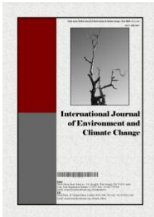

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Identifying and Using Suitable Oceanic Domains for Prediction of the Indian Monsoon Rainfall over Tamil Nadu

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Rainfall prediction are vital for agriculture which is one of the primary sectors greatly affected by climate variability and extremes. Agriculture plays a vital role in shaping the economy of India which is often affected by monsoon. Sea surface temperature (SST) plays a vital role in rainfall predictability over the land surface. A total of twelve different domains of oceanic influences of SST on monsoon rainfall over Tamil Nadu were selected for analysis. The SST of different lead times (February, March, April, and May for southwest monsoon (SWM) and June, July, August, and September for northeast monsoon (NEM) from the ERSSTv5 and ECMWF-SEAS5 model with the Canonical Correlation Analysis (CCA) were used in the Climate Predictability Tool (CPT) to identify the best predictor domains for the prediction of SWM and NEM rainfall over Tamil Nadu. The model training utilized the first 40 years (1981-2020) SST and rainfall data and prediction was done for the 2021 seasons. The results of the study revealed from Kendall tau goodness index and CCA score, the predictor domains comprised of a combination of oceanic domains, this were the Indian,

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Arabian, Bay of Bengal, and Pacific Oceans recorded the best CCA score and the goodness index. Is therefore recommended that, these domains which have the highest overall predictability can be used by the National meteorological services to early warning and monsoon rainfall information over Tamil Nadu.

Keywords: SST; Climate predictability tool; CCA; goodness index; SWM; NEM.

1. INTRODUCTION

India being an agro-economic nation, seasonal scale rainfall forecasting is inextricably tied to the country's socio-economic progress [1]. The Indian agriculture is tremendously exposed to the negative impact of climate change and variability like seasonal water shortages, rising temperatures, and added severe droughts which pose a serious threat to the country's food security [2]. Rainfall forecasts are important part of the hydrological forecasting systems and are generally used to examine the hydrological response to weather and climate conditions on a local, regional, and global scale[3]. As a result, seasonal rainfall is significant, and it necessitates the inclusion of average periods whose significance varies by geography[4]. Seasonal rainfall forecasting with acceptable accuracy helps in farm-level decision-making which can head off not only crop failure but also to increase the productivity to sustain the food production under future climate expected with more weather abnormalities.

Rain-fed agriculture accounts for one-third of all agricultural areas on the Indian mainland and agricultural activities are strictly tied to the seasonality of the monsoon [1]. Tamil Nadu is a tropical semi-arid region that is characterized by a generally tropical climate and receives rainfall during both the Southwest monsoon (SWM) and Northeast monsoon (NEM). The two seasons accounts for 35 percent (342 mm) and 48 percent (447.4 mm) of annual rainfall respectively and 15 percent annual rainfall from the summer season, with the state average annual rainfall totalling to 943.7 mm [5]. A greater understanding of the SWM and NEM rainfall patterns and their predictability is therefore important for socio-economic decisions and other policies that benefit the country and its people.

The science of estimating the seasonal rainfall for a forthcoming period is known as seasonal rainfall forecasting. There exists three methods of seasonal forecasting which are there: Empirical (or Statistical), Dynamical (GCM), and Hybrid method[6]. In empirical method, statistical techniques were used. In dynamical method, General Circulation Model (GCM) provides a forecast for large scale with coarse resolution and in hybrid method, combination of both the techniques were used; however statistical downscaling of dynamical forecast gives localized rainfall forecast from GCM products. Such downscaling can be done using CPT[7]. Monsoon rainfall is treated as a complex process that has been significantly influenced by various meteorological and oceanographical variables of land, ocean, and atmosphere [8]. Variations in SST throughout the equatorial Pacific and Indian Oceans have been connected to interannual variability of Indian Summer Monsoonal rainfall [9]. Because the ocean covers more than 70 percent of the earth's surface area and exchanges energy with the atmosphere constantly, the air and SST observations are critical variables in climate research. Tropical oceans (Atlantic, Pacific, and Indian) appear to be the primary drivers at interannual time scales (Seasonal scale), with their SST anomalies contributing to changes in cumulative seasonal rainfall [4].

Climate teleconnections such as the El Nino–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) which are related to SST changes are frequently used to make reliable seasonal forecasts [10]. And both ENSO and IOD are synergistic predictors in the monsoon core region [11]. Sea surface temperature climatology is a crucial prerequisite for ocean modelling. It may also be beneficial to investigate the climatic dynamics impacting climate extreme events such as droughts, floods, and other extreme rainfall events that have notably been experienced in the Indian subcontinent and sub-Saharan Africa region [12]. Thus, SST is one of the key variables needed when developing seasonal to decadal climate forecasts. Various model like ARIMA, Regional Climate Model, Climate forecasting system and Weather research and forecasting model were available for forecasting seasonal rainfall for Tamil Nadu. Since CPT can be used generate quality controlled and consistent seasonal climate forecasts downscaled to specific locations, or for larger regions, and also capability to verify past sets of seasonal forecasts.

Adjustment of predictor domain based on model performance is one of the main key inputs for developing seasonal climate forecast [13]. Regardless, the skill of any model is based on the selection of suitable predictor or atmospheric variables. The present study aims to identify the best SST domain from 12 major locations of the global ocean using CCA. These domains are believed to have a significant influence on Tamil Nadu region SWM and NEM rainfall. Since the monsoon is driven by a range of different meteorological factors, this study considers the influence of SST.

And this study was structured as follows: Initially fixing different domains over different ocean and various lead time of SST for analysis. After that the first section is describing goodness index and the second section is describing CCA score for identifying the suitable predictor domain and its association with SWM and NEM rainfall for Tamil Nadu.

2. MATERIALS AND METHODS

2.1 Study Area

The research was intended to identify the best oceanic domain to predict the seasonal rainfall for 32 districts of Tamil Nadu state, which is positioned in India's southern peninsular region. The total geographical area of Tamil Nadu is 130,058 Sq. Km, distributed between the latitudes of 8° 5' N and 13° 35' N and longitudes of 76° 15' and 80°20' E. Tamil Nadu state is divided climatically into seven Agro Climate Zones (ACZ) *viz*., Cauvery Delta Zone (CDZ), High Altitude Zone (HAZ), High Rainfall Zone (HRZ), North Eastern Zone (NEZ), North Western Zone (NWZ), Southern Zone (SZ) and Western Zone (WZ) were given in Fig. 13.

2.2 Data Sets

In the present study, the Climate Predictability Tool (CPT) developed by International Research Institute for Climate and Society, Columbia was used to generate the seasonal rainfall forecasts. It allows building a seasonal climate forecast model and has the facility for validation and forecast generation using the updated data. The SST of twelve different domains (Table 1) drawn around the Arabian Sea, Bay of Bengal, Indian Ocean, and the Pacific Oceans with different lead times from two models namely ERSSTv5 model (2°x2°spatial resolution) and ECMWF-SEAS5 model (Observed and GCM output SST as predictor) using CPT Version 17.5.1. The predictand was SWM (June-July-August-September) and NEM (October-November-December) rainfall data of 32 districts of Tamil Nadu from 1981 to 2020 (Table 2).

2.3 Analysis Method

In the CPT, Canonical correlation analysis (CCA) has been used to calculate the association between two multivariate sets of (or "canonical") variables, X and Y that is SST and rainfall.

$$X(SST) = (X1, X2. X3 \ldots Xn)$$
$$Y(Rainfall) = (Y1, Y2, Y3 \ldots Yn)$$

Table 1. Predictor (P1-P12) and Predictand (P13) Domain

S.NO	Predictor Region	Domain
P1	NINO 1+2 region	0°-10°S,90°W-80°W
P2	NINO 3 region	5°N-5°S,150°W-90°W
P3	NINO 3.4 region	5°N-5°S,170°W-120°W
P4	NINO 4 region	5°N-5°S,160°W-150°W
P5	Bay of Bengal region	26°N-8°N,80°E-96° E
P6	Arabian Sea region	26°N-8°N,40°E-76°E
P7	Equatorial SE Indian Ocean SST	100°E–120°E, 20°S–10°S
P8	The western equatorial Indian Ocean	50°E-70°E, 10°S-10°N
P9	The south eastern equatorial Indian Ocean	90°E-110°E, 10°S-0°N
P10	Arabian Sea+ Bay of Bengal +Indian ocean	27°N-43°S,37°W-115°E
P11	Pacific Ocean	46°N-46°S,119°W-282°E
P12	Pacific Ocean +Arabian Sea +Bay of Bengal +Indian ocean	27°N-45°S,30°W-293°E
P13	Predictand domain	14°N- 8°S,76°W-8°E

U and V are formed based on linear combinations X and Y.

$U = a^T X$ (SST), $V = b^T Y$ (Rainfall).

$$Cor(U,V) = \frac{COV(U,V)}{\sqrt{Var(U), Var(V)}}$$

The CCA model was trained using the 40 years of rainfall and SST data. A cross-validation window of 5 years was fixed for the training period. Empirical Orthogonal Function was used to determine the proper number of CCA modes based on the goodness index (GI). Principle components were calculated using a correlation matrix. Before the analysis, the predictand (observed rainfall data) were transformed into normal distribution using Gamma distribution. And also, data were zero bounded to avoid negative values. In model construction, cross-validated forecasts were calculated for the training period as hindcast and the best cross-validated result was verified with Kendall's tau goodness index. The goodness index is the average correlation transformed cross-validated forecast and observations of all the data series.

Table 2. Predictor Input file used in CCA Model with Different Lead Time

Input data used in CCA Model with different Lead Time Input Predictor Dataset (ERSSTv5 and ECMWFSEAS5)				
Predicted Season	**Predictor Lead Time (LT)**			
	LT (0)	**LT (1)**	**LT (2)**	**LT (3)**
SWM(JJAS)	May	April	March	February
NEM(OND)	September	August	July	June

Table 3. Goodness Index of results of ERSSTv5 model and ECMWF-SEAS5 SST using different lead times and different domains for SWM

SWM (Goodness Index)								
SST Source	**ERSSTv5**				**ECMWFSEAS5**			
Domain/Lead time (LT)	**LT (0)**	**LT (1)**	**LT (2)**	**LT (3)**	**LT (0)**	**LT (1)**	**LT (2)**	**LT (3)**
P1	0.077	0.021	-0.003	-0.029	0.068	0.014	0.026	0.096
P2	0.058	0.042	0.103	0.090	0.069	0.058	0.025	0.077
P3	0.047	0.023	0.051	0.063	0.065	0.027	0.034	0.058
P4	0.047	0.044	0.030	0.045	0.050	0.036	0.058	0.147
P5	0.069	0.052	0.074	0.074	0.090	0.095	0.086	0.077
P6	0.069	0.016	0.035	0.067	0.068	0.073	0.152	0.073
P7	0.060	0.016	-0.050	0.011	0.083	0.078	0.119	0.066
P8	0.136	0.085	0.049	0.016	0.087	0.046	0.085	0.073
P9	0.134	0.020	0.032	0.000	0.051	0.046	0.078	0.105
P10	0.153	0.106	0.054	0.091	0.108	0.081	0.087	0.035
P11	0.104	0.101	0.096	0.112	0.072	0.068	0.065	0.136
P12	0.101	0.068	0.086	0.090	0.080	0.064	0.070	0.108

A skill in which the correlation-based goodness measure is greater than 0.1 is the most important performance metric for the probabilistic forecast [13]. Positive values of the Goodness Index (more than 0.1) indicate better model performance than climatological data [14]. CCA defines the spatial pattern of association between SST and rainfall and CCA score outlines a prediction accuracy of CPT output. CCA score closer to one indicates better prediction [15].

The Predictor domains used include (NINO 1+2 region, NINO 3 region, NINO 3.4 region, NINO 4 region, Bay of Bengal region, Arabian Sea region, Equatorial SE Indian Ocean SST, the western equatorial Indian Ocean, the south-eastern equatorial Indian Ocean, Arabian+ Bay of Bengal +Indian ocean, Pacific Ocean, Pacific Ocean+ Arabian+ Bay of Bengal +Indian ocean) which are considered as P1-P12 respectively as depicted in Fig. 1-12 from left to right). Fig.13 showed predictand region.

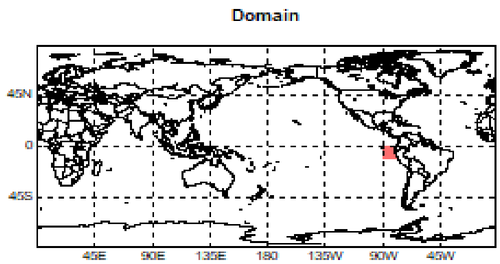

Fig. 1. Predictor domain1 (P1)

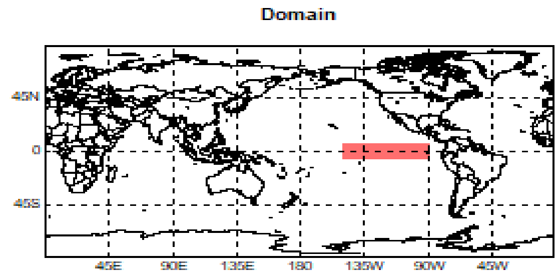

Fig. 2. Predictor domain2 (P2)

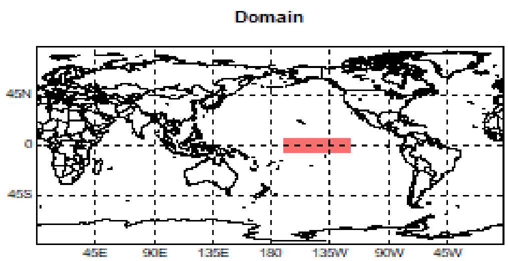

Fig. 3. Predictor domain3 (P3)

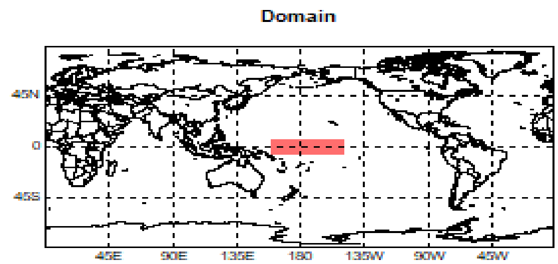

Fig. 4. Predictor domain4 (P4)

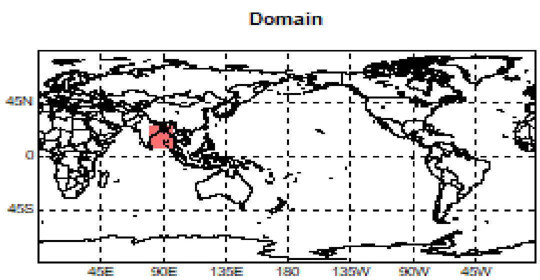

Fig. 5. Predictor domain5 (P5)

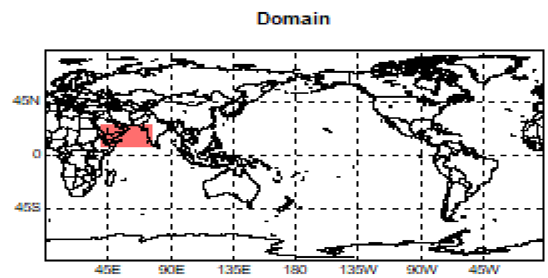

Fig. 6. Predictor domain6 (P6)

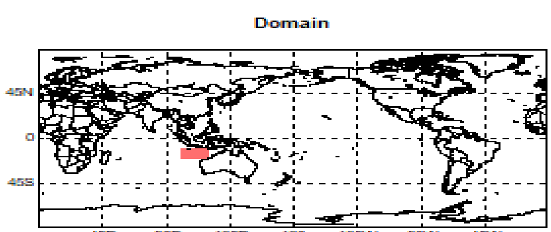

Fig. 7. Predictor domain7 (P7)

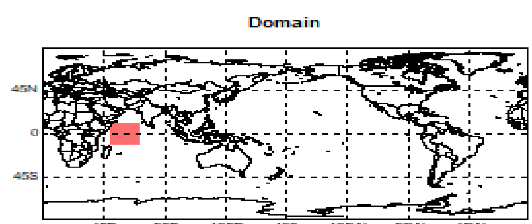

Fig. 8. Predictor domain8 (P8)

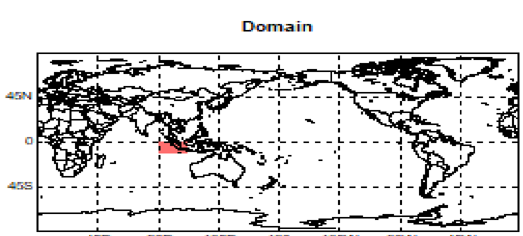

Fig. 9. Predictor domain9 (P9)

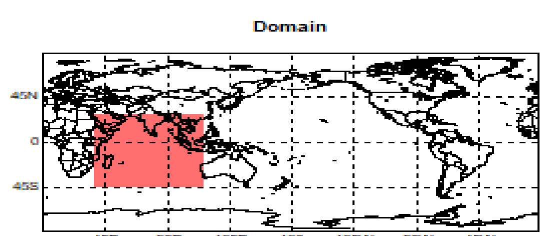

Fig. 10. Predictor domain10 (P10)

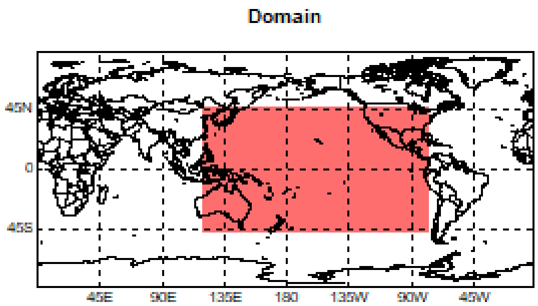

Fig. 11. Predictor domain11 (P11)

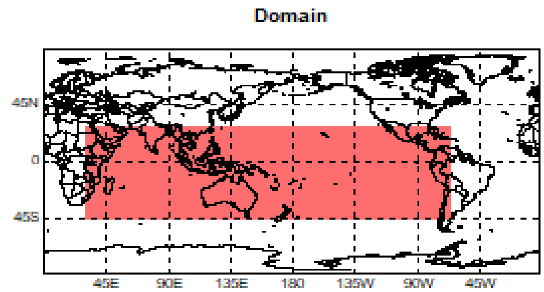

Fig. 12. Predictor domain12 (P12)

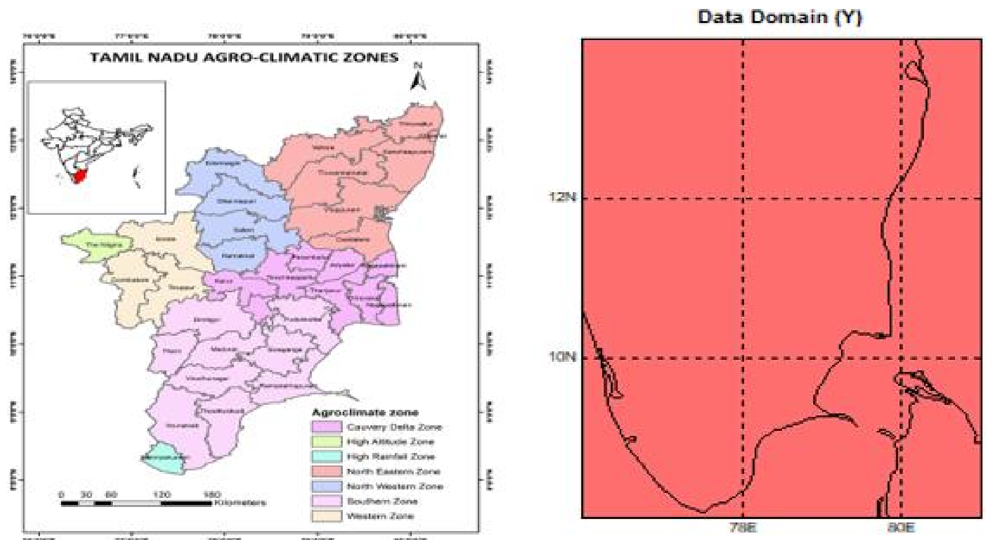

Fig. 13. Predictand domain

3. RESULT AND DISCUSSION

3.1 Goodness Index (GI)

a) South West Monsoon

When ERSSTv5 Model SST was used as a source, the goodness index of the CCA analysis observed were -0.05 to 0.153 for SWM season over different lead times. Highest GI (0.153) was observed in the P10 domain when zero lead time (LT (0)) was used as input and the lowest GI (-0.05) was observed in the P7 domain when LT (2) values were taken (Table 3).

By taking average GI values over different lead times, the domain P11 registered the highest value of 0.103 closely followed by the P10 domain with a value of 0.101. The next highest value of 0.086 was given by the analysis done with domain P12 (Fig. 14). About the different initial conditions, the average highest GI of 0.0879 was registered in the May initial condition (Zero lead time).

When ECMWF-SEAS5 SST was used as input to the model, the GI ranged from 0.014 to 0.152. The highest GI (0.152) was observed in the P6 domain with lead time two (LT (2)) and the lowest GI (0.014) was observed in the P1 domain in LT (1) (Table.3).

By taking average GI values over different lead times, the domain P6 registered the highest value of 0.092 followed by the P5 and P7 domain with GI of 0.087. The next highest GI of 0.085 was obtained from the domain P11. With regard to the different initial conditions across the various domains, the highest averageGI of 0.0876 was observed in the February initial condition (Lead time three) (Fig. 15).

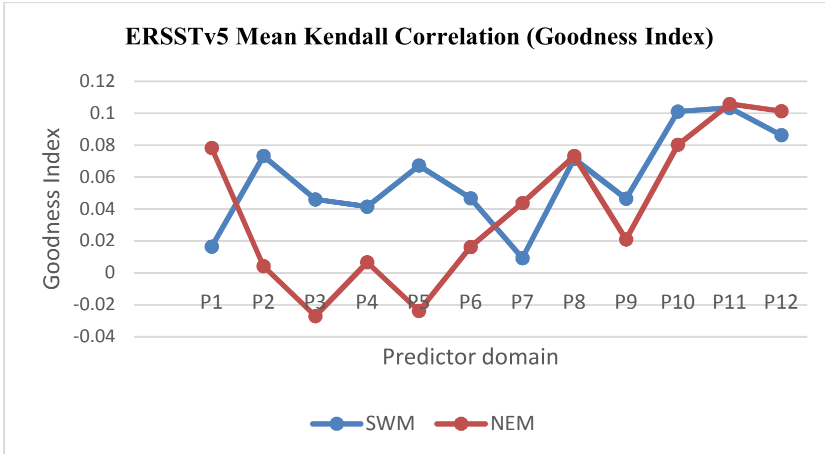

Fig. 14. Mean of Goodness index (Kendall correlation) for SWM and NEM using ERSSTv5

Table 4. Goodness Index of results of ERSSTv5 model and ECMWFSEAS5 SST using different lead times and different domains for NEM

NEM (Goodness Index)								
SST Source	**ERSSTv5**				**ECMWFSEAS5**			
Domain/Lead time (LT)	**LT (0)**	**LT (1)**	**LT (2)**	**LT (3)**	**LT (0)**	**LT (1)**	**LT (2)**	**LT (3)**
P1	0.154	0.114	-0.079	0.124	0.070	0.020	0.011	-0.018
P2	0.050	-0.024	-0.032	0.023	0.051	0.020	0.036	-0.007
P3	0.043	-0.066	-0.069	-0.016	0.033	-0.006	0.007	-0.004
P4	0.048	-0.014	-0.012	0.005	0.083	0.040	0.039	0.090
P5	-0.031	-0.013	-0.034	-0.017	0.099	0.087	0.003	0.045
P6	0.005	0.023	0.017	0.020	0.093	0.119	0.089	0.075
P7	0.045	0.068	-0.004	0.066	0.134	0.159	0.057	0.020
P8	0.126	0.035	0.041	0.091	0.088	0.091	0.073	0.090
P9	0.027	0.037	-0.007	0.027	0.093	0.048	0.069	0.066
P10	0.110	0.069	0.036	0.106	0.177	0.106	0.118	0.087
P11	0.168	0.076	0.122	0.057	0.150	0.170	0.121	0.093
P12	0.139	0.092	0.053	0.121	0.163	0.079	0.121	0.090

Table 5. CCA Score of results of ERSSTv5 model and ECMWF-SEAS5 SST using different lead times and different domains for SWM

SWM (CCA Score)								
SST Source	**ERSSTv5**				**ECMWFSEAS5**			
Domain/Lead time (LT)	**LT (0)**	**LT (1)**	**LT (2)**	**LT (3)**	**LT (0)**	**LT (1)**	**LT (2)**	**LT (3)**
P1	0.26	0.20	0.40	0.47	0.48	0.41	0.17	0.54
P2	0.16	0.17	0.39	0.52	0.15	0.64	0.10	0.88
P3	0.38	0.12	0.34	0.80	0.61	0.11	0.07	0.72
P4	0.74	0.59	0.48	0.39	0.53	0.38	0.46	0.57
P5	0.24	0.67	0.47	0.54	0.49	0.86	0.72	0.30
P6	0.53	0.42	0.36	0.63	0.63	0.83	0.85	0.72
P7	0.28	0.44	0.53	0.61	0.28	0.60	0.65	0.56
P8	0.42	0.46	0.59	0.13	0.26	0.20	0.76	0.81
P9	0.45	0.26	0.40	0.37	0.31	0.20	0.29	0.66
P10	0.90	0.82	0.60	0.68	0.80	0.98	0.98	0.95
P11	0.96	0.95	0.94	0.91	0.91	0.22	0.47	0.90
P12	0.91	0.98	0.96	0.94	0.87	0.17	0.85	0.77

Table 6. CCA Score of results of ERSSTv5 model and ECMWF-SEAS5 SST using different lead times and different domains for SWM

	NEM (CCA Score)							
SST Source	**ERSSTv5**				**ECMWFSEAS5**			
Domain/Lead time (LT)	**LT (0)**	**LT (1)**	**LT (2)**	**LT (3)**	**LT (0)**	**LT (1)**	**LT (2)**	**LT (3)**
P1	0.51	0.54	0.32	0.14	0.67	0.64	0.55	0.50
P2	0.72	0.57	0.43	0.56	0.84	0.57	0.76	0.59
P3	0.68	0.54	0.42	0.62	0.78	0.79	0.83	0.85
P4	0.31	0.64	0.64	0.60	0.32	0.71	0.58	0.57
P5	0.43	0.51	0.34	0.49	0.66	0.32	0.66	0.74
P6	0.55	0.51	0.43	0.37	0.71	0.88	0.61	0.48
P7	0.51	0.36	0.45	0.38	0.59	0.73	0.39	0.62
P8	0.62	0.62	0.49	0.58	0.66	0.67	0.48	0.93
P9	0.34	0.63	0.55	0.49	0.71	0.65	0.75	0.66
P10	0.95	0.78	0.76	0.95	0.86	0.94	0.98	0.81
P11	0.96	0.94	0.98	0.73	0.96	0.96	0.93	0.98
P12	0.97	0.93	0.61	0.86	0.97	0.98	0.91	0.98

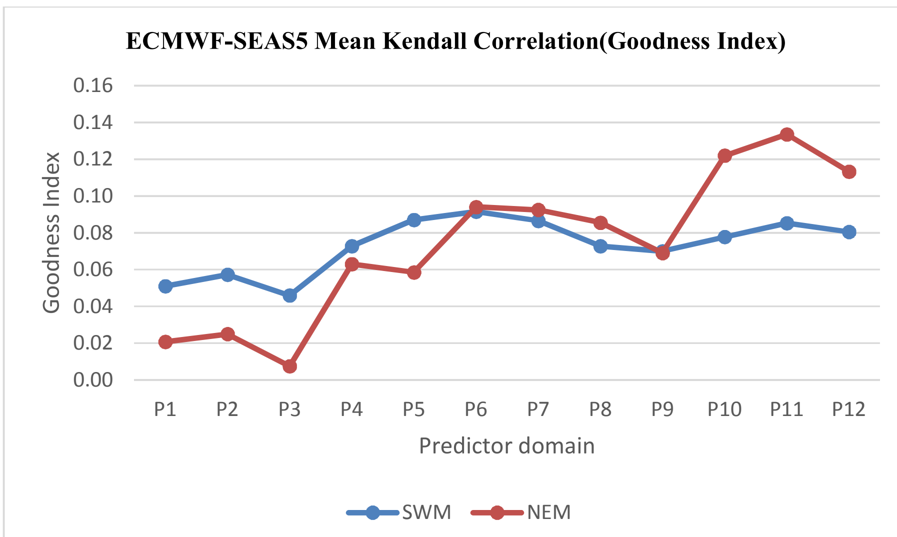

Fig. 15. Mean of Goodness index (Kendall correlation) for SWM and NEM using ECMWF-SEAS5

From the above result based on average GI values, the best domain for SWM was P11 (46°N-46°S,119°W-282°E) domain for ERSSTv5 source and P6 (26°N-8°N,40°E-76°E) for ECMWF-SEAS5.

b) Northwest Monsoon

Concerning the NEM, the observed GI for CCA analysis ranged from -0.079 to 0.168 with ERSSTv5 SST data source. Highest GI (0.168) across the different initial conditions was observed in the P11 domain with zero lead time and the lowest GI (-0.079) was observed in the P1 domain with LT (2) (Table 4).

By taking average GI values over different lead times, the domain P11 registered the highest value of 0.106 closely followed by the P12 domain with a GI value of 0.101. Analysis done with the P10 domain gives the next higher GI value of 0.08. With regard to the initial conditions, the highest GI of 0.0737 was registered by average values of analysis done with September as the initial condition (Zero Lead time) (Fig. 14).

In the ECMWF-SEAS5 model, observed GI was ranged from -0.018 to 0.177. The highest GI (0.177) was obtained from the P10 domain with September initial condition and the lowest GI (-0.018) was observed in the P1 domain in June initial condition (Table 4). Overall averaged highest value of 0.134 was registered in the P11 domain and followed by the P10 domain with a value of 0.122 and P12 domain (0.113). With regard to the initial conditions, the highest averaged goodness Index of 0.103 was registered in the September initial conditions (Zero Lead time) (Fig. 15).

From the above result, based on average GI values overall best domain for NEM was identified in both the sources was P11. In both monsoons next to P10 and P11, the highest GI values are observed in the P12 domain. So that, this domain is also considered the best domain. And as with P10 and P11, this domain also covers the entire four Oceans domains (Fig. 12).

Related work was done by Tim and Guenni et al. [16] using CCA score and GI for identifying the influences of the Pacific and the Atlantic Ocean SST on rainfall prediction over Venezuela using CPT with CCA technique and found that in most cases the North Tropical Atlantic has a stronger influence than the Nino regions.

And corresponding work done by Esquivel et al. [13] to investigate seasonal rainfall across Columbia, using observed and modelled (NCEP-CFSv2) SSTs, as well as CFSv2 forecasted precipitation fields. In that, 74.4 percent of the prediction cases studied had correlation-based goodness index (Kendall's tau) values greater than 0.1, 38.8 percent greater than 0.2, and 18.8 percent greater than 0.3. Prominently, the ERSST and CFSv2-driven forecasts produced similar findings, showing that both can provide useful forecasts for Colombia.

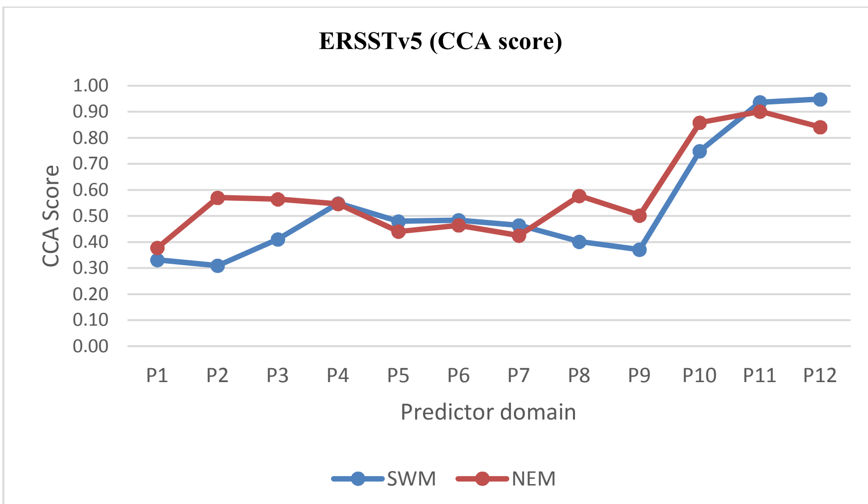

Fig. 16. Mean of CCA score for SWM and NEM using ERSSTv5

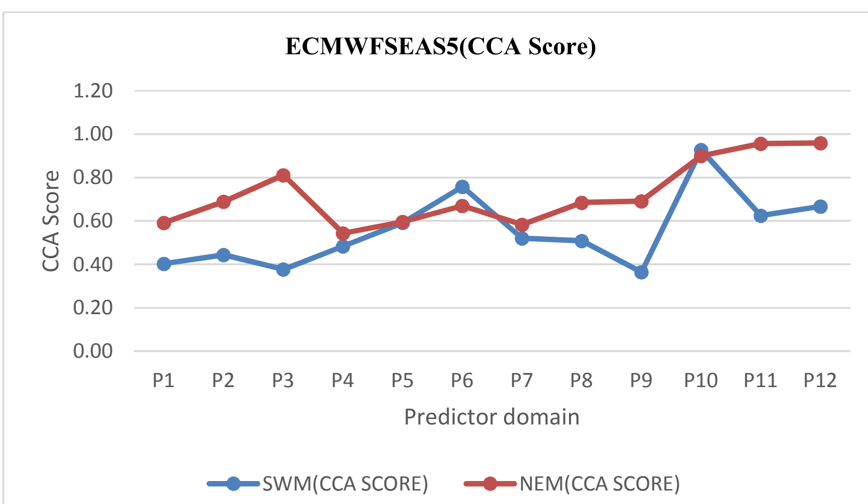

Fig. 17. Mean of CCA score for SWM and NEM using ECMWF-SEAS5

3.2 Canonical Correlation Analysis Score (CCA Score)

a) South West Monsoon

The prediction results from the CPT indicated that during SWM, the correlation coefficient of the CCA analysis observed was in the range of 0.12 to 0.98 for the ERSSTv5 source. The highest CCA Score was observed in the analysis done withthe P12 domain (0.98) and the lowest score was observed in the P3 (0.12) domain (Table 5). By taking an average of CCA the domain P12 registered the highest value of 0.95 closely followed by the P11 domain with a correlation coefficient value of 0.94. The next highest correlation coefficient of 0.75 was registered bythe P10 domain (Fig. 16).

With regard to the ECMWF-SEAS5 based predictions, the observed CCA score was in the range of 0.07 (P3) to 0.98 (P10) (Table.5). Based on the average CCA score, the highest CCA score (0.93) was observed in the P10 domain followed by P6 and P12 (Fig. 17). When the average value of lead-time across the domains was taken, February initial conditions performs well, However, in the domain P10, March and April initial conditions performs best with a value of 0.98 (Table 5).

The average value of the CCA score of different initial conditions across various domains selected didn’t show any significant variations. However, the average of the three best domains selected based on the average GI, the registered value of 0.92 observed in April and May initial conditions in ERSSTv5 source and in ECMWF-SEAS5 source February initial conditions showed the highest value of 0.79.

b) Northwest Monsoon

CCA score of the NEM ranged from 0.14 (P1) to 0.98(P11) when the ERSSTv5 source was used (Table.6). Based on the average CCA score, the highest CCA score of 0.90 was observed in the P11 domain across the initial conditions and the followed by P10 (0.86) and P12 (0.84) domain (Fig. 16).

In ECMWF-SEAS5 based predictions, observed CCA was ranged from 0.32 (P5) to 0.98 (P10, P12) (Table 6). Based on the average CCA score, the highest CCA score (0.96) was observed in P11 & P12 domains and followed by the P10 domain (0.90) (Figure.17). With regard to the initial conditions, the average of the three best domains showed the highest average correlation coefficient value in September initial conditions in ERSSTv5 and August initial condition for ECMWF-SEAS5 source.

From the above results, based on the average CCA score best domains were identified in both the sources were P10, P11, P12. When the obtained score was high means model can predict rainfall with good skill. It can be used to forecast seasonal rainfall with acceptable accuracy and also to avoid various extreme events caused by monsoon rainfall over agriculture. Comparable work done by Rustiana et al. [17] for prediction of rainfall over the Cimanuk watershed region using CPT tool with the CCA technique with an average CCA score of 0.7. A similar analysis was done to identify the best predictor for Sri Lanka September rainfall. In that SST over the equatorial central Pacific (15^{o} N-15^{o} S,160^{o} E-230^{o} W) showed the highest overall predictability with good skill [7].

Monsoon in India is a highly variable and complicated system that is influenced by several atmospheric and oceanic phenomena. A warm pool of SST over the Indian Ocean and SST anomalies in the Western Arabian Sea [12] and the Eastern and Central Pacific El Nino Southern Oscillation, SST over the Bay of Bengal and the Arabian Sea are the primary sources of precipitation anomalies of the Indian monsoon rainfall [18]. El Nino (La Nina) condition over the Pacific ocean had a good (bad) impact on seasonal rainfall [19]. SST anomalies over the Indian ocean affect the Indian ocean dipole effect which invariably affectsthe Indian monsoon. During the Positive phase (Negative phase) increased (decreased) rainfall was observed in ISMR [20]. Based on the above studies monsoon rainfall is influenced by the entire four ocean SST anomaly and their internal dependent ocean mechanism. In this study also, the predictor domain which covers the combined oceanic domain (Pacific Ocean, Arabian Sea, Bay of Bengal, and Indian Ocean) showed the highest GI and CCA score.

4. CONCLUSION

In the present study, CPT was used to investigate the relationship between SST and Monsoon rainfall based on the Goodness Index, and CCA score of 12 predictor domains. The results indicated that both the GI and CCA were consistently higher in the region P10 (27^{o}N-

43°S,37°W-115°E), P11 (46°N-46°S,119°W-282°E), P12 (27°N-45°S,30°W-293°E) which includes the Pacific Ocean, Arabian Sea, Bay of Bengal, and the Indian Ocean. Hence the prediction of monsoon rainfall for Tamil Nadu using CPT with SST data can be done by using these domains which include all four oceanic regions. And it can be concluded that SST of the combined oceanic domain can bea promising predictor for monsoon rainfall over Tamil Nadu.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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