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Letter

Decadal drought prediction via spectral transformation of projected Sea Surface Temperatures

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ABSTRACT

Knowledge of impending drought can help significantly with water planning and management. This study introduces a novel forecasting framework for decadal drought projection which relies on climate model projections of Sea Surface Temperature Anomaly (SSTA) indices over the next decade and a spectral transformation methodology to maximise forecast skill. Decadal SSTA projections from the Decadal Climate Prediction Project (DCPP) undergo spectral transformation using Wavelet System Prediction (WASP). WASP modulates the frequency spectrum of predictor variables to better mimic the response spectrum of drought indices. The transformed SSTA indices are then used in a multiple linear regression (MLR) model to forecast drought indices across multiple time scales. This framework significantly improves drought forecasting skills, especially for lead times exceeding 24 months. While demonstrated for Australia, the MLR-WASP framework is transferable to other regions, offering a reliable tool for long-term water resource management by projecting drought risk over the coming decade. The implications of this research extend beyond hydroclimatology, impacting environmental science and engineering, sustainable planning, and adaptation efforts to climate change.

Plain language summary: Projecting drought risk over the next decade is essential for effective long-term water resources management. This study presents a new framework that reliably projects drought conditions up to 10 years ahead by optimizing decadal climate model data. It uses a spectral transformation technique to adjust predictors like Sea Surface Temperature Anomalies to better match drought patterns. These transformed predictors are then integrated into a regression model to forecast drought indices. When applied to Australia, this approach significantly outperformed existing methods, especially for 2-year forecasts. By combining advanced climate predictions with prediction-oriented data transformation, this framework enables reliable drought risk projections a decade out, offering invaluable insights for proactive planning in drought-prone regions worldwide.

1. Introduction

Projecting drought risk over the coming decade can significantly enhance water management and planning over a 10–20 year horizon (Deb et al., 2020; Liang et al., 2017; Roderick et al., 2020; Xu et al., 2020). While climate model simulations of rainfall over the coming 10–20 years have improved in quality, they remain of little relevance for such drought risk projections (Gu et al., 2019). In their absence, attention has focused on more reliable descriptors of climate variability, often embodied in Sea Surface Temperature Anomalies (SSTAs) (Westra and Sharma, 2010), which are better simulated by climate models than precipitation (Chikamoto et al., 2015; Choudhury et al., 2015; Johnson and Sharma, 2009; Liu et al., 2012; Meehl and Teng, 2014; Mehta et al., 2013).

This study aims to develop a framework for forecasting drought across multiple scales and extending predictability to decadal time frames. Two existing developments can assist in this task. Firstly, the Decadal Climate Prediction Project (DCPP) provides near-term climate projections that capture climate signals and variability over the coming decades (Boer et al., 2016; IPCC, 2021; Moemken et al., 2021). These projections have shown particular promise in simulating SSTA as compared to direct measures of precipitation or drought (Mehrotra et al., 2014; Smith et al., 2019). Secondly, in addition to existing approaches for assessing and correcting systematic biases in climate model simulations (Mehrotra and Sharma, 2012; Nahar et al., 2017), there now exists a new possibility for overcoming limitations in simulated SSTA indices, through the use of a mathematical post-processing transformation that modulates the frequency spectrum of predictor variables

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to better correspond with that of the response (Jiang et al., 2020). This spectral transformation, referred to as the Wavelet System Prediction (WASP) (Jiang et al., 2021a), has been shown to optimize the predictability of the response of interest by transforming the predictor variable into a "localized" predictor for each local response, imparting the highest predictive skill that is mathematically feasible (Jiang et al., 2025; Jiang et al., 2023).

In this study, we modify the WASP transformation framework to explore its applicability to decadal drought forecasting. Specifically, we propose a novel and reliable forecasting framework that projects drought over the coming decade with significant improvements compared to existing approaches. The modeling framework uses a multiple linear regression (MLR) model for simplicity and has been termed the MLR-WASP forecasting framework in the remainder of this document.

2. Materials and methods

Projecting drought risk at a decadal time scale requires (a) climate model projections of climate indicators relevant to the onset and propagation of drought, and (b) a mathematical framework that optimally utilizes these indicators to project drought robustly and accurately. In this section, we first introduce the SSTA indices from DCPP, followed by the target response of multi-scale drought indices, and then explain how the spectral transformation can create localized SSTA indices to enhance predictive performance.

2.1. Decadal projection skill for SSTA indices relevant to drought risk quantification

The DCPP, part of the Coupled Model Intercomparison Project (CMIP), investigates decadal climate prediction, predictability, and variability through retrospective forecasts, i.e., hindcasts, and ongoing production of decadal climate predictions (Boer et al., 2016; Eyring

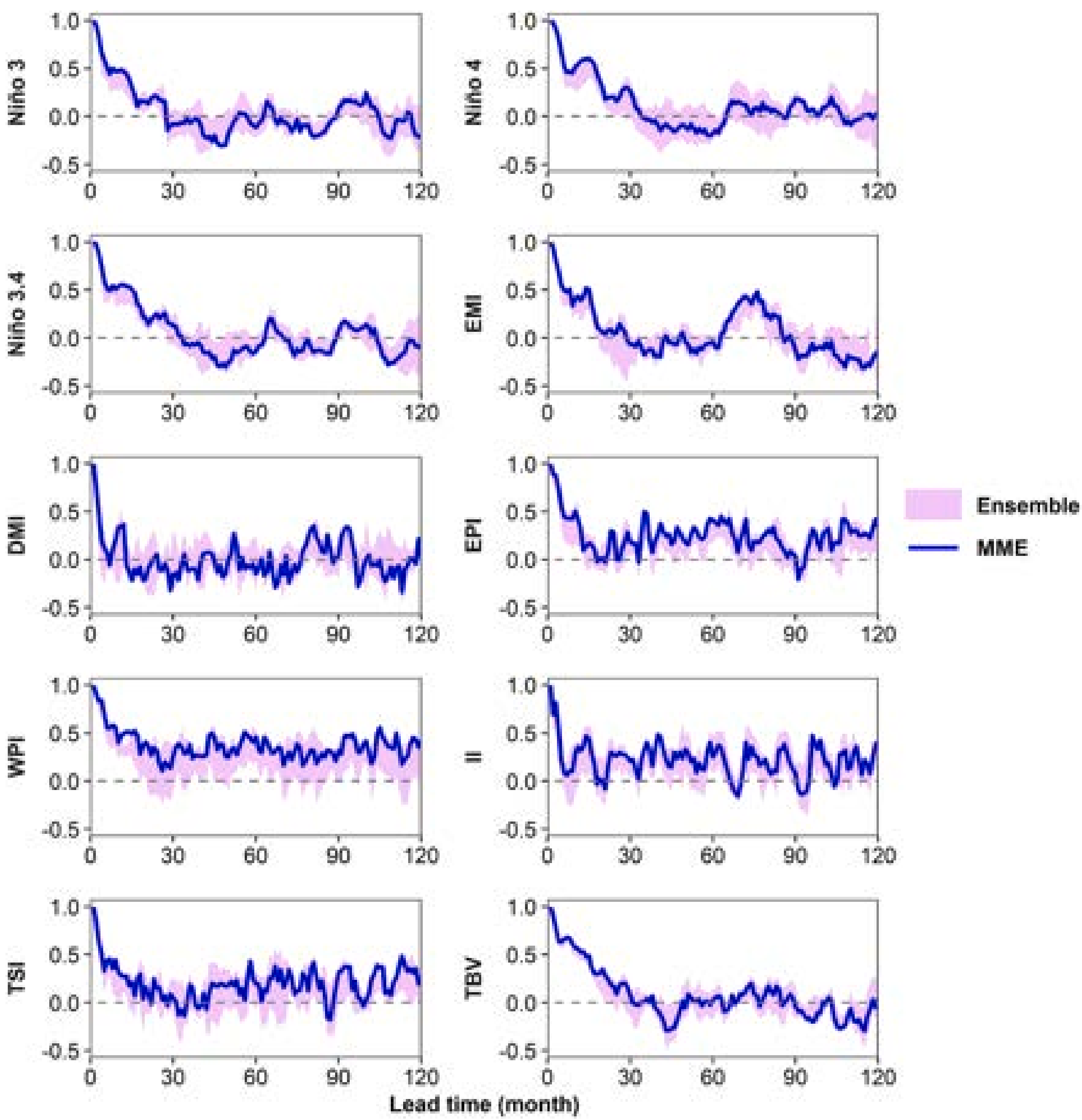

Fig. 1. Decadal projection skill of SSTA indices against varying lead times from the ensemble of five CMIP6 DCPP models, Ensemble, and the multi-model ensemble mean (MME).

et al., 2016). It bridges seasonal-to-interannual predictions and long-term climate change projections, whose projection skills are influenced by both the initial value problem and external forcing problem. A schematic of the contribution to forecast skill can be found in Fig. S1.

Ten SSTA indices derived from decadal climate projections, including Niño 3, Niño 4, Niño 3.4, the El Niño Modoki index (EMI), the Dipole Mode Index (DMI), the Indian Ocean East Pole Index (EPI), the Indian Ocean West Pole Index (WPI), the Indonesian Index (II), the Tasman Sea Index (TSI) and the Tropical Trans-basin Variability Index (TBV), have been shown to have a significant relationship with Australian rainfall (Choudhury et al., 2019; Schepen and Wang, 2015; Schepen et al., 2014). While other climate variables, such as soil moisture or atmospheric circulation patterns, may also influence regional drought conditions, this study focuses on these ten SSTA indices to assess the performance of the proposed forecasting framework. To ensure robustness, we utilized SSTA projections from decadal hindcast simulations with a total number of 41 decades, commencing from 1961 onwards, separated by a one-year interval covering the period from 1961 to 2010. These projections were derived from five CMIP6 climate models, considering multi-models for robustness (Zhou et al., 2024). Detailed information on ten SSTA indices and five CMIP6 climate models used is presented in Tables S1 and S2.

Fig. 1 shows the decadal projection skill of SSTA indices against varying lead times from the ensemble of five CMIP6 DCPP models, denoted as Ensemble, and the multi-model ensemble mean (MME). Although the skill presented here is computed from the drift-corrected SSTA indices (Choudhury et al., 2017), the predictability of these indices decreases notably with increasing lead times. There is marginal skill when the lead time exceeds 24 months for most indices, with particularly poor skills for indices like II and DMI. The projection skill of raw decadal simulations can be found in Fig. S2, raising the question of how such limited skill indices can enable meaningful drought projections.

2.2. Standardized Precipitation Index for drought forecasting

The Standardized Precipitation Index (SPI) is widely utilized for drought assessment due to its simplicity and adaptability across variable time scales (Guttman, 1998; Hayes et al., 1999; Mishra and Desai, 2005). While other drought indices, such as the Standardized Precipitation Evapotranspiration Index (SPEI), account for temperature-induced changes in evaporative demand, SPI was selected for this study because of its broad applicability and exclusive reliance on precipitation. This characteristic makes SPI particularly suitable for quantifying diverse drought types, from short-term flash droughts to prolonged multi-year droughts, which are important for agricultural and water resources management. For instance, soil moisture conditions respond to precipitation anomalies on relatively short time scales, while groundwater, streamflow, and reservoir storage reflect the longer-term precipitation deficits.

Initially introduced by McKee et al. (1993), the SPI calculation is comprised of two steps: (1) aggregation of precipitation over a specific period, and (2) transformation of one frequency distribution (e.g., gamma) of aggregated precipitation into a normal (Gaussian) distribution. This transformation standardizes the aggregated precipitation, so the SPI has a mean of zero and variance of one, thereby allowing consistent comparison across different regions and time scales. The SPI is commonly computed for various time scales such as 3, 6, and 12 months, which capture different types of droughts, with shorter scales (e.g., 3–6 months) often associated with agricultural drought (Dai et al., 2020) and longer scales (e.g., 12 months) related to hydrological drought (Vicente-Serrano, 2006). For these reasons, this study focuses on SPI covers 3, 6, and 12-month time scales. Observed gridded rainfall data for SPI calculation is obtained from the Australian Gridded Climate Data (AGCD)/Australian Water Availability Project (AWAP) led by the Bureau of Meteorology, Australia. The data was re-gridded from its original resolution of $0.05^\circ \times 0.05^\circ$ to $2.5^\circ \times 2.5^\circ$, accounting for the resolution of the DCPP model simulations used. The grid layout across Australia is illustrated in Fig. S3.

2.3. Drought forecasting framework using spectrally transformed decadal SSTA projections

To ensure robust and accurate drought projections, a mathematical framework that optimally uses these indicators is essential. This study introduces the MLR-WASP forecasting framework, which comprises two main components: data transformation using WASP and a predictive model utilizing MLR.

SSTA indices derived from the DCPP hindcasts are transformed using WASP according to the drought index at individual grids. These spectrally transformed indices are then integrated into stepwise linear regression, guided by the Akaike information criterion (AIC), to establish the MLR model. The forecasting model is developed for each lead month, with a two-fold cross-validation approach to evaluate its predictive performance. Forecast skill is quantified using correlation coefficients of forecasted drought indices across multiple aggregation periods (SPI3, 6, and 12 months) (Jiang et al., 2021a). These correlations are compared with baseline, non-transformed, and spectrally transformed models, utilizing an ensemble of five DCPP model projections to ensure robustness in performance evaluation. The baseline model, which can be regarded as the empirical model, is an autoregressive order 1 model that uses the response variable (drought index) at lead 0 as predictor variables. Non-transformed and spectrally transformed models, termed MLR and MLR-WASP models respectively, use all ten climate indices with and without spectral transformation, including the empirical component from the baseline model. The mathematical formulations of the three models are given as follows:

Empirical model (referred to as baseline model):

$$SPI^{e}_{k,l} = \beta^{e}_{0} + \beta^{e}_{1} SPI_{k,0} + \varepsilon^{e}_{l} \tag{1}$$

Multiple linear regression (MLR) model:

$$SPI_{k,l} = SPI^{e}_{k,l} + SPI^{d}_{k,l}$$

$$SPI^{d}_{k,l} = \beta^{d}_{0} + \sum_{i=1}^{p} \beta^{d}_{i} CI^{i}_{l} + \varepsilon^{d}_{l} \tag{2}$$

where $SPI_{k,l}$ is the target response of time scales k months at lead time l months, and superscripts e and d represent the empirical and dynamical components of the model. $SPI_{k,0}$ is known SPI with a time scale of k months at lead 0, and the SSTA index, CI^{i}_{l}, represents the corresponding SSTA index derived from DCPP at lead l; β_0 is the intercept while β_i represents the regression coefficients of associated input variables, and ε_l is the error term of the model. p is the total number of predictors considered in the regression model.

The difference between the MLR and MLR-WASP models is the spectral transformation of the input predictors. As a result, the three models used in the study can be simplified as follows:

$$\begin{aligned} \text{Baseline}: \quad & SPI^{e}_{k,l} = f\left(SPI_{k,0}\right) + \varepsilon^{e}_{l} \\ \text{MLR}: \quad & SPI_{k,l} = f\left(SPI_{k,0}, {CI_{l}}^{1,2,\dots,p}\right) + \varepsilon_{l} \\ \text{MLR-WASP}: \quad & SPI^{\prime}_{k,l} = f\left(SPI^{\prime}_{k,0}, {CI^{\prime}_{l}}^{1,2,\dots,p}\right) + \varepsilon^{\prime}_{l} \end{aligned} \tag{3}$$

where $CI^{\prime}_{l}$ and $SPI^{\prime}_{k,0}$ represents the spectrally transformed CI_l and $SPI_{k,l}$ corresponding to the SPI at a given lead time (l) and time scale (k). Note that stepwise linear regression is applied with the AIC as the means for model selection, and thus the total number of predictors, p, included in MLR and MLR-WASP models might be different. As a result, three forecast models are assessed from lead 1 to 60 months using 41 data points (from 41 decades) with two-fold cross-validation.

To sum up, a flowchart depicting the above formulations is presented in Fig. 2, and the proposed decadal drought forecasting framework is composed of three stages, including decadal prediction of SST and spectral transformation, model setup under two-fold cross-validation, as well as the assessment of forecast skill from three aspects.

3. Results and discussions

The developed drought forecasting framework is assessed using SSTA projections from a multi-model ensemble for SPI at multiple time scales. The spectral or decomposition-based approach has shown great potential in the context of forecasting in different fields such as rainfall forecasting (Quilty and Adamowski, 2021; Tao et al., 2023), drought prediction (Ghozat et al., 2023), and wind power prediction (Chen et al., 2022). Here, we will present the capability of this proposed framework in long-lead drought forecasting across multiple time scales.

3.1. Multi-model forecast skill of SPI12 using spectrally transformed SSTA projections

To assess the capability and robustness of the proposed forecasting framework, Fig. 3 compares the forecast skill of SPI12 using spectrally transformed SSTAs across three models within the ensemble of five CMIP6 models, shown as color bands, with their ensemble mean illustrated as solid lines. The prediction skill along lead time was smoothed using loess to account for the input and model uncertainty. The associated contribution of each SSTA index to the forecast skill is further examined in Fig. S4 of the Supplementary material.

The results demonstrate that the baseline model consistently performed worse compared to the other models, except for the short lead times during validation, where the empirical component plays a major role in the forecast skill. Fig. S4(a) illustrates the regression coefficients of the MLR against lead time, highlighting the empirical component's predominant contribution to forecast skill, with coefficients substantially higher than those of other predictors (SSTA indices). Overall, the MLR-WASP model outperforms other approaches, especially at longer lead times, with skill levels exceeding the 90 % significance threshold (0.26, corresponding to the 39 degrees of freedom, as we have 41 decades in total). In contrast, models without spectral transformation exhibit a marked decrease in forecast skill, becoming insignificant beyond 12 months.

Two primary factors contribute to the superior performance of the MLR-WASP model. First, spectral transformation enhances the

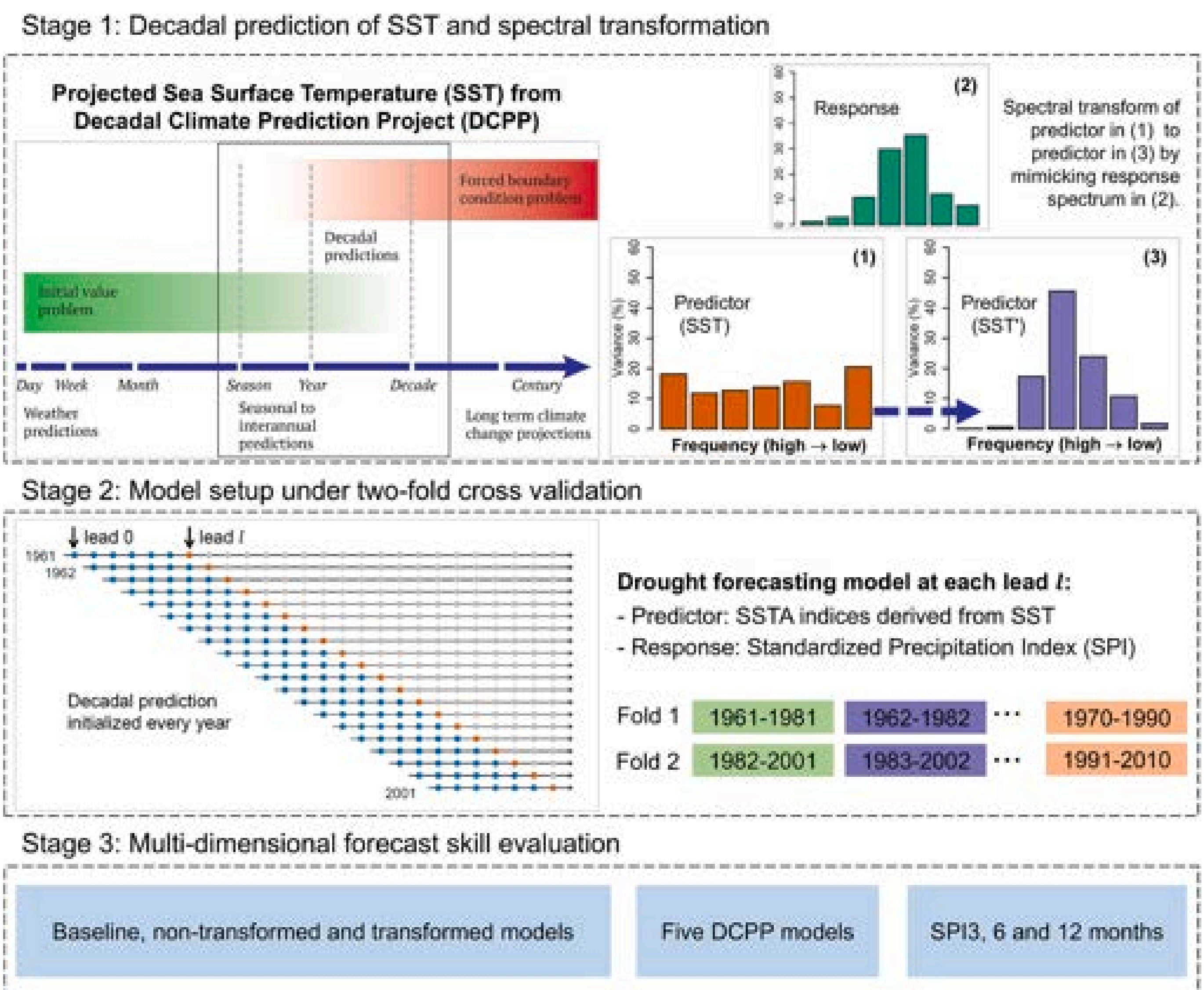

Fig. 2. The proposed decadal drought forecasting framework includes three stages: decadal prediction of SST and spectral transformation, model setup under two-fold cross-validation, as well as the assessment of forecast skill from three aspects.

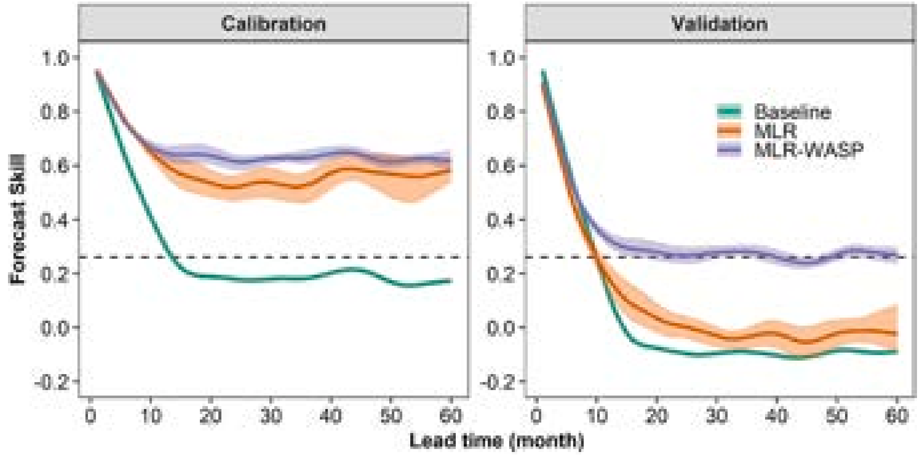

Fig. 3. Improved forecasting skill of SPI12 using spectrally transformed SSTAs across the ensemble of five CMIP6 models, shown as color bands, with their ensemble mean given in solid lines. Improvements are shown under the calibration and validation. The black dashed line marks the 90 % significant correlation value.

correlation between SSTA indices and drought conditions, improving the predictive utility of these indices. Second, as shown in Fig. S4(b), the MLR-WASP model incorporates a broader range of relevant predictors, identifying approximately one additional predictor compared to the referenced MLR model. This expanded predictor set improves the model's ability to capture multi-scale climate variability, further

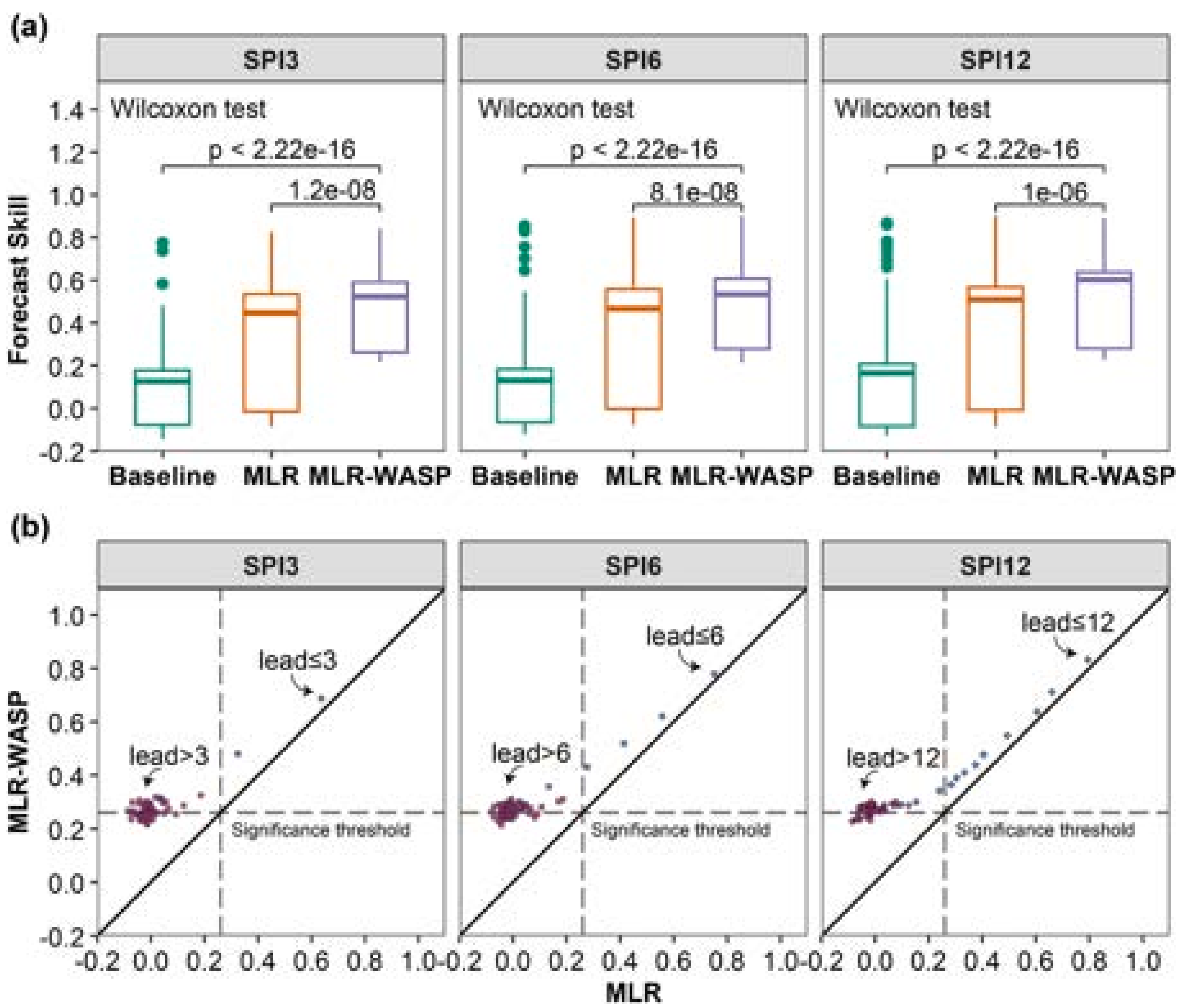

Fig. 4. (a) Comparison of forecast skills of Standardized Precipitation Index (SPI) between non-transformed and transformed models across multiple time scales using multi-model ensemble mean. (b) Comparison between MLR and MLR-WASP models across all lead times. The grey dashed line marks the 90 % significant correlation value. Purple points represent forecast skill of lead time larger than time scales of drought indices, while blue points stand for those of lead time smaller than the time scales of drought indices. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

enhancing forecast skill.

This enhancement in performance underscores the effectiveness of the MLR-WASP framework in capturing decadal drought dynamics. The spectral transformation process optimizes predictor variables, aligning them more closely with drought patterns and thereby improving forecast accuracy (Jiang et al., 2020). Additionally, the MLR-WASP model's ability to identify and incorporate a greater number of predictors enhances its predictive power, enabling more comprehensive and robust drought projections. These findings are consistent with previous studies emphasizing the importance of advanced modeling techniques and data transformations in improving hydroclimate forecasts (Khan et al., 2017; Kim et al., 2023). By leveraging spectral transformation and regression modeling, the MLR-WASP framework represents a significant advancement in decadal drought forecasting.

3.2. Multi-scale SPI forecasts using spectrally transformed SSTA projections

As noted, the SPI effectively captures various drought types, with shorter timescales (e.g., 3–6 months) typically associated with agricultural drought, and longer timescales (e.g., 12 months) linked to hydrological drought. Many previous studies have SPI across multiple timescales to differentiate drought types (Dai et al., 2020; Lloyd-Hughes and Saunders, 2002; Szalai et al., 2000; Vicente-Serrano, 2006). To broaden the framework's applicability, assessing its performance at varied timescales is essential. Fig. 4 illustrates the forecast skills of SPI across multiple time scales, including (a) SPI3, (b) SPI6, and (c) SPI12, comparing three different forecast models. Fig. 4(a) presents that the model with spectral transformation (MLR-WASP) significantly outperforms the non-transformed models (Baseline and MLR), with the p-value of the Wilcoxon test less than the significance level, $\alpha = 0.05$. Compared to the Baseline mode, the MLR model exhibits significantly higher forecast skill, but this skill drops notably thereafter. On the other hand, as shown in Fig. 4(b), the MLR-WASP model consistently shows higher forecast skill than the MLR model across all lead months. While the forecast skill at longer leads decreases sharply with respect to the time scales of drought indices (i.e., those longer than 3, 6, and 12 months), most of them remain above the 90 % significance threshold. The diminished forecast skill with increasing lead time primarily stems from decreased projection skill in SSTA indices, a trend observed across all methods. However, spectral transformation extends the effective forecasting horizon, maintaining significant forecast skill up to 24 months. Beyond two years, forecast skill shows minimal variation across all models, as depicted in Fig. S5. Additionally, it is found that the turning point of forecast skills corresponds with the time scales of drought indices, suggesting that the empirical component may have a limited contribution to forecast skills. Further details are provided in Fig. S4.

These findings further underscore the importance of spectral transformation in enhancing the performance of decadal drought forecasting models. By improving the alignment between predictor variables and drought patterns, spectral transformation enables more accurate and reliable forecasts across various time scales. This aligns with previous research emphasizing the significance of advanced modeling techniques and data transformations in enhancing climate forecasts (Jiang et al., 2021b).

Drought propagation is a multifaceted process that unfolds across both temporal and spatial dimensions, significantly impacting various components of the hydrological cycle. In this study, we focus on drought prediction using decadal SST anomalies at individual grid points. However, as droughts propagate, their spatial extent and connectivity can change. For example, in Central Europe, droughts tend to have larger spatial extents as they propagate from precipitation to streamflow, but this extent decreases when reaching groundwater due to subsurface heterogeneity (Brunner and Chartier-Rescan, 2024). While we acknowledge the importance of spatial prediction, incorporating spatial variability into the drought forecasting framework requires advanced methodological approaches, such as multivariate prediction models (Ali et al., 2019; Hao et al., 2016). Future research will aim to integrate these approaches to enhance predictive capabilities across different spatial scales and validate them in other regions under different climatic conditions. Understanding the temporal and spatial dynamics of drought propagation is essential for effective drought management and mitigation. This knowledge helps in developing early warning systems and informing robust water resource management strategies that consider both upstream and downstream interactions (Han et al., 2023; Schilstra et al., 2024). By integrating these insights, policymakers and water managers can improve drought preparedness and response, thereby reducing adverse impacts on agriculture, water resources, and socio-economic sustainability.

4. Conclusions

This study introduces the MLR-WASP framework, a novel and reliable tool for decadal drought projection. By integrating decadal climate projections from the DCPP with the spectral transformation technique (WASP), this framework optimizes the spectrum of predictor variables (SSTAs) to better align with the response variable (drought index). The transformed SSTAs are then employed in a multiple linear regression (MLR) model to forecast drought indices across multiple time scales.

Results indicate that the MLR-WASP framework outperforms existing approaches, including the baseline model (the empirical component only model) and non-transformed MLR model. The spectral transformation of SSTAs enhances their association with drought indices and enables the inclusion of more relevant predictors in the MLR model. Consequently, the MLR-WASP framework achieves significant forecast skills for drought indices up to 24 months ahead, surpassing non-transformed models that exhibit decreasing skills beyond 12 months.

The MLR-WASP framework offers a promising approach to extend drought predictability to decadal time frames, addressing the critical need for long-term drought risk assessment and water resource management. Future research could explore further refinements to the MLR-WASP framework, including the incorporation of additional climate variables, the extension of multivariate predicton across various spatial scales, and the exploration of real-time forecasting using decadal climate forecasts. Additionally, assessing the framework's performance across different regions and under different climatic zones would provide valuable insights into its robustness and applicability in diverse settings. Continued research efforts in these areas will contribute to advancing our understanding of decadal drought forecasting and enhancing preparedness for future water resource challenges. The enhanced predictive capabilities can help mitigate the impacts of drought on ecosystems, agriculture, and water resources, ultimately contributing to more resilient environmental management strategies.

CRediT authorship contribution statement

Ze Jiang: Methodology, Software, Validation, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition. **Ashish Sharma:** Conceptualization, Methodology, Validation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Disclaimer

Ashish Sharma serves as the Editor-in-Chief for Journal of Hydrology-X. At no stage was he involved in any editorial decisions regarding this article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.hydroa.2025.100203.

Data availability

Decadal Climate Prediction Project (DCPP) runs of GCM models are part of Phase 6 of the Coupled Model Intercomparison Project (CMIP). The World Climate Research Program's Working Group on Coupled Modeling is responsible for CMIP, and relevant model outputs are accessible online at https://esgf-node.llnl.gov/search/cmip6/. Observed SSTA data are derived from monthly SST values of the Hadley Centre Global Ice and Seal Surface Temperature (HadISST) dataset: https://www.metoffice.gov.uk/hadobs/hadisst/. Observed gridded rainfall data for SPI calculation is obtained from the Australian Gridded Climate Data (AGCD)/Australian Water Availability Project (AWAP) led by the Bureau of Meteorology, Australia: http://www.bom.gov.au/climate/data/.

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