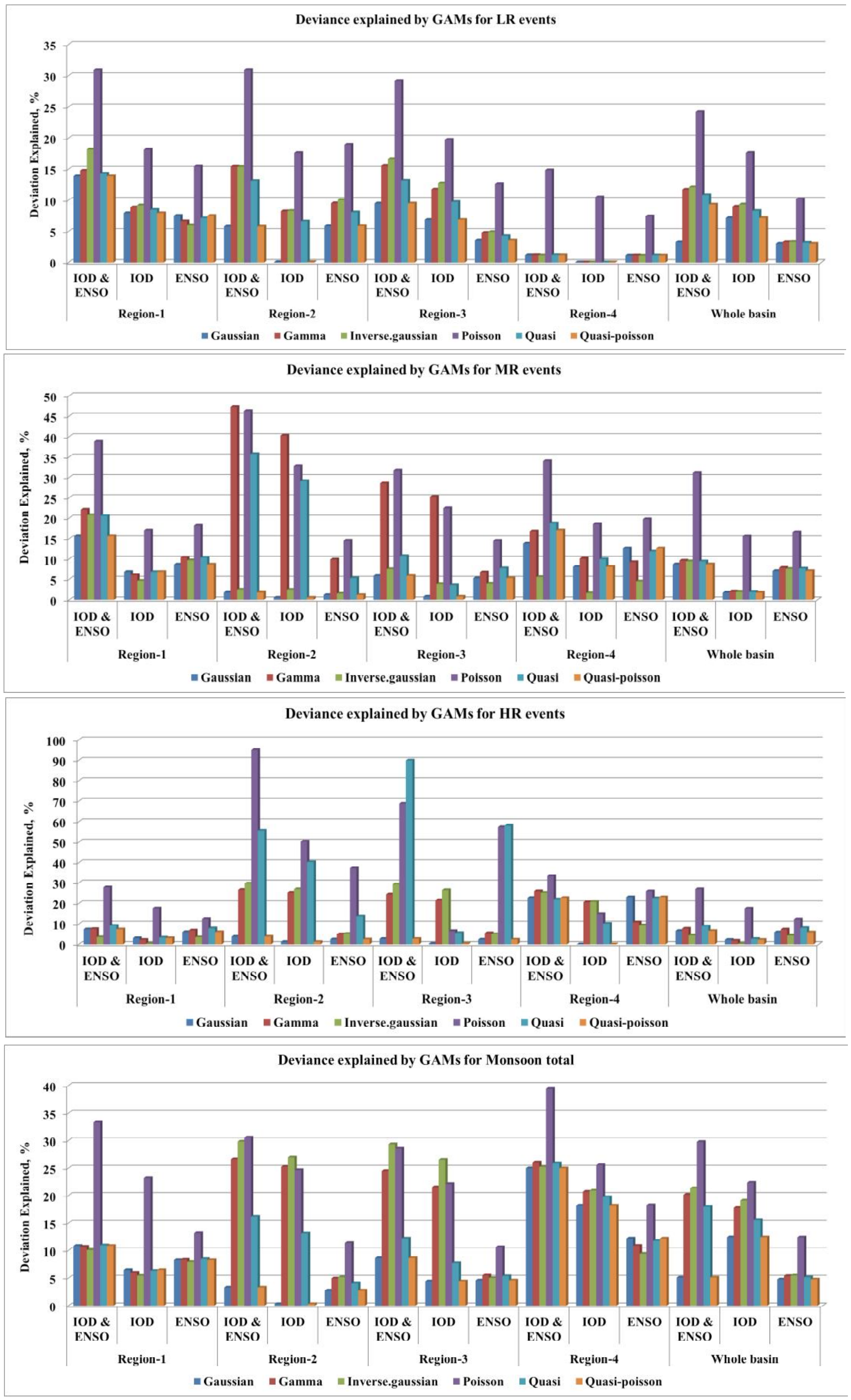

Fig. 2(a-d): Deviance explained of dependent variable (LREs, MREs, HREs and MN) by GAMs with different distribution and covariates ENSO and IOD selected as individually and together.

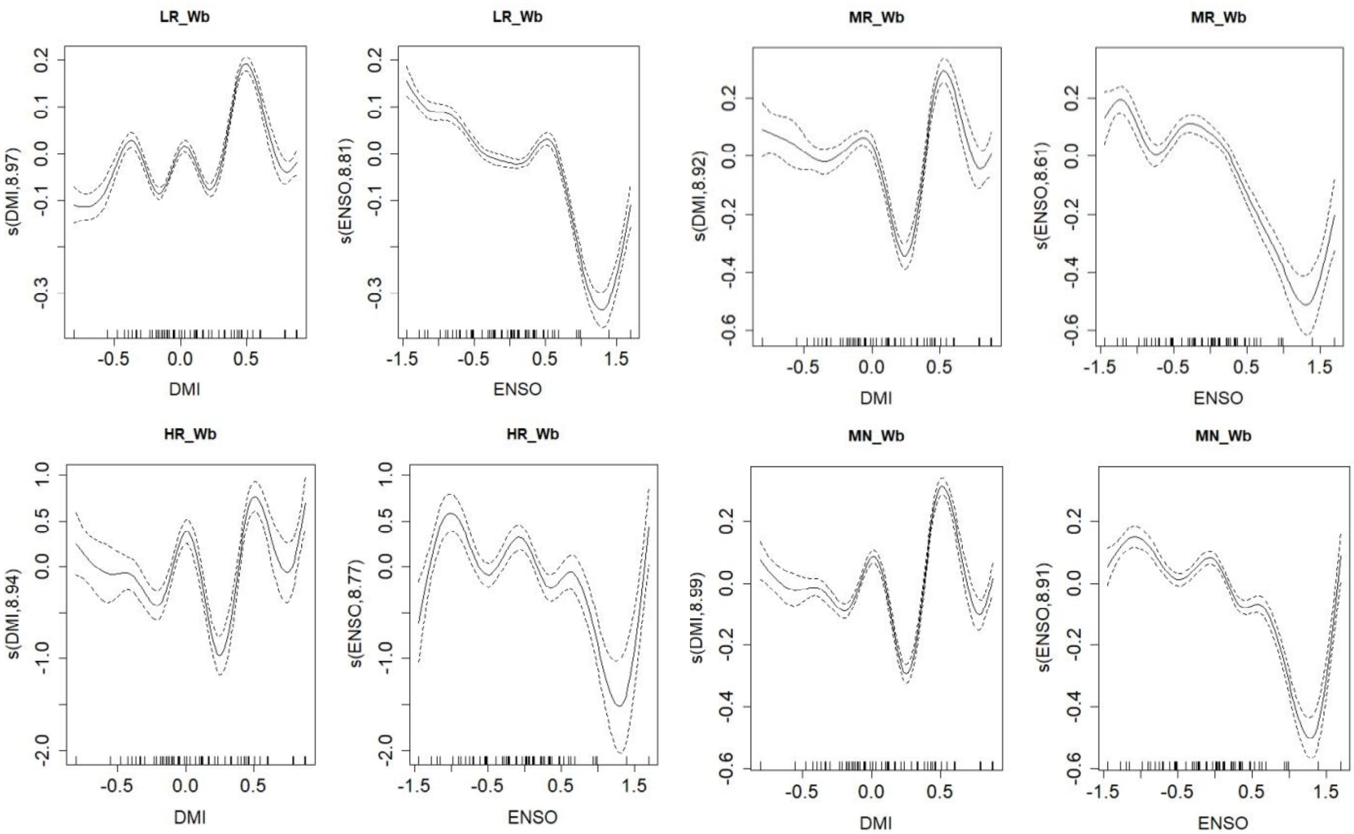

Fig. 3 (a-h): Non linear response of LREs, MREs, HREs and MN with ENSO and IOD using GAMs with Poisson distribution at basin scale.

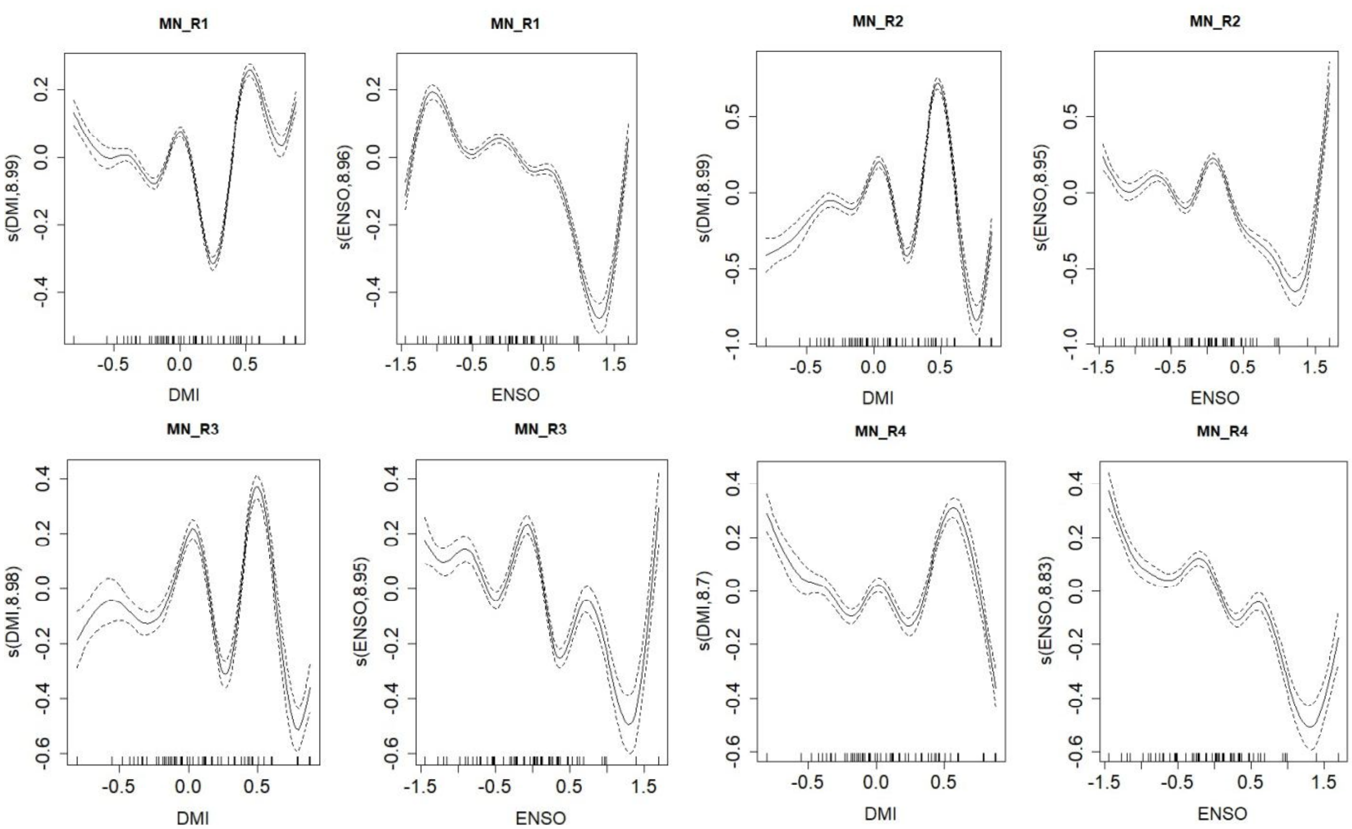

Fig. 4 (a-h): Non linear response of MN with ENSO and DMI (IOD) using GAMs with Poisson distribution at regional scale.

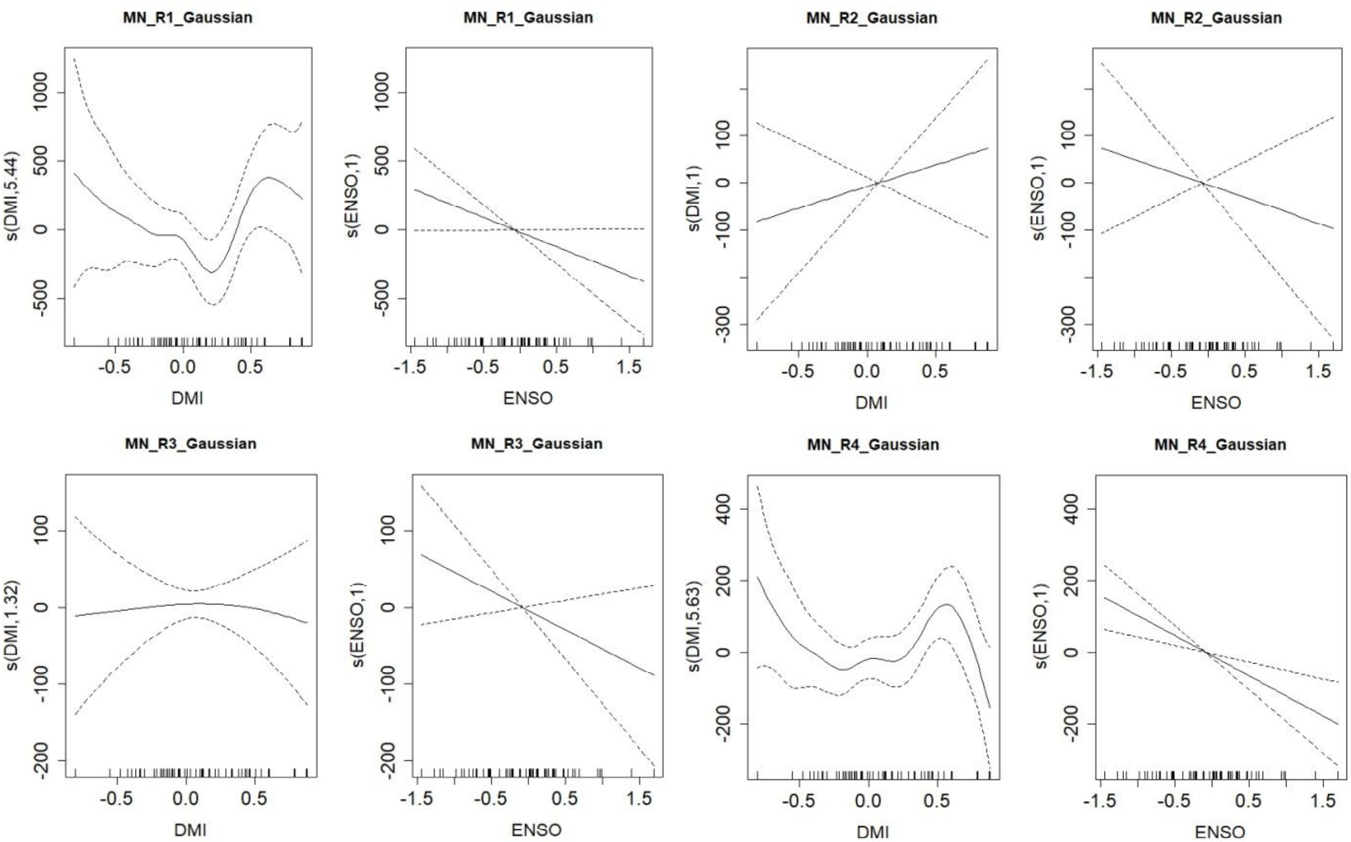

Fig. 5 (a-h): Non linear response of MN with ENSO and IOD using GAMs with Guassian distribution at regional scale.

teleconnection of MN-ENSO-IOD at region scale as well as at basin scale.

CONCLUSION

The comprehensive analysis of nonlinear influences of ENSO and IOD on rainfall events at different thresholds (LREs, MREs and HREs) and monsoon rainfall has been carried out using GAMs over Krishna river basin. The p-values and deviance explainedby the GAMs revealed that, both ENSO and IOD has displayed significant ($p < 0.001$) non-linear responses to the LREs, MREs, HREs and MNin the study area. Further, study outcome suggests that GAMs with Poisson distribution is superior to GAMs with the other distributions for assessing non-linear influence of ENSO-IOD with MN and rainfall events over Krishna river basin.

The non-linear influence of IOD (pIOD and nIOD phase) on LREs, MREs, HREs and MN were found positive for some regions and negative for other regions in the study area. Overall, study results highlighted the utility of GAMs with different distributions in assessing the tele-connection of ENSO-MN-IOD at regional scale of the Indian subcontinent. The strength of GAMs in modelling the relationship in compared with traditional regression methods.

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