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A stochastic weather generator for multisite, multivariate climate scenarios with transient climate change

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Abstract

Reliable assessment of water resources under climate change requires climate forcing data that preserve multivariate dependence, spatial coherence, and transient climate signals within large ensembles. However, many stochastic weather generators assume stationarity or apply simplified climate change adjustments that do not fully maintain these properties in multisite, high-dimensional applications. We develop a stochastic weather generation framework that integrates a k-nearest-neighbor (k-NN) resampling approach with a transient climate perturbation module derived from ensembles of global climate models (GCMs). The k-NN component generates spatially coherent, multivariate weekly temperature and precipitation sequences by resampling historical observations, representing internal climate variability. The perturbation module applies time-evolving climate change signals from CMIP6 projections across multiple shared socioeconomic pathways, enabling non-stationary climate trajectories while preserving the dependence structure of the stochastic generator. Applied to the Maipo River Basin in central Chile, the framework produces large ensembles of multisite climate scenarios suitable for a high-resolution Water Evaluation and Planning (WEAP) model. Results show that the method preserves key spatial and cross-variable dependence structures while reproducing transient climate change signals and expanding the range of plausible future trajectories. The approach provides a scalable and computationally efficient tool for linking climate projections with stochastic weather generation for hydrological impact modeling under uncertainty.

1 Introduction

Assessing water resource systems under climate change requires evaluating performance amid deeply uncertain future hydroclimatic conditions (Brown et al., 2020; Kasprzyk et al., 2013; Lempert, 2019; Lempert and Groves, 2010; Whateley et al., 2014). Planning and management decisions are sensitive to uncertainty arising from differences among global climate models, emissions pathways, and internal climate variability (Brown et al., 2020; Cosgrove and Loucks, 2015; Herman et al., 2020). Stress-testing decisions across plausible future conditions can help identify robust strategies (Brown et al., 2020, 2019; Steinschneider et al., 2019, 2015; Steinschneider and Brown, 2013), requiring ensembles of climate scenarios.

To be useful for climate stress testing, climate scenario ensembles for hydrological modelling require several key features. First, ensembles must be large enough to capture the full range of uncertainty from both future climate change and stationary hydrological variability (Borgomeo et al., 2014; Glenis et al., 2015). Second, ensembles must be multivariate for hydrological modeling. In snow-influenced basins, for example, precipitation and temperature control phase partitioning and melt timing so climate variables must be modeled jointly (Ayala et al., 2025, 2020). Third, many hydrological models require multi-site, spatially correlated ensembles to capture basin-scale runoff dynamics (Sparks et al., 2018). Fourth, ideally, generation should be user-friendly and computationally efficient, given that it serves as one step in larger analyses (Burton et al., 2010; Glenis et al., 2015). Stochastic weather generators are therefore needed that represent multivariate dependence, spatial coherence, and transient climate signals within a unified approach.

While stationary climate scenarios represent a fixed climate, transient scenarios represent the trajectory and sequencing of climate conditions over time, which can be important for modeling systems with hysteresis. First, some hydrologic processes, like snow accumulation and ice melt (Ayala et al., 2020; McCarthy et al., 2022), are sensitive to how climate variability and mean conditions evolve over time. Stationary scenarios miss representing consequential shifts in the sequencing of wet and dry periods as climate change progresses (Wang et al., 2024). Second, infrastructure planning depends on the timing, not just the magnitude, of climate shifts. Systems with long operational lifetimes, such as reservoirs and water supply networks, must operate under long term shifts in climate conditions. Decisions, such as the timing of capacity expansions or retrofits (e.g., Bertoni et al., 2020, 2019; Cohen and Herman, 2021; Fletcher et al., 2019; Skerker et al., 2023), depend on both *how* conditions change and *when* specific conditions occur. Discrete stationary epochs can indicate that adaptation is unnecessary at one future epoch and then immediately necessary at the next since stationary scenarios omit the evolving risk profile between them (Glenis et al., 2015). Transient scenarios instead can identify the intervention timing directly, such as the specific year a given supply-side option must be implemented to keep failure risk below an acceptable threshold (Borgomeo et al., 2014). Therefore, there is a need for climate scenario generation methods that explicitly represent non-stationary and evolving climate conditions in forms suitable for hydrologic simulation.

Ensembles of general circulation model (GCM) projections are commonly used in climate impact assessment and water resources planning (Chae et al., 2025; Nover et al., 2016; Whateley et al., 2014; Zha et al., 2022) and provide readily available transient representations of multiple climate variables, but have limitations for stress testing. Small ensemble size limits exploration of plausible climate impacts for stress testing (Brown and Wilby, 2012; Whateley et al., 2014). Recent single-condition, initial-condition large ensembles increase sample size, but remain limited to approximately 100 members, do not capture model uncertainty (Deser et al., 2020), and have coarse spatial resolutions that limit representation of hydrological variability at the basin scale (Nover et al., 2016; Zha et al., 2022).

Stationary stochastic weather generation methods aim to produce synthetic meteorological time series that preserve key statistical properties of observed climate while enabling large ensembles for robust hydrologic and water resources analyses. Method classes vary in their ability to develop scenarios that are multivariate and multi-site, while assumptions of stationarity prevent representation of long-term warming trends, changes in precipitation variability, or shifts in seasonal structure. First, parametric models, including Markov chain precipitation occurrence models (Jeong et al., 2013; Richardson, 1981), are computationally efficient and widely used but often rely on simplified representations of spatial dependence and may not fully capture cross-variable or spatial coherence. Second, latent-variable and regime-based models, including hidden Markov and multivariate latent Gaussian approaches (Kleiber et al., 2012; Sparks et al., 2018; Zha et al., 2022), introduce unobserved climate states that govern transitions between weather regimes. These can represent wet and dry spell persistence and shared variability across locations, but require structural assumptions and can be difficult to calibrate for multivariate, multi-site applications. Third, non-parametric resampling methods such as k-nearest neighbor approaches (Beersma and Buishand, 2003; Buishand and Brandsma, 2001; Lall and Sharma, 1996; Rajagopalan and Lall, 1999; Zorita and Storch, 1999), sampling from historical observations, preserving observed temporal and spatial dependence without strong parametric assumptions, but, without modification, cannot represent non-stationary changes. Multi-site, multivariate k-NN methods extend this approach by sampling historical periods based on similarity across multiple stations and variables, jointly preserving multi-site and multivariate structure (Buishand and Brandsma, 2001).

Previous studies have extended stationary weather generation methods to develop non-stationary scenarios, commonly by applying transient perturbations derived from general circulation model (GCM) projections. These approaches modify statistical properties of weather generators over time using transformation factors such as delta change factors derived from climate model outputs (e.g. (Burton et al., 2010; Glenis et al., 2015; Haasnoot et al., 2015)). While this enables the introduction of non-stationary signals, existing implementations often rely on coarse temporal updating or simplified scaling assumptions that may not fully preserve multivariate and spatial dependence structures as climate evolves. For example, Haasnoot et al. (2015) develop vectors of change factors for temperature based on plausible future temperature scenarios, but do not jointly consider how precipitation changes may co-evolve over the

planning horizon, leaving precipitation–temperature relationships and multi-site coherence under transient forcing a key methodological challenge.

In this study, we develop a stochastic weather generation approach to produce large ensembles of multi-site, multi-variable weekly temperature and precipitation time series for water resources systems modeling and climate impact assessment, including infrastructure stress testing and long-term planning. The approach extends a non-parametric multi-site, multi-variable k-nearest-neighbor resampling structure (Buishand and Brandsma, 2001) with time-varying climate change perturbations derived from GCM projections (Haasnoot et al., 2015), generating synthetic weather sequences that represent observed temporal variability and dependence structures while incorporating transient climate change. We demonstrate the approach using CMIP6 projections to generate transient ensembles of weekly precipitation and temperature at 257 locations in the central Chile’s Maipo River Basin, a highly managed watershed that has experienced a prolonged “megadrought” (McCarthy et al., 2022; Neme, 2022; Web Desk, 2019). Long-term water resources planning is sensitive to reductions in snowpack, shifts in melt timing, and increasing drought frequency and severity (Fernandez and Gironas, 2021; Vicuña et al., 2021). An official WEAP model used for regional water management and climate adaptation planning (Meza et al., 2014; Vicuña et al., 2018a) requires temporally consistent weekly climate inputs at 257 spatial locations, making the basin a demanding test case for our stochastic weather generation approach.

2 Case Study Application

We apply our approach to the Maipo River Basin in central Chile (Figure 2), a highly managed and economically critical watershed that supplies water to the Santiago metropolitan region (Ocampo-Melgar et al., 2016; Ricalde et al., 2022). The basin has experienced a prolonged multi-decadal drought (“megadrought”) (Neme, 2022; Web Desk, 2019) and faces increasing pressure from climate change, including declining snowpack, reduced glacier melt, and increasing drought frequency and severity (Ayala et al., 2025, 2020; Chadwick et al., 2018; Fernandez and Gironas, 2021; McCarthy et al., 2022; Vicuña et al., 2021), all of which pose substantial challenges for long-term water resources planning (McCarthy et al., 2022; Ocampo-Melgar et al., 2016; Ricalde et al., 2022). We select this basin as a case study because it provides a test case where uncertainty in future climate places substantial pressure on long-term water resources planning and drought management.

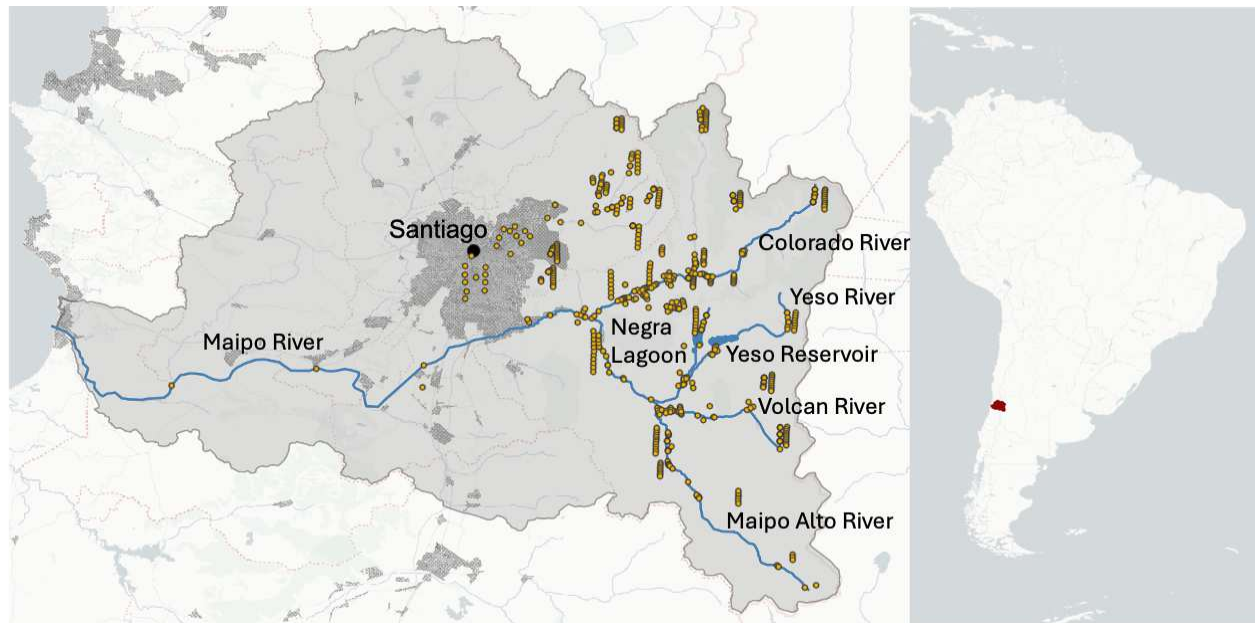


Figure 2. Map of the Maipo Basin in Chile. The map shows main rivers and bodies of water (blue) and micro-catchment locations in the official WEAP model of the basin (yellow).

The Maipo Basin spans approximately 15,000 km² and is a Mediterranean, snowmelt-dominated hydrological system with strong seasonal variability in streamflow (Cai et al., 2006; McPhee, 2018). The upper basin is fed by four main tributaries—the Maipo, Colorado, Volcán, and Yeso rivers—and includes key regulated water bodies such as the El Yeso reservoir and Laguna Negra (Ricalde et al., 2022). Winter precipitation in the Andes is stored as snow, and streamflow is primarily generated through snowmelt during spring and early summer, producing a pronounced seasonal hydrograph (Bonelli et al., 2014a). This seasonal cycle creates a mismatch between water availability and demand, as peak urban and agricultural demand occurs during the dry summer period when flows are lowest (Ricalde et al., 2022). As a result, the system is highly sensitive to interannual climate variability and shifts in snow accumulation and melt timing.

Future hydrologic responses to climate forcing are simulated using the official Water Evaluation and Planning (WEAP) model of the upper Maipo Basin. WEAP is a semi-distributed, process-based hydrological modeling platform that represents basin hydrology through a network of spatially discretized catchment units, simulating the snow accumulation and melt, soil moisture dynamics, groundwater interactions, and surface runoff generation in response to climate inputs (Yates et al., 2005). The goal of the model is to simulate these processes across the mountainous headwaters of the Maipo Basin, producing streamflow estimates at key tributary gauging stations that feed downstream water supply and allocation modeling for the Santiago metropolitan region. The model delineates the upper basin into 26 sub-catchments encompassing the Maipo, Colorado, Volcán, and Yeso tributaries. These are further subdivided into 250–500 m elevation bands to capture the strong altitudinal gradients in precipitation and

temperature that govern the snow-dominated hydrology of the basin. Key hydrological control points represented in the model include streamflow gauges at Maipo en El Manzano, Volcán at Queltehue, Colorado before Maipo, and Embalse El Yeso. The model was calibrated against naturalized weekly streamflow records at these stations over the period 1984–2008, achieving Nash-Sutcliffe Efficiency values of up to 0.85 at Maipo en El Manzano (CCG-UC, 2016), and has since been applied by water authorities and researchers to inform basin-scale water resources planning and climate impact assessment in the basin (Centro UC Cambio Global, 2016; Meza et al., 2014; Ricalde et al., 2022; Vicuña et al., 2018a). The WEAP model requires weekly temperature and precipitation time series at 257 spatial locations distributed across the basin (Figure 2). These requirements define the spatial and temporal resolution of the climate scenarios developed in this study and motivate the need for multi-site, multivariate model inputs. All climate input data used in this application are defined in Section 3.1.

3 Methods

3.1 Data and preprocessing

We apply our approach to a high-dimensional spatio-temporal dataset of temperature and precipitation defined over $L = 257$ subcatchment node locations in the WEAP model. The dataset consists of two components: (i) historical observational climate data used to represent internal climate variability, and (ii) climate model projections used to represent external climate forcing. These datasets serve as inputs to the stochastic generator and climate perturbation modules described in Sections 3.2–3.4.

Weekly historical precipitation and temperature time series at each subcatchment node from 1979 to 2019 were obtained from the historical dataset developed for the WEAP model. Specifically, the historical time series were derived from DGA (Dirección General de Aguas) station records — primarily San José de Maipo, Embalse El Yeso, and DGA central offices — using an elevation-dependent precipitation gradient ($R^2 = 0.948$) and a weekly-varying temperature lapse rate calibrated between El Yeso and Las Melosas gauging locations (Centro UC Cambio Global, 2016). This elevation-based interpolation approach was established in the original development of the official upper Maipo Cordillera WEAP model and has been used in climate change impact studies (Bonelli et al., 2014b; Meza et al., 2014; Vicuña et al., 2018b).

Climate change projections are obtained from general circulation models (GCMs) participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6). The nine selected GCMs include ACCESS-CM2, CNRM-CM6-1, INM-CM4-8, INM-CM5-0, MIROC6, MIROC-ES2L, MPI-ESM1-2-LR, MRI-ESM2-0, and NorESM2-MM, chosen based on data availability and coverage for the study region (see Section 2). We use all four Shared Socioeconomic Pathways (SSPs): SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5. The corresponding projections of daily precipitation and near-surface air temperature (minimum and maximum) through 2100 are obtained for our study area from the Copernicus Climate Data Store (“CMIP6

climate projections,” n.d.) and aggregated to a weekly time scale. Spatial resolution varies across GCMs, ranging from 100–500 km. (“CMIP6 climate projections,” n.d.).

GCM outputs are then bias-corrected and spatially downscaled using Unbiased Quantile Mapping (UQM). UQM adjusts distributional biases in GCM outputs relative to a local observational reference while explicitly preserving projected changes in both the mean and standard deviation of the corrected series (Chadwick et al., 2023). The weekly historical time series at each node location serves as the observational reference for bias correction and ensures that the GCM outputs are consistent with the spatial locations necessary for the hydrological model (Centro UC Cambio Global, 2016). UQM has been applied previously in the Maipo Basin (Vicuña et al., 2018b) and in other semi-arid Chilean basins (Poblete et al., 2025) and has been shown to reliably reproduce both the central tendency and variability of hydroclimatic variables, making it suitable for impact modeling applications (Chadwick et al., 2023).

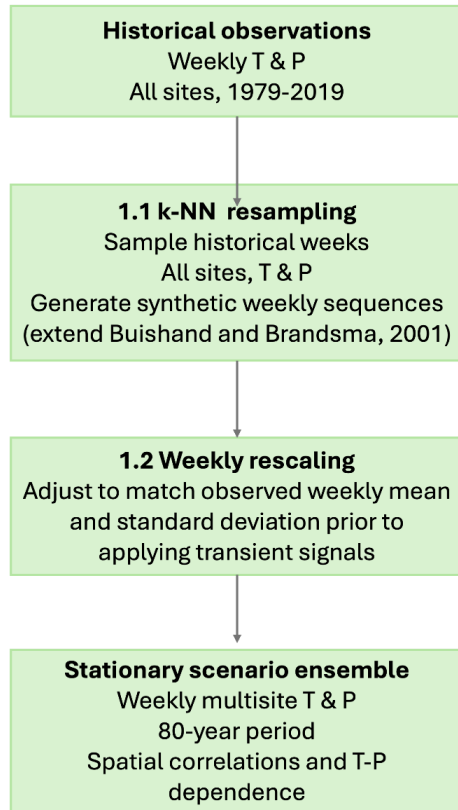
3.2 Method overview

We develop a stochastic weather-generation approach for producing ensembles of multi-site, multivariate weekly time series that combines internal climate variability with transient climate change signals derived from general circulation models (GCMs). The method generates large ensembles of climate scenarios for use in distributed hydrological models that require spatially coherent climate inputs.

The approach consists of two components that are combined to develop an ensemble of transient multi-site, multi-variable scenarios (Figure 1). The first is a stationary k-nearest neighbor (k-NN) block resampling module that generates synthetic weather time series by jointly resampling climate variables across locations from the historical record and then rescaling them to correct for any statistical drift and ensure consistency with historical weekly means and standard deviations prior to applying transient changes (Section 3.3). Each realization corresponds to a different resampling path through the historical record, producing distinct but statistically consistent sequences of temperature and precipitation. This component preserves observed spatial dependence, temporal structure, and cross-variable correlations, thereby representing internal climate variability. The second is a transient perturbation module that imposes time-evolving, week-specific climate change signals. We use an ensemble of downscaled GCMs to calculate plausible climate change signals over the century. This component introduces non-stationary behavior consistent with projected climate change while capturing model and forcing uncertainty. GCM projections are downscaled and bias-corrected to the local observational reference, after which time-evolving climate change signals are calculated relative to a fixed historical baseline for each week and location (Section 3.4). Finally, we combine the two components by applying the GCM climate change perturbation signals to each k-NN generated realization, producing large ensembles of transient, weekly multi-site climate realizations that jointly reflect internal variability and long-term uncertainty in future climate projections. We validate the results again both historical data and GCM projections

We use the resulting ensemble of transient, weekly multi-site climate realizations to force a WEAP model of the upper Maipo Basin and generate corresponding streamflow time series under future climate conditions. This application demonstrates that the proposed framework generates climate inputs that are directly compatible with process-based hydrological models. To evaluate the hydrological implications for drought planning and compare stationary and transient climate assumptions, we calculate the Standardized Precipitation Index (SPI-12) and Standardized Runoff Index (SRI-12) from the simulated outputs. These indices provide standardized measures of meteorological and hydrological drought, enabling assessment of how climate signals in temperature and precipitation propagate through the hydrological system and manifest in different drought characteristics across scenarios.

1. STATIONARY WEATHER GENERATION (internal variability)



2. TRANSIENT CLIMATE SIGNALS (External forcing)

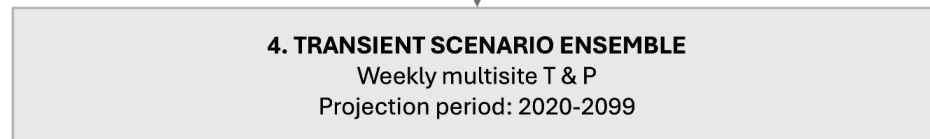
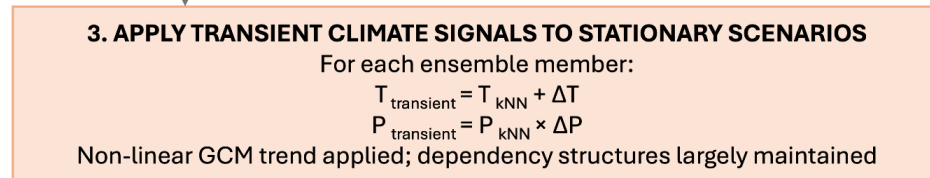
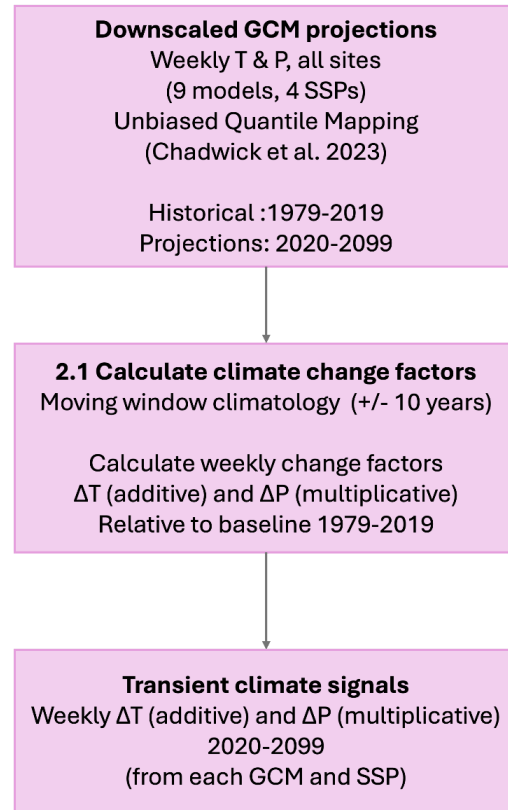


Figure 1. Methods schematic. First, we generate weekly multi-site, multivariable time series via a k-nearest neighbor resampling approach. Second, we calculate transient climate change signals from downscaled GCM projections. Ensembles of transient scenarios are generated by applying the transient change factors to the stationary scenarios.

3.3 Stationary Multisite k-NN Weather Generator

The purpose of the stationary k-nearest neighbor (k-NN) weather generator is to produce synthetic multi-site, multivariate weekly climate time series that preserve the joint statistical dependence structure of observed temperature and precipitation, providing the internal-variability foundation onto which the transient perturbation module (Section 3.4) later imposes climate change signals. We build on Buishand and Brandsma (2001), adding a full per-site state-matching distance metric. This approach reproduces realistic climate variability by jointly sampling temperature and precipitation across sites from historical sequences that are statistically similar to the current state (Buishand and Brandsma, 2001; Rajagopalan and Lall, 1999).

The k-NN generator samples from historical weekly time series of temperature (T , °C) and total precipitation (P , mm week⁻¹) at L spatial locations, over the period 1979–2019. For a given week t , $\mathbf{T}_t = [T_{1,t}, \dots, T_{L,t}]$ and $\mathbf{P}_t = [P_{1,t}, \dots, P_{L,t}]$ are vectors of length L containing temperature and precipitation, respectively, at sites $l = 1, \dots, L$. For each week t in the historical record, the system state is represented by the $2L$ -dimensional vector

$$\mathbf{x}_t = [\mathbf{T}_t, \mathbf{P}_t] \quad (1)$$

The k-NN resampling step generates single-week state transitions by identifying historical states that are statistically similar to the current state. By jointly sampling temperature and precipitation across all sites, the approach preserves observed spatial and cross-variable dependence without assuming a parametric form.

To ensure seasonal consistency, candidate historical states are restricted to those occurring during the same calendar week of the year as the current simulation week. Because temperature and precipitation differ in both units and variability, the physical state vectors $\mathbf{x}$ are standardized before distances are calculated. The resulting standardized feature vector is denoted $\mathbf{z}$. Similarity between the current synthetic state and each eligible candidate historical state is then measured by Euclidean distance in standardized feature space, following the general multi-site k-NN framework of Buishand and Brandsma (2001) using the full per-site state vector for distance. For candidate predecessor week j :

$$d_j = \|\mathbf{z}_j - \mathbf{z}_{current}\|_2 \quad (2)$$

where d_j is the Euclidean distance between the standardized feature vector $\mathbf{z}_j$ for candidate historical week j and the standardized feature vector $\mathbf{z}_{current}$ for the current synthetic state. Standardization is performed separately for temperature and precipitation across sites using statistics specific to the corresponding calendar week. Thus, standardization is used only to

place the features on comparable scales for neighbor identification; the historical values subsequently resampled into the synthetic sequence remain in physical units.

The $k = 10$ candidate states with the smallest d_j values are retained as nearest neighbors and ranked in ascending order of distance. One of these neighbors is selected probabilistically, with selection probability inversely proportional to its rank. The historical week immediately following the selected neighbor is then appended to the synthetic sequence in physical units. Repeating this procedure generates a temporally evolving synthetic sequence while retaining the observed spatial, cross-variable, and temporal dependence structures. The resulting stationary synthetic temperature and precipitation sequences are denoted by $\mathbf{T}_{kNN,t}$ and $\mathbf{P}_{kNN,t}$, respectively, where each is a vector of length L containing the simulated values across all sites at synthetic time step t . Collectively, $\mathbf{T}_{kNN}$ and $\mathbf{P}_{kNN}$ denote the complete synthetic temperature and precipitation time series generated by the stationary k-NN model. These sequences provide the stationary climate realizations to which the transient climate change signals are applied in Section 3.4.

3.4 Transient Climate Change Perturbation

The purpose of the transient climate change perturbation module is to transform stationary stochastic weather sequences generated by the k-NN resampling model into non-stationary climate trajectories consistent with projected changes from general circulation models (GCMs). This module builds on the established delta-change approach to transient stochastic weather generation (Burton et al., 2010; Glenis et al., 2015; Haasnoot et al., 2015), applying time-evolving climate change signals to the stationary k-NN sequences $\mathbf{T}_{kNN}$ and $\mathbf{P}_{kNN}$ (defined in Section 3.3) while retaining the spatial and cross-variable dependence structure generated by the stochastic weather generator. The perturbation procedure consists of four steps: (1) defining a historical baseline climatology, (2) estimating time-evolving future climatologies from GCM projections, (3) calculating temperature and precipitation change signals relative to the baseline, and (4) applying these signals to the stationary k-NN sequences to generate transient climate trajectories.

First, the baseline climatology is defined over the period 1980–2010, representing the reference historical climate against which future changes are calculated. Let X denote the climate variable of interest, either temperature (T) or precipitation (P); y denote year; w denote calendar week; and l denote site. The observed baseline climatology for variable X is:

$$C_{base}^X(w, l) = \frac{1}{N_{base}} \sum_{y \in Y_{base}} X_{obs}(y, w, l) \quad (3)$$

where γ_{base} is the set of years in the 1980–2010 baseline period, N_{base} is the number of baseline years, and $X_{obs}(y, w, l)$ is the observed value of variable X in year (y), calendar week (w), and site (l).

Second, future climate evolution is represented using a 21-year moving window climatology from the bias-corrected and downscaled GCM projections, which captures gradual changes in mean climate conditions while smoothing interannual variability. For each year y , the future climatology is calculated using the GCM value for year y and the preceding 20 years:

$$C_{fut}^X(y, w, l) = \frac{1}{21} \sum_{r=0}^{20} X_{GCM}(y - r, w, l) \quad (4)$$

where $X_{GCM}(y - r, w, l)$ is the bias-corrected and downscaled GCM value of variable X in year $y - r$, calendar week w , and site l . Thus, $C_{fut}^X(y, w, l)$ represents the mean projected climate state over the 21-year period ending in year y .

Third, climate change signals are computed as deviations from the baseline climatology. Temperature change vectors (ΔT) are represented additively, and precipitation change vectors (ΔP) are represented multiplicatively to account for scale-dependent variability: with $\varepsilon = 10^{-6}$ to avoid division by zero.

$$\Delta T(y, w, l) = C_{fut}^T(y, w, l) - C_{base}^T(w, l) \quad (5)$$

where $\Delta T(y, w, l)$ is the additive temperature change signal for year y calendar week w , and site l . Precipitation change is represented as a multiplicative delta:

$$\Delta P(y, w, l) = \frac{C_{fut}^P(y, w, l)}{\max[C_{base}^P(w, l), \varepsilon]} \quad (6)$$

where $\Delta P(y, w, l)$ is the dimensionless multiplicative precipitation change signal and $\varepsilon = 10^{-6}$ prevents division by zero.

Before the climate change signals are applied, the stationary k-NN sequences are rescaled on a calendar-week basis so that their means and variances are consistent with the corresponding historical observations. For either temperature or precipitation, represented generically by X , the rescaled stationary sequence is:

$$X_{kNN}^*(y, w, l) = \mu_{obs}^X(w, l) + \frac{\sigma_{obs}^X(w, l)}{\sigma_{kNN}^X(w, l)} [X_{kNN}(y, w, l) - \mu_{kNN}^X(w, l)] \quad (7)$$

where $\mu_{obs}^X(w, l)$ and $\sigma_{obs}^X(w, l)$ are the historical mean and standard deviation of variable X for calendar week w and site l , $\mu_{kNN}^X(w, l)$ and $\sigma_{kNN}^X(w, l)$ are the corresponding statistics of the stationary k-NN sequence. The resulting rescaled stationary temperature and precipitation sequences are denoted by T_{kNN}^* and P_{kNN}^* , respectively.

Finally, the computed climate change signals, ΔT and ΔP , are applied to the stationary stochastic sequences generated by the k-NN model. This follows a delta-change approach where temperature is adjusted additively and precipitation is adjusted multiplicatively:

$$T_{transient}(y, w, l) = T_{kNN}^*(y, w, l) + \Delta T(y, w, l) \quad (8)$$

$$P_{transient}(y, w, l) = P_{kNN}^*(y, w, l) \Delta P(y, w, l) \quad (9)$$

Where $T_{transient}(y, w, l)$ and $P_{transient}(y, w, l)$ are the resulting transient temperature and precipitation values for year y , calendar week w , and site l . Precipitation values are constrained to be non-negative to ensure physical plausibility.

This approach generates a large ensemble of climate trajectories that explicitly represents both internal climate variability and model/forcing uncertainty. A single climate realization is defined by the combination of (i) one stochastic k-NN simulation path and (ii) one GCM–SSP transient forcing pathway. Repeating this pairing across multiple stochastic realizations yields a large ensemble of climate trajectories that jointly represent internal variability and scenario uncertainty. This ensemble structure enables systematic exploration of plausible future climate conditions and provides input for downstream hydrological impact simulations. The ensemble

described below comprises 3 stochastic realizations for each of 36 GCM–SSP combinations, yielding 108 transient climate scenarios.

3.5 Drought Analysis

Drought analysis provides a natural test case for evaluating the practical implications of using transient climate scenarios over stationary ones, as drought risk depends not only on the frequency of dry conditions but on their sequencing and persistence, and on how that risk profile evolves over a planning horizon. A stationary ensemble can characterize the range of drought severity a system might face at a single climate condition but does not capture whether or when that risk is intensifying, which is important for informing water resources planning decisions. We therefore use the transient and stationary scenario ensembles generated in Sections 3.3–3.4 to evaluate both the magnitude of projected drought conditions and how that magnitude and persistence evolve over the 21st century, and to compare this evolving risk against the static picture a stationary approach would provide. Specifically, we compute drought indices from the ensemble of simulated precipitation and streamflow: the 12-month Standardized Precipitation Index (SPI-12) from simulated precipitation and the 12-month Standardized Runoff Index (SRI-12) from simulated WEAP streamflow outputs, following the standard SPI formulation of McKee et al. (1993) and its runoff-based analog, SRI (Shukla and Wood, 2008). Weekly simulated values of the variable of interest (precipitation for SPI, streamflow for SRI) are first aggregated to monthly totals:

$$X_{month}(m, y) = \sum_{w \in month(m, y)} X_{week}(w) \quad (10)$$

where $X_{month}(m, y)$ is the aggregated value of precipitation or total streamflow for calendar month m of year y , and $X_{week}(w)$ is the simulated weekly value of precipitation or streamflow for week w falling within that month. A rolling 12-month accumulation is then computed at each month:

$$A(m, y) = \sum_{i=0}^{11} X_{month}(m - i, y) \quad (11)$$

where $A(m, y)$ is the trailing 12-month accumulation ending in month m of year y . For each calendar month m , a two-parameter gamma distribution with location fixed at 0 is fit by maximum likelihood to the accumulation values $A(m, y)$ drawn from the 1980–2010 historical baseline period (the same baseline period used to compute the climate change perturbation signals in Section 3.4), with the location parameter fixed at zero:

$$f_m(a; \alpha_m, \beta_m) = \frac{1}{\Gamma(\alpha_m)\beta_m^{\alpha_m}} a^{\alpha_m-1} \exp\left(-\frac{a}{\beta_m}\right), \quad a > 0 \quad (12)$$

where $f_m(a; \alpha_m, \beta_m)$ is the gamma probability density function for calendar month m , α_m, β_m are the shape and scale parameters estimated for month m , and $\Gamma(\cdot)$ is the gamma function, with

the location parameter equal to zero. The fitted distribution for each calendar month defines a cumulative distribution function:

$$F_m(a) = \frac{\gamma(\alpha_m, a/\beta_m)}{\Gamma(\alpha_m)} \quad (13)$$

where $F_m(a)$ is the cumulative probability of accumulation value a under the fitted gamma distribution for calendar month m , and $\gamma(\alpha_m, a/\beta_m)$ is the lower incomplete gamma function. This same baseline-fitted distribution is then applied to the 12-month accumulation totals from every scenario, both stationary and transient, across all realizations, transforming each accumulation value into a standardized index via the inverse standard normal distribution:

$$SPI(m, y) = \Phi^{-1}[F_m(A_p(m, y))] \quad (14)$$

$$SRI(m, y) = \Phi^{-1}[F_m(A_q(m, y))] \quad (15)$$

where $\Phi^{-1}(\cdot)$ is the inverse standard normal cumulative distribution function, and $A_p(m, y)$ and $A_q(m, y)$ are the 12-month rolling accumulations of precipitation and streamflow, respectively, for month m of year y in a given scenario. Applying the baseline-fitted F_m to every scenario ensures that departures from normal conditions are measured consistently against a common historical reference rather than against each scenario's own statistics. The resulting index values are expressed in standard-deviation units relative to the baseline distribution, with negative values indicating drier-than-normal conditions and positive values indicating wetter-than-normal conditions.

A 12-month accumulation period is used because it captures the multi-season and interannual drought conditions most relevant to reservoir carryover storage and long-term water supply planning in the Maipo Basin, rather than the shorter-term meteorological variability captured by shorter accumulation periods. Computing SPI-12 from precipitation and SRI-12 from simulated streamflow allows us to assess how climate signals in temperature and precipitation propagate through the hydrological system: differences between the two indices reveal how basin storage, snowmelt timing, and other hydrological processes modulate meteorological drought signals into hydrological drought outcomes, and comparing these indices between stationary and transient scenario ensembles isolates the effect of representing non-stationary climate change on projected drought characteristics.

4 Results

To assess whether the k-NN stochastic weather generator reproduces the historical seasonal cycle independent of any climate-change forcing, we compare weekly basin averaged precipitation and temperature from the stationary generator against the 1979–2019 historical

reference, aggregated by calendar month (Fig. 3, panels a–b). The stationary generator closely follows historical temperature across the full annual cycle (Fig. 3b). Monthly medians and interquartile ranges from the k-NN series track the reference in every month, with only minor differences in spread (e.g., slightly wider boxes in April and October), indicating that the generator captures both the seasonal temperature trajectory and its historical variability with high fidelity. The stationary generator also reproduces the timing of the wet season correctly, with both reference and generated series peaking between May and August and declining sharply toward the austral summer (Fig. 3a).

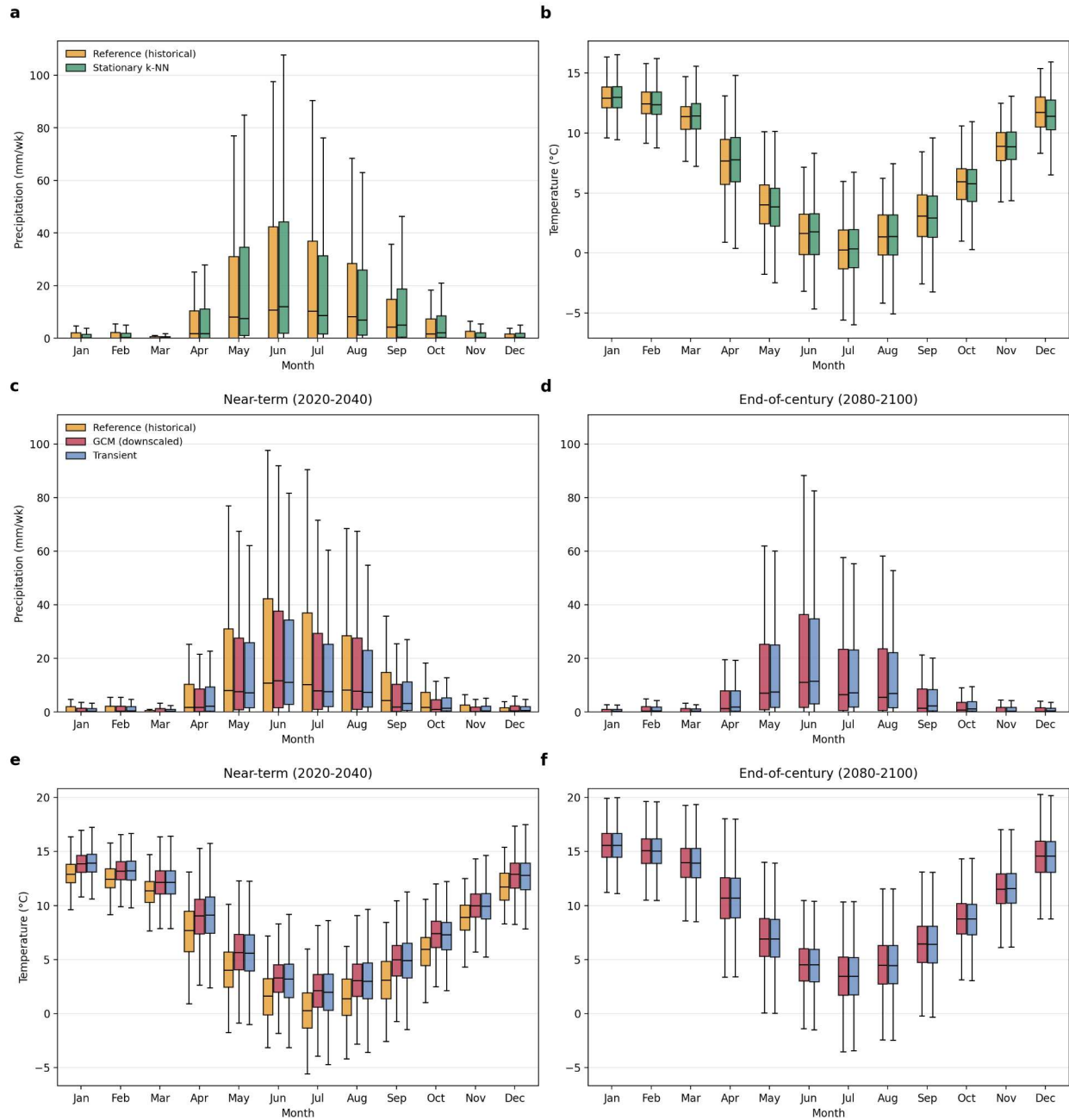


Figure 3. Boxplots comparing seasonality of generated scenarios against historical observations and GCM projections. Panels a,b compare the stationary KNN generator outputs to the reference historical period (1979–2019) for (a) precipitation and (b) temperature. Panels c,e compare the transient generated scenarios to the reference historical period and the downscaled GCMs over the near-term horizon (2020–2040) for (c) precipitation and (e) temperature. (a) monthly temperature and (b) monthly precipitation. Panels d,f compare the transient generated scenarios to downscaled GCMs over the end-of-century horizon (2080–2100) for (d) precipitation and (f) temperature.

We next compare weekly precipitation among the historical reference, GCM-downscaled projections (bias-corrected via UQM and pooled across nine CMIP6 models and four SSPs), and the transient k-NN scenarios for two future periods: Near-term (2020–2040) and End-of-century (2080–2100) (Fig. 3c–d). This comparison allows us to assess the extent to which the transient approach captures GCM-projected changes over the course of the century. In the near-term period (Fig. 3c), GCM-downscaled precipitation retains a seasonal distribution broadly similar to the historical reference, with comparable median values during the wet season. The transient series closely tracks the GCM distribution across this period, with wet-season monthly medians within 3–6% of the corresponding GCM values and interquartile ranges reaching 80–91% of the GCM spread. This correspondence persists into the end-of-century period: transient medians remain within a similar range of GCM values, and in several wet-season months, notably August, modestly exceed them (Fig. 3d). The transient interquartile range converges toward the GCM spread by the end of century (89–95% of the GCM interquartile range across May through August, compared to 80–91% in the near-term period).

Weekly temperature comparisons between the reference, GCM-downscaled, and transient series show a different pattern (Fig. 3e–f). In both the near-term and end-of-century periods, GCM and transient temperature distributions are nearly indistinguishable from one another across all months, and both show a consistent warm shift relative to the historical reference (Fig. 3e–f). This warming is largest in absolute terms during the historically coldest months (June–August) and intensifies further from the near-term (Fig. 3e) to the end-of-century period (Fig. 3f), with monthly medians shifting upward across the full annual cycle. The close correspondence between GCM and transient temperature in both periods indicates that the transient forcing approach transfers both the GCM's projected warming into the transient scenarios.

The stationary k-NN generator similarly captures the weekly variability of the historical seasonal cycle independent of any climate-change forcing (Fig. 4a–b). The stationary generator closely follows the historical standard deviation of precipitation (Fig. 4a) and temperature (Fig. 4b) across the full annual cycle. Monthly medians of standard deviation from the k-NN series tend to track the reference, with minor differences in medians (e.g., higher median standard deviation in precipitation in June and September; higher median standard deviation in temperature in April), indicating that the generator captures both the seasonal temperature trajectory and its historical variability. The stationary generator also reproduces the timing of the wet season variability correctly, with both reference and generated series peaking between May and August and declining sharply toward the austral summer (Fig. 4a).

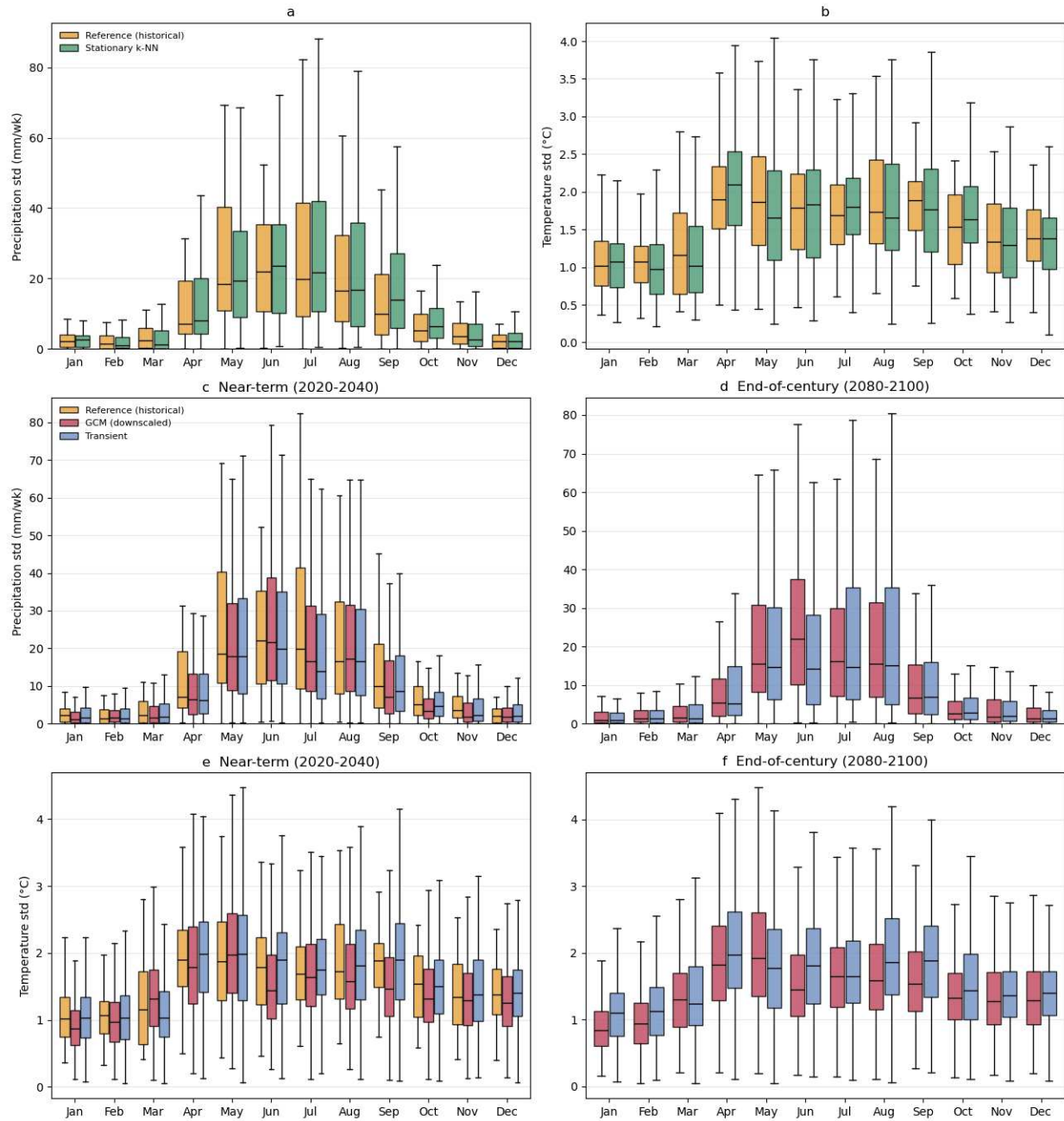


Figure 4. Boxplots comparing weekly standard deviations generated scenarios against historical observations and GCM projections. Panels a,b compare the stationary KNN generator outputs to the reference historical period (1979–2019) for basin averaged (a) precipitation and (b) temperature. Panels c,e compare the transient generated scenarios to the reference historical period and the downscaled GCMs over the near-term horizon (2020-2040) for basin-averaged (c) precipitation and (e) temperature. (a) monthly temperature and (b)

monthly precipitation. Panels d,f compare the transient generated scenarios to downscaled GCMs over the end-of-century horizon (2080-2100) for (d) precipitation and (f) temperature.

The remainder of the result section is organized as follows. Section 4.1 presents the ensemble of generated temperature and precipitation time series and the resulting streamflow time series after using them to run the WEAP model. Section 4.2 evaluates the extent to which the generated scenarios preserve spatial dependence, both within each variable and jointly between temperature and precipitation. Finally, Section 4.3 compares resulting drought characteristics under stationary and transient climate assumptions in order to demonstrate the implications of non-stationary changes to temperature and precipitation on water resources planning risks.

4.1 Ensemble Characteristics and Transient Climate Behavior

Figure 5 shows rolling 20-year mean trajectories of temperature, precipitation, and streamflow from 2020 to 2100 for the downscaled GCM ensemble (orange) and the stochastic transient realizations (gray) for the 108 transient scenarios representing three stochastic variations of each of the 36 climate forcings. Streamflow time series are developed by using the GCM ensemble and stochastic transient realizations respectively to force the WEAP model. We use a 20-year moving window to illustrate and compare multi-decadal variability and long-term trends.

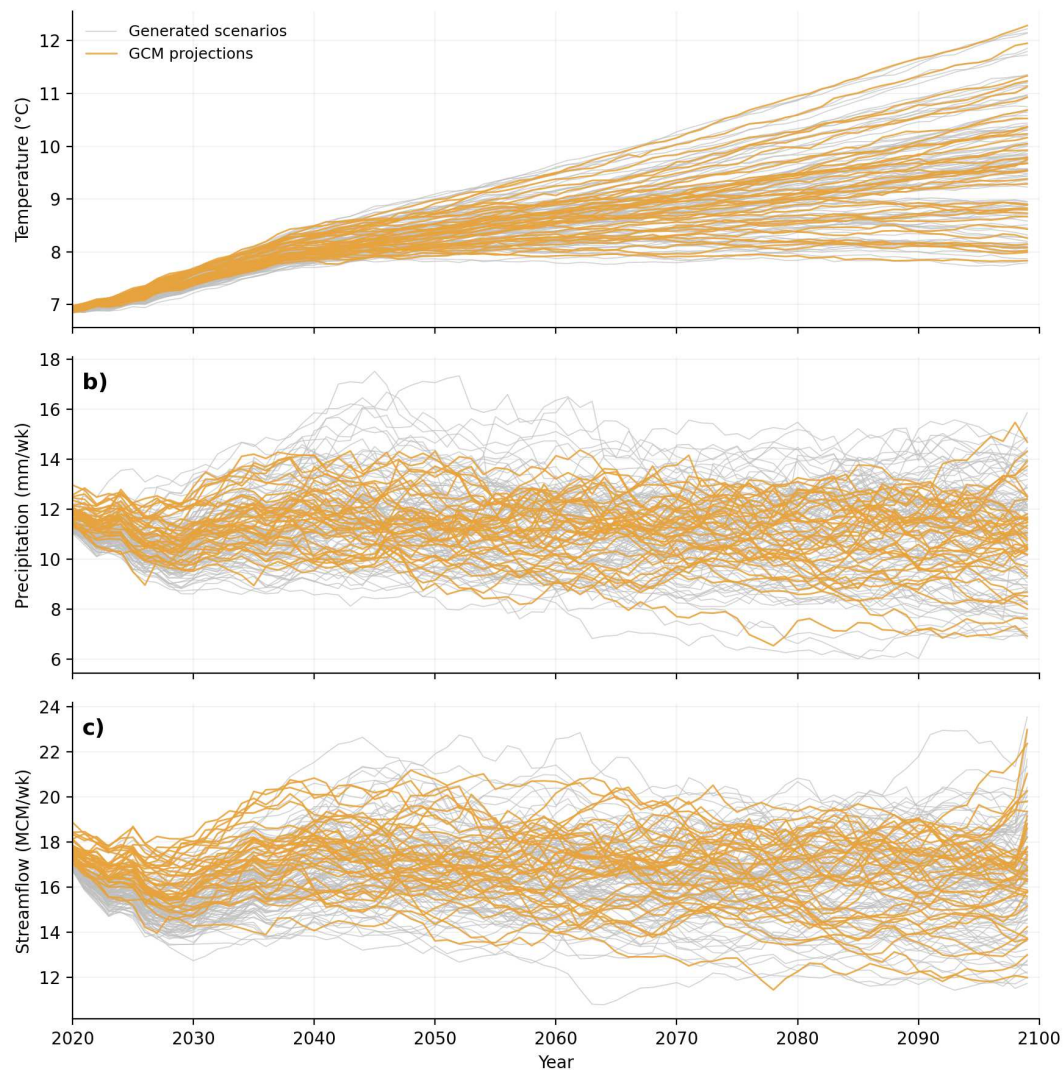


Figure 5. Moving 20-year average temperature, precipitation, and streamflow time series. 36 GCM projections are plotted in orange and 108 generated transient scenarios are plotted in gray. **(a)** mean weekly basin temperature trajectories. **(b)** mean total weekly precipitation trajectories **(c)** mean weekly total simulated streamflow from the WEAP model of the basin.

Temperature trajectories from both the GCM ensemble and the stochastic realizations increase consistently over the century, with the stochastic ensemble expanding modestly beyond the GCM ensemble's range (Figure 5a). Temperature values begin within a narrow range in the early period (2020–2030) across ensemble members, and diverge steadily thereafter. By the end of the century, the GCM ensemble and stochastic realizations span a similar range, with the stochastic realizations extending slightly beyond the GCM ensemble range, indicating close alignment with the GCM ensemble.

In contrast, the precipitation trajectories exhibit no consistent directional trend over the century, and the stochastic ensemble's added spread relative to the GCM ensemble is substantially larger than for temperature (Figure 5b). Across the century, individual GCM trajectories showing both increases and decreases depending on the model and no consistent trend across scenarios. The stochastic realizations reproduce a similar range of variability, but result is a wider late-century range. Standard deviation is modestly higher for the generated ensemble in the early period, but modestly lower at the end of the century.

Simulated streamflow shows similar variability and trends across the GCM projections and generated scenarios, with moving 20-year average values broadly ranging from 12 to 24MCM/week over the simulation period (Figure 5c). Streamflow captures the compounding effect of long-term shifts in temperature and precipitation over the century, which alter hydrological conditions and runoff generation processes in the basin. Early in the simulation period (2020-2040), the stochastic ensemble averages slightly lower at mean streamflow, with comparable variability between the two. Divergence in streamflow increases over the century for both ensembles: in the late-century (2080-2099), GCM and generated scenarios show comparably wider dispersion relative to early century. The generated ensemble's range slightly exceeds the GCM ensemble's, indicating a slightly wider late-century envelope due to the larger sample size.

4.2 Preservation of Spatial and Cross-Variable Correlation Structure

Figure 6 evaluates whether the generated scenarios preserve the same spatial dependence structure as the GCM ensemble. Preserving spatial dependence across sites is important because basin-scale hydrological models combine climate inputs from many locations to simulate variables such as streamflow, and the degree of correlation between those inputs shapes how the combined climate forcing propagates through the modeled hydrological processes across the basin. The 257 locations used in this study span inter-site distances of up to approximately 120 km across the Maipo Basin. For each pair of sites, we compute the Pearson correlation between their weekly time series within a given future period, separately for temperature and precipitation, and examine how this pairwise correlation varies with the geographic distance between sites. Pairwise correlations are then averaged across all scenarios within a group, yielding one mean correlation value per site pair, per period. Because the large number of site pairs makes it impractical to plot each one individually, results are summarized with a two-dimensional kernel density estimate (KDE) as a function of inter-site distance and mean correlation, with color indicating the relative density of site pairs at each combination of distance and correlation. Results are shown separately for temperature (top two rows) and precipitation (bottom two rows), comparing the GCM ensemble to the generated scenarios across three future periods: 2020–2040, 2050–2070, and 2080–2100.

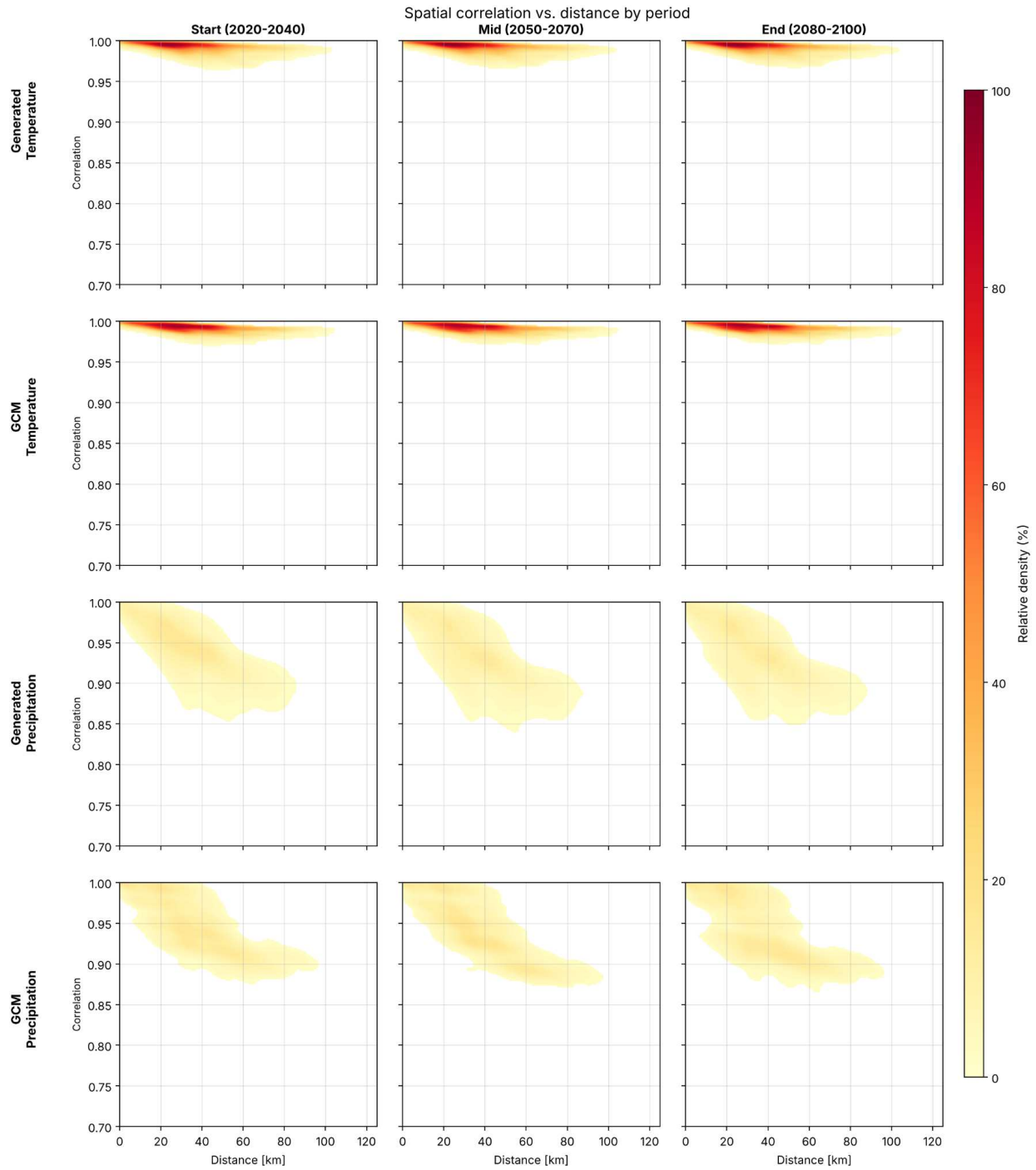


Figure 6. Spatial correlation for temperature and precipitation for GCMs and generated scenarios across distance and time periods. For each pair of the 257 locations, we compute the Pearson correlation coefficient between their weekly time series within each future period, separately for temperature and precipitation. Results are summarized with a two-dimensional kernel density estimate (KDE) as a function of inter-site distance and mean correlation. Density

is normalized to a common 0–100% scale across all 12 panels, so colors are directly comparable across variables, scenario groups, and periods; regions where pairwise correlations are absent are left. Rows show, from top to bottom: generated temperature, GCM temperature, generated precipitation, and GCM precipitation. Columns represent three future periods: Start (2020–2040), Mid (2050–2070), and End (2080–2100).

Temperature exhibits consistently high spatial correlations across all inter-site distances for both the GCM ensemble (Figure 6a-c) and the generated scenarios (Figure 6d-f). Correlation values remain close to 1.0 at short distances and show only a slight decrease with increasing distance. This pattern is consistent across all three time periods, with similar distributions observed in 2020–2040, 2050–2070, and 2080–2100. The generated scenarios reproduce the same general correlation structure as the GCM ensemble, with closely overlapping distributions across distance and time. The overall shape of the correlation–distance relationship remains consistent throughout the simulation period for both ensembles.

In contrast, precipitation spatial correlations decrease more visibly with increasing inter-site distance compared to temperature (Figure 6g-l). Correlation values are highest at short distances (approximately 0.95–1.0 for distances <50 km) and gradually decline toward lower values at larger separations (approximately 0.85–0.90 for distances >50 km). The generated scenarios reproduce this general distance-dependent structure across all three time periods, with broadly similar correlation patterns to the GCM ensemble. This pattern is consistent across all three time periods (2020–2040, 2050–2070, and 2080–2100). Given the small magnitude of these differences and the overall preservation of the correlation–distance relationship, this represents a strong validation of the generator's ability to capture spatial correlation structure.

Beyond spatial coherence within each variable individually, joint spatial structure between temperature and precipitation is also relevant to hydrological simulation, since hydrologic routing depends on the combined pattern of both variables across the basin. The spatial coupling between temperature and precipitation is well preserved by the generated scenarios across the century. Figure 7 evaluates this by computing, for each week, the Pearson correlation across the 257 sites between their temperature and precipitation values. This captures whether sites that are relatively warmer in a given week also tend to be relatively wetter or drier. The distribution of these weekly correlations is shown pooled by calendar month for the GCM ensemble (orange) and the generated stochastic scenarios (blue) across two future periods: 2020–2040 (panel a), and 2080–2100 (panel b).

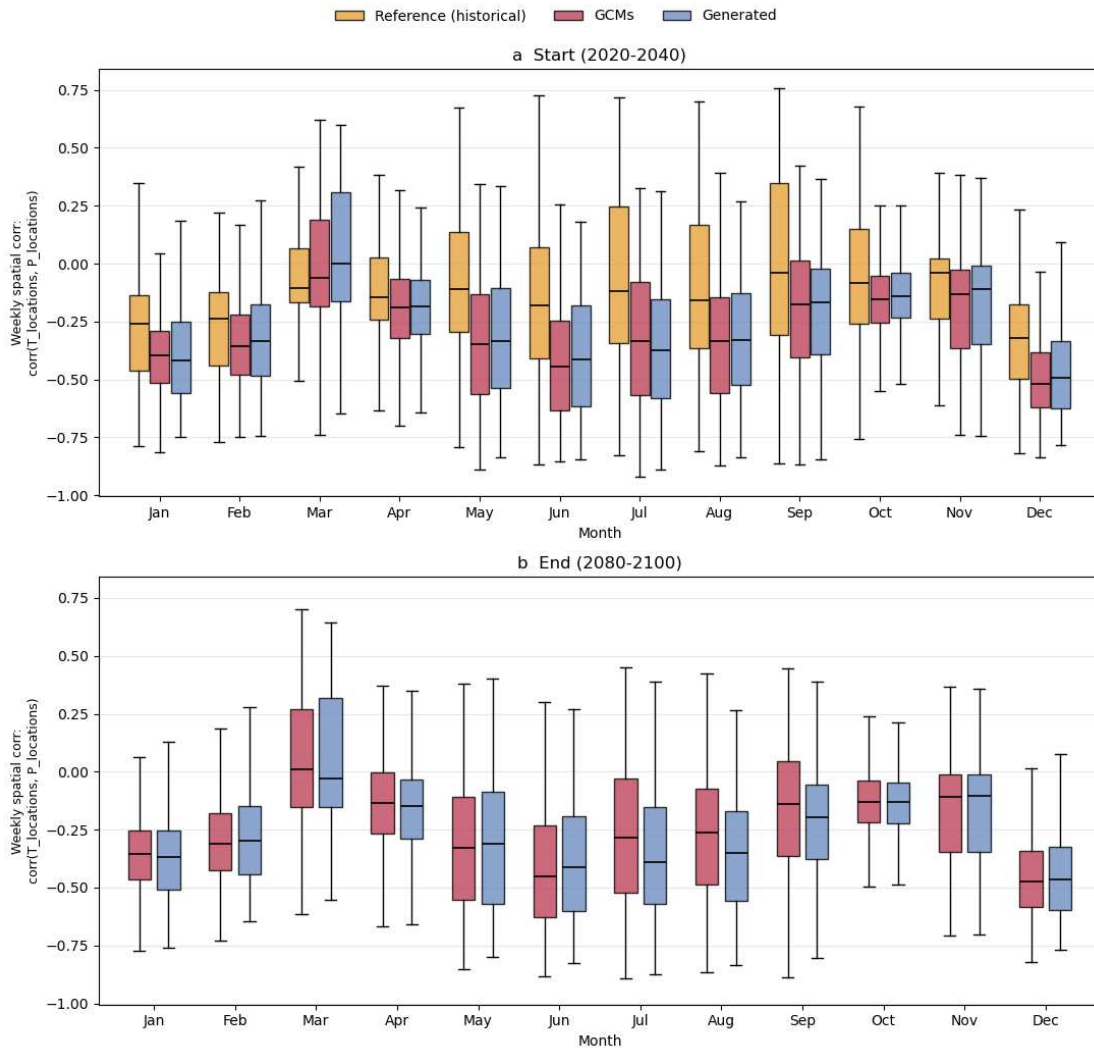


Figure 7. Boxplots of temperature–precipitation correlation coefficients by month of year across all spatial locations for the GCM ensemble and generated stochastic scenarios for (a) 2020–2040 and (b) 2080–2100. Panel a also provides a comparison with the reference historical period (1979-2019).

Correlation values are predominantly negative and follow a pronounced seasonal cycle, driven primarily by the basin's orographic precipitation gradient (Figure 7a–b). Higher-elevation sites in the basin are colder and, particularly during winter, receive substantially more precipitation, producing the negative cross-variable correlation between temperature and precipitation seen across most months. The near-zero correlation in March is consistent with this month marking the transition out of the dry season, before winter precipitation emerges.

The generated scenarios closely reproduce this seasonal structure across periods, with only modest departures from the GCM ensemble (Figures 7a–b). Both the relative ordering of months and the comparable spread of correlation values across locations are preserved. The

generated scenarios show slightly more negative median correlation values compared to the GCM ensemble in several months, particularly in April to September, though this discrepancy is small relative to the overall seasonal range. The dispersion of correlation values is generally comparable between ensembles, although the generated scenarios exhibit a marginally narrower distribution in some months. This spatial correlation structure remains stable across the century in both ensembles, with no evidence that the generator introduces spurious transient drift (Figure 7a vs. 7b). No abrupt shifts in the seasonal pattern are visible across time periods, and the relative differences between GCM and generated ensembles persist throughout the century.

4.3 Impact of Transient Climate Signals on Drought Characteristics

Transient climate forcing produces progressively more severe drought conditions over the 21st century than stationary climate variability alone, with a substantially stronger drying signal in streamflow than in precipitation. We examine this divergence to evaluate how representing climate change as an evolving trajectory alters estimates of drought risk relative to a stationary representation and how meteorological changes propagate through basin hydrology. To illustrate this, we compare stationary and transient k-NN realizations under SSP5-8.5, the most severe of the four SSPs considered in this study, where transient climate impacts are most pronounced. This effect is evaluated using two standardized indices: the Standardized Precipitation Index (SPI-12), which quantifies precipitation deficits relative to a fixed historical baseline, and the Standardized Runoff Index (SRI-12), computed analogously from simulated streamflow to capture the combined effect of precipitation and temperature on basin runoff (see Section 3.5). Figure 8 shows the underlying rolling precipitation and temperature time series that drive the difference between the stationary and transient realizations (Figure 8a-b), and the resulting SPI-12 and SRI-12 trajectories (Figure 8c,d) that translate this difference into drought characteristics for precipitation and streamflow, respectively.

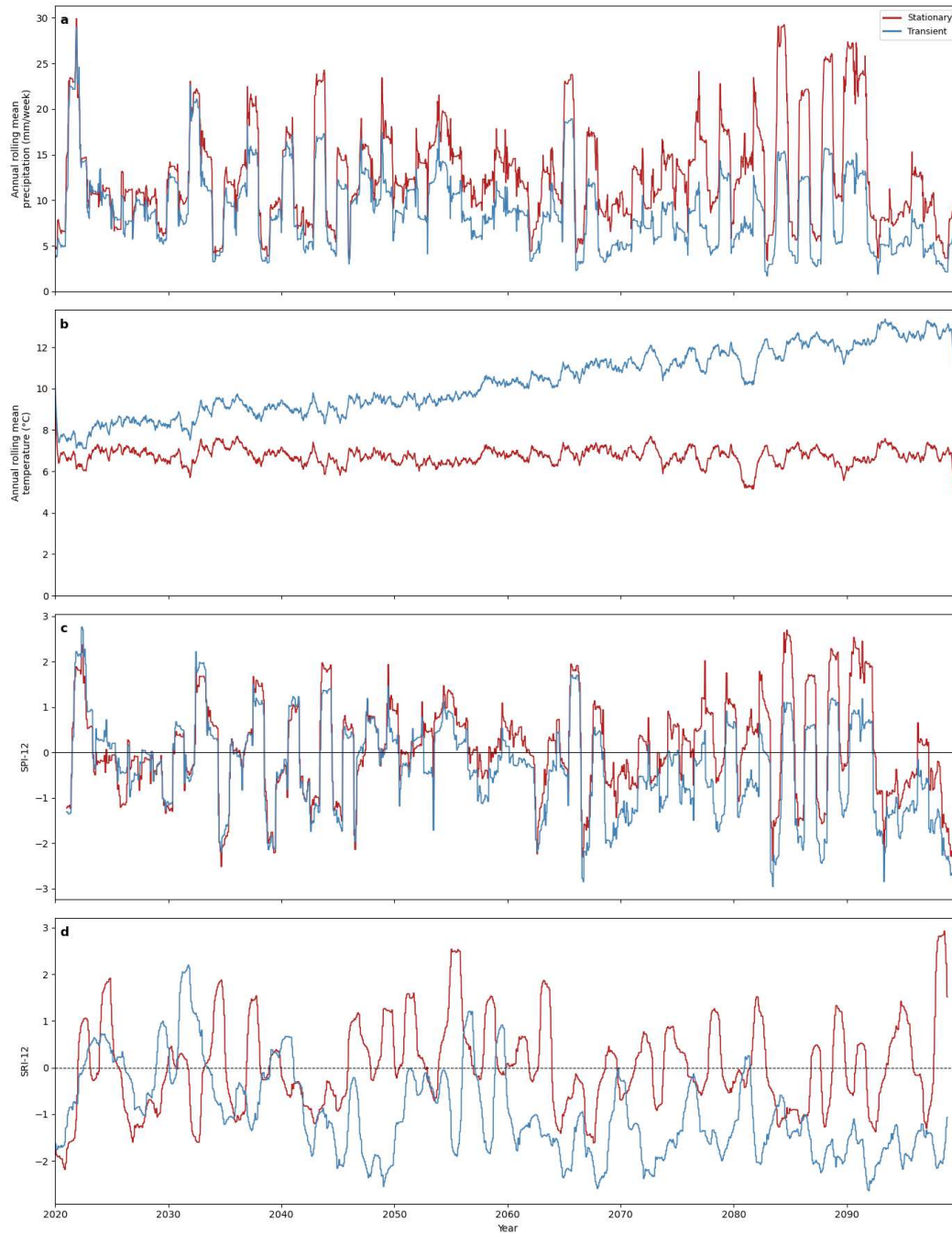


Figure 8. Comparison of precipitation- and streamflow-based drought indices (SPI-12 and SRI-12) for the basin under a stationary vs. transient warming scenario. The SPI-12 and SRI-12 for both the stationary and transient scenarios were calculated using a stationary historical baseline over the century. **(a)** Comparison of rolling annual mean of weekly stationary and transient precipitation time series. **(b)** Comparison of rolling annual mean of weekly stationary and transient temperature time series. Example realization of **(c)** SPI-12 and **(d)**

SRI-12 computed from stationary k-NN weather generator output and the corresponding transient scenario..

Precipitation and temperature diverge increasingly between the stationary and transient realizations over the century. The stationary precipitation realization fluctuates around a stable central tendency of approximately 15 mm/week throughout the record, with no long-term trend, while the transient realization tracks closely with the stationary series in the early decades but increasingly falls below it from roughly 2050 onward, with the gap between the two series widening further by the end of the century (Figure 8a). Temperature shows the reverse pattern: the stationary realization remains roughly stable between 6°C and 8°C throughout the century, while the transient realization rises steadily from approximately 7.5°C in 2020 to approximately 12–13°C by 2100, an increase of roughly 5°C (Figure 8b).

The transient climate signal progressively intensifies drought severity relative to the stationary realization, with substantially greater amplification in hydrological than meteorological drought. SPI-12 becomes increasingly negative under transient forcing, particularly after mid-century, indicating that declining precipitation produces progressively more severe meteorological drought relative to the historical baseline (Figure 8c–d). This divergence is considerably larger for SRI-12: the transient realization increasingly falls below the stationary realization after mid-century and spends much of the latter half of the century below the severe drought threshold (Figure 8e). By the end of the century, the difference between transient and stationary SRI-12 reaches approximately –5, compared with less than –2 during the early decades and a substantially smaller divergence in SPI-12 (Figure 8f). The stronger response in SRI-12 indicates that the hydrological system amplifies the transient drying signal as declining precipitation and rising temperature jointly affect streamflow, producing changes in hydrological drought that are not apparent from precipitation trends alone.

5 Discussion

This study contributes a computationally efficient and scalable approach for generating large ensembles of multisite, multivariate climate scenarios that represent both internal climate variability and non-stationary climate change signals. The approach combines k-NN resampling of historical sequences, which preserves observed spatial and cross-variable dependence structures, with a transient climate perturbation module that introduces time-varying climate change signals. Applied to the Maipo Basin, the approach produces transient climate scenarios suitable for forcing high-resolution, multisite water resources models such as WEAP without additional spatial or temporal disaggregation. This facilitates the integration of climate scenario generation with existing hydrological modeling frameworks and provides a practical basis for evaluating hydrological processes and system performance across a broad range of plausible future climates. The ability to generate large ensembles further supports systematic exploration

of uncertainty in complex basin-scale planning contexts where system performance depends on correlated climate inputs.

One key feature of the framework is the separation of internal climate variability from external climate forcing. The k-NN resampling step generates distinct realizations of temperature and precipitation by resampling from the historical record, while the perturbation module imposes transient climate change signals derived from different GCMs on these realizations. This separation allows multiple realizations of internal variability to be evaluated under alternative climate change trajectories and therefore a larger number of plausible future climate change scenarios to be analyzed. This distinction is important for water resources decision-making because system outcomes can depend on both the long-term climate trajectory and the particular sequence and timing of climate conditions experienced along that trajectory.

A second key feature of the approach is its representation of spatial and cross-variable dependence structures. The k-NN resampler selects based on multivariate similarity across all locations and variables and therefore captures the empirical dependence structure of the observed climate system that is carried into the generated sequences. Differences in the strength of spatial dependence among variables are associated with differences in temporal intermittency and distributional properties, particularly for precipitation. These characteristics increase sensitivity to resampling and to perturbation and result in the minor deviations in spatial coherence observed in Section 4.2. Similarly, cross-variable dependence is maintained because perturbations are applied consistently across variables at each time step, allowing shared correlation structures to persist even as marginal distributions evolve over the century. Remaining differences reflect limitations of resampling-based approaches in representing higher-order dependence under non-stationary forcing. These properties are relevant for hydrological modeling because system responses depend on joint variability across variables and locations rather than marginal behavior alone.

We demonstrate the importance of considering transient changes across multiple variables through a drought analysis comparing stationary and transient scenarios. The example shows how the use of transient scenarios produces trajectories that maintain similar temporal ordering of events while exhibiting systematic changes in magnitude and frequency of hydroclimatic conditions. We note that transient change along results in more severe droughts relative to the SPI over the period in the basin. Simulated SRI, which captures the joint impact of temperature and precipitation, demonstrates how over the century, these changes in both precipitation and temperature accumulate, leading to further divergence in long-term SRI drought-related. From a risk assessment perspective, this mechanism suggests that gradual changes in forcing can translate into substantial long-term differences in hydrological conditions even when short-term variability remains structurally similar. It further demonstrates how joint shifts in temperature and precipitation can result in different simulated duration and severity of drought.

Future extensions could incorporate non-stationary resampling strategies or distributional transformations that allow variability and extremes to evolve more explicitly. Enhancing the representation of precipitation occurrence and persistence would further improve applicability to

drought and flood risk analysis. Despite these limitations, the framework provides a scalable and computationally efficient method for linking climate model projections with stochastic weather generation for multisite hydrological applications.

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