Contrasting features of hydroclimatic teleconnections and the predictability of seasonal rainfall over east and west Japan

Rajib Maity¹ | Kironmala Chanda² | Riya Dutta¹ | J. V. Ratnam³ | Masami Nonaka³ | Swadhin Behera³

¹Department of Civil Engineering, Indian Institute of Technology Kharagpur, Kharagpur, India
²Department of Civil Engineering, Indian Institute of Technology (Indian School of Mines), Dhanbad, India
³Research Institute for Value-Added-Information Generation, Application Laboratory, Japan Agency for Marine-Earth Science and Technology (JAMSTEC), Yokohama, Japan

Correspondence
Rajib Maity, Department of Civil Engineering, Indian Institute of Technology Kharagpur, Kharagpur 721302, West Bengal, India. Email: rajib@civil.iitkgp.ac.in, rajibmaity@gmail.com

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Abstract
Hydroclimatic teleconnections between global sea surface temperature (SST) anomaly fields and monthly rainfall over east and west Japan (divided along 138° E longitude) are identified for summer (June–August) and winter (December–February) using the concept of global climate pattern (GCP). The analysis indicates that the hydroclimatic teleconnections over both regions vary at both intra- and inter-seasonal time scales. In addition, the teleconnections over the two regions have differing origins. The teleconnection features associated with rainfall anomalies over west Japan have origins in the tropical Pacific and Indian oceans, whereas those over east Japan are associated with high-latitude SST anomalies. The early summer (winter) rainfall over west Japan is linked to the El Niño Modoki (La Niña Modoki) phenomena, whereas the early summer and winter rainfall anomalies over east Japan are associated with the SST anomaly over the eastern subtropical Pacific and South Pacific oceans, respectively. Having identified the teleconnections, prediction model approaches—a machine-learning approach, namely support vector regression (SVR), and a hybrid graphical modelling/C-Vine copula (GM-Copula)—were developed to forecast the rainfall over both east and west Japan. The predictors were derived from the monthly SST anomalies at different lags (1–6 months), and whereas the hidden, nonlinear relationship was well captured by the SVR approach, the complex association was decidedly better captured by the GM-Copula approach. Hence, it is recommended for forecasting the rainfall over east and west Japan.

KEYWORDS
global climate pattern, hydroclimatic teleconnection, Japan, machine learning, rainfall prediction, sea surface temperature
1 INTRODUCTION

Globally, regional hydrological processes such as droughts and floods are associated with variations in the large-scale coupled oceanic–atmospheric circulation patterns (Philipp et al., 2007; Brandimarte et al., 2011; Willems, 2013; Qiu et al., 2014; Lee and Julien, 2016; Alizadeh-Chooobari, 2017; Babolcsai and Hirsch, 2018; Dogar et al., 2018). The teleconnections from the leading modes of climate variability, such as the El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), Pacific Decadal Oscillation (PDO), Dipole Mode Index (DMI), Atlantic Multidecadal Oscillation (AMO) and North Atlantic Oscillation (NAO), affect the spatial and temporal distribution of precipitation globally, leading to associated hydrological extremes (e.g. Poveda et al., 2001; Knippertz et al., 2003; Maity et al., 2007; Zhang et al., 2010; Ban et al., 2015; Xiao et al., 2017; Alizadeh-Chooobari et al., 2018; De Beurs et al., 2018; Frazier et al., 2018; Kim et al., 2018; Alizadeh-Chooobari and Adibi, 2019). For instance, considering the regions of China, Australia, Latin America and India, various local and global climatic forcings (e.g. the ENSO, AMO, PDO, NAO and IOD) impact rainfall at various spatio-temporal scales (Gu et al., 2009; Wu and Zhang, 2010; Fu et al., 2013; King et al., 2014; Ye, 2014; Cid-Serrano et al., 2015; Dutta and Maity, 2018; Nair et al., 2018).

The variability of rainfall over East Asia, especially over Japan, is linked to sea surface temperature (SST) anomalies in the Pacific through Pacific–Japan (PJ) and East Asia–Pacific (EAP) teleconnections (Nitta, 1987; Feng and Hu, 2004; Huang, 2004; Ha et al., 2012; Zhang et al., 2014; Wu et al., 2016; Li et al., 2018). Studies also show statistically significant correlation between the Southern Oscillation Index (SOI) and monthly precipitation over East Asia; however, the association varies significantly from region to region (Xu et al., 2004; Jin et al., 2005; Kawamura et al., 2005). The impact of global climatic forcings, such as the ENSO, are well established for the low-latitude areas around the Pacific (McKerchar et al., 1996; Chiew et al., 1998; Poveda et al., 2001). However, the connection between El Niño and unusual conditions in mid-latitudes needs further understanding (Iseri et al., 2007). The present study attempted to further the understanding of the teleconnections over the mid-latitudes, especially those affecting the precipitation over Japan, using the concept of global climate pattern (GCP) (Chanda and Maity, 2015a).

The climate of Japan is affected by several modes of climate variability. For example, the summer can be cooler and rainier during El Niño years, according to the Japan Meteorological Agency (JMA; https://www.jma.go.jp/jma/index.html). The IOD is also known to affect rainfall variability over Japan (Saji and Yamagata, 2003). The other modes of climate variability known to influence the rainfall in this region are the PDO, North Pacific Index (NPI) and DMI (Iseri et al., 2007). However, it is difficult to explain completely the influence of large-scale climatic indices as the regional impacts are determined by intrinsically complex mechanisms (Liu et al., 2018). In general, the interannual rainfall variability in Japan is locked to seasons. However, below- and above-normal rainfall events over east and west Japan are not concurrent, neither are their causal agents identical. Furthermore, the rainfall patterns in the two seasons, June–August (summer) and December–February (winter), are quite distinct and the hydroclimatological precursors of month-wise rainfall could be distinct even within the same season. Thus, inter- and intra-seasonal rainfall variations in the regions of east and west Japan require an individual assessment of global hydroclimatic association in order to identify the relevant precursors to improve the prediction performance. This forms the focus of the present study. The JMA currently provides seasonal forecast in terms of the probability of below-normal, normal and above-normal precipitation (or temperature) at the monthly, three-monthly and warm/cold seasonal scale using both dynamical methods, such as the Ensemble Prediction System, JMA/MRI-CPS2 (Takaya et al., 2018), as well as statistical and empirical techniques. Different statistical and machine-learning methods have been used to carry out rainfall prediction in different regions. Methods such as step-wise regression, canonical correlation, artificial neural network and genetic programming have also been used to develop prediction models at different spatio-temporal scales (Parthasarathy et al., 1993; Kane, 2006; Ashok and Saji, 2007; Phatak et al., 2011; Kashid and Maity, 2012; Singh et al., 2012; Guhathakurta et al., 2015). A machine-learning technique such as support vector regression (SVR) has been effectively used for several hydrological predictions (Maity et al., 2010; Bhagwat and Maity, 2012; Zakaria and Shabri, 2012; Pan et al., 2013; Hosseini and Mahjouri, 2016; Kashid and Maity, 2017). For a detailed review of the applications of different machine-learning approaches in hydrology, see Raghavendra and Deka (2014). However, a limitation of most existing models is their inability to identify the complex and dynamic associations among the large-scale climatic indices and rainfall. In fact, some of the variables in the entire set of the predictor pool may often provide redundant information for rainfall prediction. Thus, prioritizing the relevant inputs, through a conditional independence structure among the variables, from the pool of possible predictors is necessary. A graphical modelling (GM) approach can be effectively used in this regard.
because it offers a conditional independence structure for parsimonious predictor selection. In the present study, an alternative approach is developed involving (1) the identification of the hydroclimatic teleconnections specifically associated with season-wise monthly rainfall; and (b) using such information as effective predictors in advanced data-driven approaches.

The objectives of the present study are: (1) to extract the hydroclimatic teleconnection features from global SST fields that influence inter- and intra-seasonal rainfall variability in Japan (east and west) using the concept of the GCP; and (2) to use the hydroclimatic teleconnection information for the development of a model for the season-wise prediction of monthly rainfall for Japan (east and west). The GCP approach provides a methodology to extract global hydroclimatic precursors from several zones to obtain a comprehensive predictor pool. Next, two different methods are adopted for the prediction of regional rainfall. The first is based on a machine-learning approach, namely the SVR, where all the predictors identified through the GCP are used irrespective of redundant information. In the second approach, the prediction is attempted using a hybrid graphical modelling/C-Vine copula (GM-Copula) approach by pruning the predictors using the conditional independence structure. Both approaches have merits, and their potential needs to be assessed for the prediction of rainfall over east and west Japan.

The paper is organized as follows. Section 2 presents the study area and data used in the analysis. Section 3 presents the methodological approach. Section 4 provides the results and discussions. Section 5 concludes.

2 | STUDY AREA AND DATA

East Japan (lying between 32° N and 46° N and between 138° E and 144° E) and west Japan (lying between 26° N and 40° N and between 126° E and 138° E) are the domains of current interest. Figure 1 shows the map and spatial extents of the two study domains. As such, there is no physical explanation for dividing east and west Japan through 138° E longitude except that the nature of rainfall over east and west Japan are different. Various methods have been used by the researchers to identify the regions with spatially coherent rainfall patterns in different countries (Klingaman et al., 2013; Lee and Julien, 2016). In Japan, Ohba et al. (2015) classified the weather patterns during the Baiu season using a self-organizing map (SOM). The present study shows a difference in the precipitation to the east and west of 138° E. West Japan experiences higher rainfall. Also, the intense high-frequency rainfall of 150 mm·day⁻¹ is mostly confined to west Japan (Ohba et al., 2015). In general, the climate of Japan is different over these two regions. For details, see the webpage of the JMA (http://www.data.jma.go.jp/gmd/cpd/longfcst/en/tourist.html, accessed June 2019). Furthermore, as per the Koppen-Geiger climate classification, Japan has three climatic zones (Kottek et al., 2006; Peel et al., 2007): (1) temperate without a dry season and with a hot summer (Cfa) (or a humid subtropical climate) covering most parts of west Japan; (2) cold without a dry season and with a hot summer, Dfa (or a humid continental climate); and (3) cold without a dry season and with a warm summer (Dfb) (or a humid continental climate). The climatic zones Dfa and Dfb cover most parts of east Japan and Hokkaido. Following this classification, the line dividing the climatic zones Cfa and Dfa, Dfb, travels approximately along 138° E. Thus, 138° E longitude is used as a separation line that approximately divides the country into east and west regions.

Monthly rainfall for east and west Japan are obtained from “Asian Precipitation—Highly-Resolved Observational Data Integration Towards Evaluation of Water Resources” (APHRODITE) (Yatagai et al., 2012), which uses a high-density-of-quality station network. The below- and above-normal precipitation events for the chosen study areas are identified by standardizing the monthly rainfall and characterizing it in terms of the standardized precipitation anomaly index (SPAI) (Chanda and Maity, 2015b) using the monthly rainfall data for the period 1979–2015.

The SST data used are the National Oceanic and Atmospheric Administration (NOAA) Extended Reconstructed V5 data, which are available at a spatial
resolution of $2^\circ$ latitude $\times 2^\circ$ longitude from 1948 to the present. These are derived from the International Comprehensive Ocean–Atmosphere Dataset (ICOADS). The data set for the period 1979–2015 was used.

3 | METHODOLOGY

The analysis was carried out for two seasons, namely boreal summer (summer, hereafter; June–August) and boreal winter (winter, hereafter; December–February) considering the two regions of Japan (east and west). Thus, there are a total of six parallel analyses for each region since both seasons have three months each.

3.1 | Categorization of monthly rainfall

To identify the below- and above-normal monthly rainfall, it was necessary to standardize the monthly precipitation. For this purpose, the SPAI is used, which is suitable for characterizing below- and above-normal rainfall events for periodic as well as non-periodic precipitation series (Chanda and Maity, 2015b). To obtain the index values, the month-wise precipitation anomalies were calculated as follows.

$$y_{ij} = (x_{ij} - \bar{x}_j)/s_j,$$  \hspace{1cm} (1)

where $y_{ij}$ is the precipitation anomaly for the $i$-th year and $j$-th time step of the year; $x_{ij}$ is the precipitation for the $i$-th year and $j$-th time step of the year; and $\bar{x}_j$ and $s_j$ are the long-term mean and standard deviation of precipitation for the $j$-th time step of the year. The anomalies were fitted to an empirical probability distribution (a gamma distribution is not used as it cannot take negative values) and then transformed to normal variates giving index values between $-\infty$ and $\infty$. Values $< 0$ indicate the dry side, while values $> 0$ indicate the wet side. For each of east and west Japan, the SPAI (at a one-month temporal scale) is calculated using monthly rainfall data from 1979 to 2015, considering 1979–2008

FIGURE 2 (a) 1–6 months lagged global fields of the sea surface temperature (SST) anomaly difference obtained by subtracting the mean global field associated with above-normal rainfall events from the mean global field associated with below-normal rainfall events in June over west Japan; (b) same as for (a), but in July over west Japan; and (c) same as for (a), but in August over west Japan.
30 years) as the base period for calculating $\bar{x}_j$ and $s_j$. The two seasons comprising summer and winter were then analysed. Considering each month of summer and winter, the SPAI $< -0.8$ are designated as below-normal events, those between $-0.8$ and 0.8 are designated as normal events, while those $> 0.8$ are designated as above-normal events. This categorization is motivated by the US Drought Monitor classification (https://droughtmonitor.unl.edu/) based on thresholds of the Standardized Precipitation Index (SPI) (McKee et al., 1993, 1995).

3.2 Global climate pattern (GCP)

The GCP approach was applied in a previous study for the Indian subcontinent. It was observed that the use of a comprehensive GCP as the input improved the future categorization of above- and below-normal rainfall events compared with the use of known existing teleconnection patterns (Chanda and Maity, 2015a). In the present study, the global SST fields were inspected at several preceding time steps (1–6 months) for each below- and above-normal rainfall event in the concerned study area. The composites of the SST anomaly fields associated with all below-normal rainfall events were obtained during the base period, that is, 1979–2008. Thus, the mean anomaly field associated with below-normal rainfall events for different temporal lags is obtained. A similar technique is applied to obtain the mean anomaly field for above-normal rainfall events at different temporal lags. For any given lag, the mean anomaly field of above-normal rainfall events is spatially subtracted (grid-point wise) from the mean anomaly field of below-normal rainfall events to obtain the mean anomaly difference field which reveals the climatic signals/patterns. Such patterns are obtained for lags of 1–6 months, considering the length of the expected teleconnections. The patterns revealed by the global fields of anomaly differences are inspected to select the influential zones. Regular, rectangular zones are selected for convenience in further processing.

**FIGURE 3** (a) 1–6 months lagged global fields of the sea surface temperature (SST) anomaly difference obtained by subtracting the mean global field associated with above-normal rainfall events from the mean global field associated with below-normal rainfall events in December over west Japan; (b) same as for (a), but in January over west Japan; and (c) same as for (a), but in February over west Japan.
although the regions with significant (at 5% level) anomaly difference are of course irregular in shape. In order to avoid dilution of the signals, the regular zones are selected from the core of the significant irregular regions. The average SST anomaly from each zone at a certain lag comprises of one predictor variable. Thus, the possible predictor pool to be used for the prediction of monthly rainfall is the SST anomaly data from different zones with different lags.

In general, the predictors with lower lags (such as 1–3 months) may be more useful in a prediction model due to their immediacy. However, prediction lead time will be more if the information comes from the pattern with higher lags. Thus, a trade-off must be worked out between the two. In the present study, it is observed from the plots that at lag 1, distinct signals are perceptible for both the cases (below and above normal). Hence, the anomaly zones from a one-month lag are mostly selected. When some strong pattern is visible at a higher lag, then that zone is also considered in the predictor pool. However, the zones at higher lags are not considered if that signature is already incorporated from lower lags.

### 3.3 Development of the prediction model

#### 3.3.1 SVR approach

Support vector machine (SVM), which is a machine learning approach, can be used for both classification and regression problems. The SVM for regression, also known as the SVR, has been previously used for several hydrological applications (Choy and Chan, 2003; Yu and Liong, 2007; Maity et al., 2010). For details of the methodology on the SVR, see Maity et al. (2010). In the present study, the SVR is used to predict the monthly rainfall using the identified predictor variables, which consist of the SST anomalies from distinct zones for specific lags. While fitting the SVR model to the training data, the goal is to find a function \( y = f(x) \), such that any observation

![Figure 4](image-url)  
**Figure 4** (a) 1–6 months lagged global fields of the sea surface temperature (SST) anomaly difference obtained by subtracting the mean global field associated with above-normal rainfall events from the mean global field associated with below-normal rainfall events in June over east Japan; (b) same as for (a), but in July over east Japan; and (c) same as for (a), but in August over east Japan.
(y) does not deviate from the predicted value ($\hat{y}$) by more than a threshold value $\varepsilon$, known as $\varepsilon$-margin for the corresponding input/predictor data ($x$). Also, the function should be as flat as possible so as not to overfit the data. In this process, a positive numeric value, known as regularization parameter, is optimized. The regularization parameter ($\lambda$) controls the penalty imposed on observations that lie outside the $\varepsilon$-margin (Maity et al., 2010). In the present study, both $\varepsilon$ and $\lambda$ are optimized for different seasons and regions.

### 3.3.2 GM-Copula approach

The GM approach, as stated above, provides a conditional independence structure, also referred to as the graph structure, among the predictor and predictand variables. A graph consists of a set of vertices and nodes, where each variable is a node and each edge is associated with a pair of nodes (Whittaker, 2009). The graph structure can be used to prioritize the inputs for the prediction model, hence reducing the redundancy of the model (Jordan, 2004; Bang-Jensen and Gutin, 2007; Whittaker, 2009). The conditional independence structure, also referred to as the graph structure, provides information on dependent (directly connected/parents to the target variable), independent (not connected to the target variable) and conditionally dependent (not directly connected to the target variable) predictors with respect to the target variable.

The graph structure among the predictors (the SST anomalies from distinct zones for specific lags) and the target variable (monthly rainfall) is developed using the maximum likelihood approach (Whittaker, 2009). In this approach, initially a fully interconnected graph structure (also referred to as a saturated model) is considered where all the nodes are connected to each other. Next, the edge exclusion deviance (EED) is used for testing if an edge can be eliminated from the saturated model (Whittaker, 2009). The threshold of the EED is 3.84 (at a 5% significance level with 1 degree of freedom), so the edges for which the EED < 3.84 are to be excluded. To

![FIGURE 5](image)

(a) 1–6 months lagged global fields of the sea surface temperature (SST) anomaly difference obtained by subtracting the mean global field associated with above-normal rainfall events from the mean global field associated with below-normal rainfall events in December over east Japan; (b) same as for (a), but in January over east Japan; and (c) same as for (a), but in February over east Japan.
check the acceptability of the obtained graph structure at a particular confidence level, a test statistic, known as the deviance, can be used (Dutta and Maity, 2018).

Next, the predictors directly connected (parent variables) to the target variable are used to develop the prediction model discarding the independent and conditionally independent variables, as identified by the graph structure. The prediction model is developed using C-Vine copula approach, in which a sequence of trees is identified to develop the conditional distribution of the target variable given the parents (Xiao, 2011; Bauer et al., 2012; Liu et al., 2015; Righi et al., 2015; Dalla Valle et al., 2016). The selection of each tree is based on a maximum deviance, can be used (Dutta and Maity, 2018).

The remaining set as the testing period.

4 RESULTS AND DISCUSSION

In order to extract the global hydroclimatic signals, below- and above-normal monthly rainfall events in the two regions of Japan during 1979–2008 are identified in terms of the SPAI. The months and years of below- and above-normal rainfall are reported in Table A1 (west Japan) and Table A2 (east Japan) in Appendix S1 in the additional supporting information. Note that the number of observed events varies from three to eight for different cases. These are indeed less in number, which is due to the shortage of data length. However, global composites are developed with the SST anomaly difference fields for below- and above-normal events in each of the six months (Figures 2a–c). Thus, for each event, several predictors (regions) are identified across the globe. Similar plots are also prepared at the seasonal scale for comparison. However, these are presented only in Figures A1–A4 in Appendix S1), as it is observed that the signals are more prominent at the monthly time scales. Global general circulation model (GCM) experiments are

| Season  | Month  | Symbol | Lag (months) | Latitude | Longitude |
|---------|--------|--------|--------------|----------|-----------|
| Summer  | June   | SST1   | 1            | 0° N to 20° N | 180° W to 140° W |
|         |       | SST2   | 1            | 25° N to 35° N | 145° E to 180° E |
|         |       | SST3   | 1            | 15° S to 5° S  | 145° W to 130° W |
|         |       | SST4   | 2            | 15° S to 5° N  | 85° E to 115° E  |
| July    | SST1   | 1      | 5° N to 15° N | 100° E to 125° E |
|         | SST2   | 2      | 5° N to 20° N | 135° E to 155° E |
|         | SST3   | 2      | 25° S to 15° S| 80° E to 110° E |
| August  | SST1   | 1      | 0° N to 15° N | 115° E to 145° E |
|         | SST2   | 1      | 40° S to 30° S| 75° E to 95° E  |
|         | SST3   | 2      | 35° N to 45° N| 160° E to 170° E |
| Winter  | December| SST1  | 1            | 5° S to 5° N  | 170° E to 170° W |
|         |        | SST2   | 1            | 45° S to 35° S| 80° E to 100° E |
|         |        | SST3   | 2            | –5° S to 10° N | 95° E to 135° E |
| January | SST1   | 1      | 15° S to 0° S | 45° E to 85° E |
|         | SST2   | 1      | 35° S to 25° S| 45° E to 85° E |
|         | SST3   | 1      | –15° S to 10° S| 180° W to 160° W |
| February| SST1   | 1      | 35° N to 45° N| 150° W to 140° W |
|         | SST2   | 2      | 0° N to 20° N | 115° E to 125° E |
|         | SST3   | 2      | 30° S to 20° S| 105° W to 85° W |

Note: The SST regions selected as the input variables for the hybrid graphical modelling/C-Vine copula (GM-Copula) model are highlighted in bold.
underway to understand the teleconnections from the identified SST regions, and the results will be reported elsewhere. In the present study, the identified hydroclimatic signals are further used for the prediction of monthly rainfall from both seasons using the SVR- and GM-Copula-based approaches.

4.1 West Japan: Hydroclimatic teleconnection for monthly rainfall in summer

The global fields of the SST anomaly difference between the below- and above-normal rainfall events in June–August are shown in Figure 2a–c, respectively, for west Japan at lags 1–6 months. When comparing Figure 2a–c with the corresponding fields for seasonal rainfall (see Figure A1 in Appendix S1 in the additional supporting information), it can be observed that a distinct boomerang pattern usually associated with the El Niño/Southern Oscillation (e.g. McBride et al., 2003; Weng et al., 2009) of a positive anomaly difference evident in Figure A1 in Appendix S1 is even more distinct in Figure 2a (June). This pattern is also visible for events in July (Figure 2b), but not so much for events in August (Figure 2c). In June (Figure 2a), strong negative anomaly differences are observed in the southern Indian and southern Atlantic oceans, and also in the western Pacific, around 30°–40° N up to a lag of five months, indicative of Pacific decadal variability. It is remarkable that these strong patterns are

| Season | Month | Symbol | Lag (months) | Latitude | Longitude |
|--------|-------|--------|--------------|----------|-----------|
| Summer | June  | SST1 1 | 0° N to 15° N | 140° E to 155° E |
|        |       | SST2 1 | 15° S to 0° S | 90° E to 125° E |
|        |       | SST3 1 | 30° S to 15° S | 70° E to 90° E |
|        |       | SST4 1 | 75° S to 45° S | 165° E to 180° E |
|        |       | SST5 1 | 15° S to 0° S | 130° W to 100° W |
|        |       | SST6 1 | 30° N to 40° N | 75° W to 45° W |
|        |       | SST7 1 | 45° N to 65° N | 40° W to 10° W |
|        |       | SST8 1 | 40° S to 25° S | 0° E to 25° E |
|        |       | SST9 2 | 5° N to 15° N | 145° W to 125° W |
|    | July  | SST1 1 | 0° N to 15° N | 100° E to 130° E |
|        |       | SST2 1 | 5° S to 5° N | 60° E to 90° E |
|        |       | SST3 1 | 55° S to 35° S | 120° E to 150° E |
|        |       | SST4 1 | 10° N to 30° N | 140° W to 120° W |
|        |       | SST5 1 | 40° S to 20° S | 110° W to 80° W |
|    | August| SST1 1 | 15° N to 30° N | 140° W to 120° W |
|        |       | SST2 1 | 10° N to 20° N | 120° E to 150° E |
|        |       | SST3 1 | 15° S to 0° S | 135° E to 175° E |
|        |       | SST4 2 | 45° S to 30° S | 45° E to 75° E |
|    | Winter| December| SST1 1 | 5° S to 5° N | 60° E to 90° E |
|        |       | SST2 1 | 20° N to 40° N | 140° W to 120° W |
|        |       | SST3 1 | 10° S to 5° N | 170° E to 170° W |
|        |       | SST4 1 | 45° S to 25° S | 135° W to 115° W |
|        |       | SST5 2 | 10° S to 10° N | 125° E to 145° E |
|    | January| SST1 1 | 5° S to 10° N | 60° E to 85° E |
|        |       | SST2 2 | 45° N to 55° N | 170° E to 170° W |
|    | February| SST1 1 | 20° S to 5° S | 90° E to 120° E |
|        |       | SST2 1 | 15° N to 40° N | 40° W to 15° W |
|        |       | SST3 1 | 30° N to 45° N | 145° W to 135° W |
|        |       | SST4 2 | 0° N to 20° N | 90° E to 120° E |

Note: The SST regions selected as the input variables for the hybrid graphical modelling/C-Vine copula (GM-Copula) model are highlighted in bold.
largely weakened in July (Figure 2b) and become completely opposite in nature (marked by positive anomaly differences in the southern Indian and Atlantic and western Pacific oceans) in August (Figure 2c). Overall, it may be observed that early summer (June) rainfall in west Japan is linked to the central Pacific (CP) El Niño events (also known as the El Niño Modoki) rather than the classic eastern Pacific (EP) El Niño. This is in agreement with previous observations of anomalous rainfall in east Asia during the EP El Niño in response to phase changes in the AMO (Yuan and Yang, 2012; Yu et al., 2015).

4.2 | West Japan: Hydroclimatic teleconnection for monthly rainfall in winter

When comparing Figure 3a–c with Figure A2 in Appendix S1 in the additional supporting information, more distinct features are observed in case of month-wise analysis than the seasonal analysis. Figure 3a shows that rainfall anomalies in early winter are linked to a pattern of colder CP SST anomalies, flanked by warmer west and east Pacific SST anomalies, representative of the La Niña Modoki phenomenon (Ashok et al., 2007). On the other hand, events in January (Figure 3b) are associated with strong negative anomaly differences in the Indian Ocean rather than the Pacific Ocean, which may be related to the transition between El Niño and La Niña events (Yoo et al., 2010). None of the Indo-Pacific SST features are too distinct for events in February (Figure 3c), which are associated more with negative anomaly differences in the tropical Atlantic Ocean in the Southern Hemisphere.

4.3 | East Japan: Hydroclimatic teleconnection for monthly rainfall in summer

It has been observed that compared with the season-wise SST composites (see Figure A3 in Appendix S1 in the additional supporting information), the features are sharper and changing quickly from month to month in month-wise SST composites (Figure 4a–c). There is a signature of a positive SST anomaly difference in the eastern subtropical Pacific Ocean, particularly in June and July. In June (Figure 4a), negative anomalies are prominent in the eastern Equatorial regions, while in July (Figure 4b), positive anomalies are seen in higher latitudes in the Southern Hemisphere. In August (Figure 4c), the anomaly feature is seen on a smaller spatial extent and almost imperceptible beyond three months, unlike that for June and July.

The positive SST anomaly difference in the western Pacific Ocean, near Indonesia and Papua New Guinea, as well as in the southern Indian Ocean (which may be indicative of the IOD formation) is strong for June (Figure 4a), but it gradually weakens and fades through July (Figure 4b) and August (Figure 4c).

### Table 3

| Region | Season | Fold | Correlation coefficient (R) | Root mean squared error (RMSE) (cm) | Nash-Sutcliffe efficiency (NSE) | Degree of agreement (Dr) | Co-efficient of determination ($R^2$) |
|--------|--------|------|-----------------------------|----------------------------------|-------------------------------|--------------------------|-----------------------------|
| West   | Summer | Set 1 | 0.735 (0.646) | 5.231 (5.620) | 0.123 (−0.009) | 0.523 (0.455) | 0.540 (0.418) |
|        |        | Set 2 | 0.699 (0.650) | 7.020 (7.450) | 0.096 (0.055) | 0.547 (0.491) | 0.487 (0.423) |
|        |        | Set 3 | 0.712 (0.632) | 7.694 (8.248) | 0.621 (0.541) | 0.596 (0.422) | 0.507 (0.399) |
| Winter | Set 1  | 0.450 (0.373) | 2.785 (3.159) | 0.012 (−0.999) | 0.421 (0.335) | 0.203 (0.139) |
|        | Set 2  | 0.525 (0.502) | 2.961 (3.126) | 0.284 (0.279) | 0.145 (0.009) | 0.276 (0.252) |
|        | Set 3  | 0.488 (0.424) | 2.533 (2.752) | 0.493 (0.377) | 0.479 (0.332) | 0.238 (0.180) |
| East   | Summer | Set 1  | 0.563 (0.450) | 3.475 (4.080) | −1.028 (−2.690) | 0.116 (0.105) | 0.317 (0.202) |
|        |        | Set 2  | 0.429 (0.340) | 4.301 (4.630) | −0.069 (−3.620) | 0.178 (0.090) | 0.184 (0.116) |
|        |        | Set 3  | 0.510 (0.430) | 3.129 (3.717) | −0.542 (−0.770) | 0.374 (0.367) | 0.260 (0.185) |
| Winter | Set 1  | 0.494 (0.383) | 1.522 (1.739) | −0.230 (−0.659) | 0.474 (0.354) | 0.244 (0.147) |
|        | Set 2  | 0.620 (0.527) | 1.674 (2.076) | −0.963 (−3.075) | 0.148 (0.005) | 0.384 (0.278) |
|        | Set 3  | 0.521 (0.455) | 2.159 (2.408) | −0.214 (−0.833) | 0.257 (0.251) | 0.271 (0.207) |
4.4  East Japan: Hydroclimatic teleconnection for monthly rainfall in winter

It is observed that extensive positive anomaly differences in the south Pacific Ocean are associated with rainfall in December (Figure 5a) and February (Figure 5c), but not in January (Figure 5b). The signature of La Niña Modoki (cold anomalies in the CP, flanked by warm anomalies on both sides) is also evident. In the case of January, strong negative anomaly differences are noticed in the tropical Indian Ocean, which weakens after lag 3. Rainfall in February is associated with positive anomaly differences in the Indian Ocean, which peak at a four-month lag and weaken beyond that. Thus, the SST anomaly differences associated with the intra-seasonal events are remarkably contrasting, which explains the dilution of signals at the seasonal scale (December–February) (see Figure A4 in Appendix S1 in the additional supporting information). Next, the zones of importance are selected from the global climate fields for each of the six months from the anomaly difference fields of below- and

FIGURE 6  Comparison of the observed and support vector regression (SVR) predicted season-wise monthly rainfall for east and west Japan during the model testing period considering threefold (Sets 1–3) cross-validation. The correlation co-efficient (R) obtained for each case is also provided with the scatter
above-normal rainfall. These are presented for east and west Japan in Tables 1 and 2, respectively.

Another point is also important with respect to all the regions explained so far. In general, the SST anomaly regions, which are near the Equator or in the tropical regions of the Pacific and Indian oceans (Table 1), affect west Japan through the PJ teleconnection. Considering east Japan, the SST anomaly regions are mostly located in the high latitudes (Table 2), so waves along the 200 hPa jet or the fluctuations of the subtropical high in the north Pacific mostly affect the region. Thus stated, the possible link with the known teleconnection patterns revealed from the plots has been provided wherever possible; however, all the teleconnection patterns could not be attributed to known large-scale circulation phenomena. There could be a bigger pool of atmospheric–oceanic climatic precursors which are not yet well known. Further investigations on these identified features are required, which is beyond the scope of the present study. However, the predictive potential of the identified teleconnection pattern is investigated.

4.5 | Prediction model and performances

Two different approaches are adopted to assess the predictability of season-wise monthly rainfall: a machine-learning approach, namely the SVR, and a GM-Copula approach. The performances of these models are explored and discussed separately.

4.5.1 | SVR model

The strong SST anomaly signals based on the discussions above (Tables 1 and 2, respectively) are used to develop the SVR model prediction system. In order to optimize the parameters of the model, both \( \varepsilon \) and \( \lambda \) are optimized for different seasons and regions. If the training is optimum, the model performance during model training and testing should be comparable. A threefold cross-validation is also carried out to check the model performance for different folds, as mentioned in the methodology. The results are presented in Table 3. The testing periods for each fold are identified as Set 1, Set

**FIGURE 7** Graph structures obtained for each month for the summer and winter for west Japan. In each case, V1 is the target variable (rainfall of the month) and V2, V3, ..., V5 are the SST1, SST2, ..., SST4, respectively (see Table 1 for details). The parents of the target variable are used for the prediction of monthly rainfall
2 and Set 3, respectively. The SVR predicted monthly rainfall is compared with the observed rainfall for summer and winter for all three folds (Sets 1–3), again as mentioned in the methodology. The scatter plots for all these cases are shown in Figure 6. The performance statistics namely correlation co-efficient ($R$), root mean squared error (RMSE), degree of agreement (Dr), Nash–Sutcliffe efficiency (NSE) and co-efficient of determination ($R^2$) are presented in Table 3. Absence of overfitting is apparent from the results for almost all combinations of region, season and fold.

It is observed that using the SVR approach, a reasonably good prediction performance is obtained. The SVR model is found to capture only the long-term monthly mean rainfall. In general, the performance is slightly better during the summer, but poorer in winter, for both east and west Japan. In the above-mentioned analysis, all SST zones, identified through the GCP, are used for the prediction of rainfall. In order to access the prediction skill of individual predictors, another analysis is carried out where prediction models are developed using an individual predictor. The model performance for a typical month (June) and region (east Japan) for all three folds is presented in Table A3 in Appendix S1 in the additional supporting information. This typical example is taken up as a substantial number of SST zones are identified to influence the rainfall in June for east Japan. The results obtained using the individual inputs indicate significant variation in the performance between different folds (see Table A3 in Appendix S1). However, while using all the inputs (the last row of Table A3) for prediction, the model provides better and almost uniform performances across all the folds (considering all performance statistics). This is because the independent inputs each have a hydroclimatic association with the target, and this is how these are selected. They may be the different manifestations of same physical mechanism. In other words, there could be redundant information from multiple inputs, and it is clear that individual predictive potentials are not sufficient to identify the less informative and/or redundant inputs. Here lies the benefit of the GM that effectively identifies the most informative inputs while sifting out the redundant ones. Hence, the GM-Copula hybrid model is adopted and the prediction performance is compared.

**FIGURE 8** Graph structures obtained for each month for summer and winter for east Japan. In each case, V1 is the target variable (rainfall of the month) and V2, V3, ..., V10 are the SST1, SST2, ..., SST9, respectively (see Table 2 for details). The parents of the target variable are used for the prediction of monthly rainfall.
FIGURE 9  Comparison of the observed and hybrid graphical modelling/C-Vine copula (GM-Copula) predicted season-wise monthly rainfall for summer considering west Japan: (a) time-series plot of the observed and predicted rainfall during the model testing period considering threefold (Sets 1–3) cross-validation; (b) scatter plot of the observed and predicted rainfall along with the correlation co-efficient ($R$) and co-efficient of variation (CV); and (c) box plot showing the variation in the observed and predicted rainfall for each month in summer.
4.5.2 GM-Copula hybrid model

Using the identified SST zones (Tables 1 and 2), six graph structures are developed for each region (east and west Japan) and input variables (highlighted in bold) are selected based on the conditional independence among the variables. The graph structure obtained for each month, explaining the complete dependence structure among all the variables, for both the regions is shown in Figures 7 and 8, respectively. Selected input variables are different for each month of analysis with varying degree of associations. Based on the graph structures obtained for each month, probabilistic models are developed for prediction of the target variable (monthly rainfall) using the parents of the target variable as identified from the graph structure. The SST regions discarded from the input set are either “conditionally independent” or “independent” considering the monthly rainfall in east and west Japan. Note that only two to three predictors are in use considering both the seasons. Pruning down the input variables helps to avoid redundancy in the model as the same information may be provided by multiple variables, increasing the complexity of the model without improving the performance.

After selection of the input variables, a C-Vine copula is used for the prediction of the monthly rainfall given

FIGURE 10 Comparison of the observed and hybrid graphical modelling/C-Vine copula (GM-Copula) predicted season-wise monthly rainfall for winter for east Japan: (a) time-series plot of the observed and predicted rainfall during the model testing period considering threefold (Set 1–3) cross-validation; (b) scatter plot of the observed and predicted rainfall along with the correlation co-efficient (R) and coefficient of variation (CV); and (c) box plot showing the variation in the observed and predicted rainfall for each month in winter.
the parent variables. As mentioned above, the prediction model is validated using threefold cross-validation. The season-wise monthly observed and predicted rainfalls for different regions are compared using the results obtained for each fold (Figure 9 and Figure A5 in Appendix S1 in the additional supporting information, and Figure 10 and Figure A6 in Appendix S1). The prediction performance metrics are shown in Table 4. For both regions, better prediction performance is obtained for the summer. It is perhaps due to a stronger association for rainfall in June–August with the SST anomaly (Figure 9 and Figure A6 in Appendix S1). The scatter plots depict good performance in predicting monthly rainfall as the majority of the observed-predicted data are distributed around the 1:1 line. The box plot shows that the prediction model successfully captures the mean rainfall. The variation is also appropriately captured for west Japan. In winter, the predictions are in general underestimated for both west and east Japan (Figure 10 and see Figure A5 in Appendix S1). Certain peak values in February 1985, February 1990, January 1998, and so on could not be captured by the model. However, the mean and variance, as shown by the box plot, are very well captured for west Japan (see Figure A5 in in Appendix S1). The prediction performance is also satisfactory for east Japan (see Figure A5 in Appendix S1). The prediction performance is also satisfactory for east Japan (Figure 10). Comparing the observed rainfall during model development and testing for the third fold, it may be seen that the range and variation of rainfall during this season exhibits drastic temporal variations. These variations may be considered as the reason for the slightly poorer performance of the model for the third fold in east Japan.

However, overall the prediction model provides satisfactory performance and the model can appropriately capture the association between the variables and satisfactorily predict the monthly rainfall for both east and west Japan.

Thus, it is observed that the prediction performance is decidedly better for the GM-based approach during the testing period. It is thus concluded that establishing a conditional dependence structure of the predictor pool is an important step to resolve the complexity and dimensionality of the model, which may not be successfully done by machine-learning algorithms. Note that a periodic scrutiny may be necessary to update the model in order to cater the time-varying characteristics in the hydroclimatic teleconnection, if any (Rajeevan, 2001; Rajeevan et al., 2007, 2012; Wang et al., 2015; Dutta and Maity, 2018). The proposed methodology is applicable for any other geographical region; however, the extent of useful hydroclimatic information for seasonal prediction is expected to vary depending on the seasonal characteristics of regional rainfall and the areal extent of the study area.

5 | CONCLUSIONS

The study reveals the features of hydroclimatic teleconnection between global sea surface temperature (SST) fields and rainfall over east and west Japan. The analysis

| Region | Season | Fold | Correlation coefficient (R) | Root mean squared error (RMSE) (cm) | Nash–Sutcliffe efficiency (NSE) | Degree of agreement (Dr) | Co-efficient of determination ($R^2$) |
|--------|--------|------|---------------------------|------------------------------------|---------------------------------|-------------------------|---------------------------------|
| West   | Summer | Set 1 | 0.689                     | 5.718                              | 0.395                           | 0.586                   | 0.475                           |
|        |        | Set 2 | 0.660                     | 7.468                              | 0.429                           | 0.579                   | 0.436                           |
|        |        | Set 3 | 0.701                     | 7.065                              | 0.480                           | 0.655                   | 0.491                           |
| Winter | Set 1  | 0.584                     | 2.865                              | 0.312                             | 0.538                           | 0.341                   |
|        |        | Set 2 | 0.504                     | 3.135                              | 0.249                           | 0.510                   | 0.254                           |
|        |        | Set 3 | 0.646                     | 2.283                              | 0.399                           | 0.652                   | 0.418                           |
| East   | Summer | Set 1 | 0.656                     | 3.487                              | 0.415                           | 0.600                   | 0.431                           |
|        |        | Set 2 | 0.508                     | 4.042                              | 0.255                           | 0.561                   | 0.258                           |
|        |        | Set 3 | 0.702                     | 3.071                              | 0.472                           | 0.652                   | 0.493                           |
| Winter | Set 1  | 0.563                     | 1.443                              | 0.275                             | 0.526                           | 0.318                   |
|        |        | Set 2 | 0.751                     | 1.579                              | 0.516                           | 0.671                   | 0.564                           |
|        |        | Set 3 | 0.454                     | 2.645                              | 0.133                           | 0.548                   | 0.206                           |

| Table 4 | Season-wise performance statistics between the observed and hybrid graphical modelling/C-Vine copula (GM-Copula) predicted rainfall during model testing period considering threefold (Set 1–3) cross-validation for east and west Japan |
reveals that the rainfall anomalies over west Japan are influenced by the teleconnections originating in the tropical Pacific and Indian oceans, whereas the rainfall anomalies over east Japan are associated with the high-latitude SST anomalies. The El Niño Modoki (La Niña Modoki) phenomena are found to influence the early summer (winter) rainfall over west Japan, whereas the early summer (June) and winter (December) rainfall over east Japan is associated with the positive SST anomaly differences in the eastern subtropical Pacific and south Pacific oceans, respectively. In the present study, using the global climate pattern (GCP) approach, many teleconnection patterns influencing the rainfall of east and west Japan are identified. These go beyond the traditional teleconnection patterns due to the El Niño Southern Oscillation (ENSO), El Niño Modoki, Atlantic Multidecadal Oscillation (AMO), Indian Ocean Dipole (IOD), and so on. The identified teleconnections could be beneficial in improving the prediction of rainfall over west and east Japan.

The predictive potential of identified teleconnection patterns for monthly rainfall variation in Japan is assessed. Prediction models are developed based on the machine-learning technique, the support vector regression (SVR) and a hybrid graphical modelling/C-Vine copula (GM-Copula) approach using the teleconnection identified through the GCP approach. The potential of SVR is appreciable, but the model based on the GM-Copula has superior performance in predicting the rainfall over west and east Japan. It is perhaps due to the concept of a conditional independence structure among the variables that helps one to prune the redundant information in the predictor pool and finally to develop a prediction model using the pruned predictor sets. Satisfactory performance of the prediction model is obtained for both regions and for all months of both seasons with a slightly better performance in summer. The results will be highly beneficial in the operational forecast of the monthly variation of rainfall over east and west Japan.

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ORCID

Rajib Maity https://orcid.org/0000-0001-5631-9553

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