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Warming Accelerates and Intensifies Meteorological-to-Agricultural Drought Propagation in the Northern Great Plains

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Abstract

Drought propagates from atmospheric water deficits into root-zone soil–moisture stress, yet the extent to which warming will alter the severity and speed of this transition in cold, semi-arid regions remains poorly quantified, and most propagation studies rely on a single linkage measure. This study assessed meteorological-to-agricultural drought propagation across a 1.74 million km² transboundary domain in the Northern Great Plains using 11 km projections from the Canadian Regional Climate Model version 5 driven by Coupled Model Intercomparison Project Phase 6 Earth system models (CRCM5-CMIP6) and a calibrated cold-region Soil and Water Assessment Tool (SWAT) model. Climate simulations were bias-corrected by quantile delta mapping, and meteorological and agricultural droughts were characterized using the Standardized Precipitation Evapotranspiration Index (SPEI) and Soil Moisture Deficit Index (SMDI), respectively, for a historical baseline and three future periods under three Shared Socioeconomic Pathway (SSP) scenarios: intermediate (SSP2-4.5), high (SSP3-7.0), and very high (SSP5-8.5) emissions. Propagation was evaluated using multiscale Spearman correlation, run-theory event matching, copula-based conditional probabilities, and lower-tail dependence. Quantile delta mapping increased climate-variable correlations with observations to approximately 0.85–0.95, while SWAT reproduced daily warm-season soil moisture with Kling–Gupta efficiencies of 0.575–0.731. Both SPEI-12 duration and severity of meteorological drought increased with forcing and time; under far-future SSP5-8.5, local increases reached approximately 20–22 months and 60–67 severity units. Basin-mean SMDI declined to –1.08 under far-future SSP5-8.5, with the strongest drying in the southern and southeastern sectors of the region. Although the mean SPEI-3–SMDI correlation weakened slightly from 0.62 in the near future to 0.57 in the far future, the mean propagation time shortened from 2.37 to 1.81 months. The probability of agricultural drought during extreme meteorological drought was 0.69–0.82, and the translation rate increased from approximately 54–58% under SSP2-4.5 to 63–68% under SSP5-8.5. These results indicate that warming intensifies soil-moisture drought while reducing the response time available for agricultural drought preparedness. They also imply that adaptation to a warming climate will require an emphasis on agricultural practices that preserve soil moisture.

Keywords: drought propagation; SPEI; soil moisture deficit index; SWAT; CRCM5-CMIP6; Northern Great Plains; copula; tail dependence

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1. Introduction

Drought is a complex natural hazard with significant impacts on environmental, economic, and social systems, particularly in water-limited regions. Although drought affects most parts of Canada, it is generally more frequent, extensive, and severe in the Prairie Provinces [1]. The Prairies are vulnerable to drought due to their location in the lee of major mountain ranges, which results in relatively low precipitation and pronounced spatial and temporal variability [2,3]. This high variability in precipitation makes the region particularly prone to prolonged moisture deficits, especially during the growing season when water availability is most critical for agricultural productivity. Historically, the Canadian Prairies have experienced numerous severe and persistent droughts, with more than 40 major events recorded over the past 2 centuries [4]. Among these, the 1930s “Dust Bowl” remains one of the most devastating, leading to widespread land degradation, farm abandonment, and large-scale population displacement, which ultimately prompted the establishment of the Prairie Farm Rehabilitation Administration (PFRA) in 1935. The drought from 1999 to 2005 stands out as the most severe of the last century, marked by a significant and persistent lack of precipitation across multiple seasons [1,3]. This extreme weather event resulted in an estimated gross domestic product (GDP) loss of around CAD 4.5 billion for the Canadian Prairies [5,6]. Drought in 2021 caused widespread crop losses in western Canada, with its economic severity reflected in approximately CAD 2.6 billion in crop-insurance payouts in Saskatchewan alone, where crop production declined by 43% relative to the 5-year average [7].

Drought is commonly categorized into four types: meteorological, agricultural, hydrological, and socioeconomic [8]. The first three are considered environmental droughts and represent different forms of water deficit within the hydrological system. Meteorological drought results from prolonged precipitation deficits, whereas agricultural drought occurs when reduced soil moisture limits crop growth [9,10]. A hydrological drought is a sustained decline in surface and groundwater availability [11]. These drought types are closely interconnected, typically evolving from meteorological drought and propagating through the system via reduced soil moisture, runoff, and groundwater recharge [12,13]. Understanding these linkages and propagation dynamics is essential for improving early warning systems and mitigating the impacts of compound drought events.

Future climate change will play a predominant role in the frequency, intensity, and impact of droughts. Under high-emission scenarios (e.g., RCP8.5), mean annual temperatures in the Prairies are projected to increase by approximately 2.3 °C by mid-century and up to 6.5 °C by the end of the century relative to the 1986–2005 baseline, potentially exacerbating evapotranspiration and moisture deficits [14]. More frequent and severe droughts have significant implications for agriculture, water resources, ecosystems, and regional economies [15,16]. Despite extensive research on drought, many studies have focused primarily on individual drought types, particularly meteorological drought, without fully considering interactions and propagation between meteorological and agricultural droughts. For instance, various studies have evaluated meteorological drought using indices such as the Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI), and Standardized Precipitation Evapotranspiration Index (SPEI) under historical and future climate scenarios, e.g., [17–19]. Similarly, agricultural drought has often been examined independently through soil moisture-based indicators and land surface modeling approaches, e.g., [9,20]. In the Canadian Prairies, previous studies have assessed drought variability and trends using precipitation- and temperature-based metrics [1,3]. However, these studies generally treat drought types separately and do not explicitly investigate their dynamic linkages and propagation processes. Propagation studies else-

where have mostly focused on humid basins and historical periods and have usually relied on a single linkage measure such as correlation or event lag [21,22]. Their findings may not transfer to the Prairies, where snowmelt, frozen ground, and soil water storage weaken the direct link between weather and soil moisture. Correlation, lag, and conditional probability also describe different aspects of propagation, and under warming, they may not change in the same direction. This study therefore asks whether, under projected warming, meteorological drought reaches the root zone more quickly, and whether the chance of agricultural drought during severe meteorological drought increases even when average correlation remains moderate. The contribution lies less in the individual methods than in applying them together, with a cold-region hydrological model and high-resolution CMIP6 projections, to a semi-arid transboundary region where, to our knowledge, no such assessment has been made.

Therefore, this study integrates assessments of meteorological and agricultural droughts in the Northern Great Plains using CRCM5-CMIP6 projections under three Shared Socioeconomic Pathways, representing intermediate (SSP2-4.5), high (SSP3-7.0), and very high (SSP5-8.5) emissions, and the Soil and Water Assessment Tool (SWAT) hydrological model. By analyzing multiple drought indices and their interactions across historical and future periods, this research (i) evaluates changes in drought characteristics under climate change, (ii) investigates the propagation dynamics among two drought types, and (iii) provides insights to support improved drought monitoring, early warning, and adaptation strategies in the region.

2. Data and Methodology

2.1. Study Area

The study area covers a significant chunk of the Northern Great Plains of the western interior of Canada and the US. We defined it hydrographically since we used a hydrological model to simulate soil moisture. This area includes the sub-basins of the Saskatchewan River Basin and adjacent sub-basins of the transboundary Missouri and Assiniboine River Basins in Canada and the United States (Figure 1). This large hydrographically defined region spans Alberta, Saskatchewan, and Manitoba, and it extends into Montana and North Dakota. The Canadian Prairie provinces hold over 80% of Canada's agricultural land and most of its irrigated farming, making this region particularly vulnerable to climate variability, droughts, soil moisture shortages, and shifts in water availability [23]. The study area of approximately 1.74 million km² includes 13 major sub-basins: Bow, Red Deer, Upper North Saskatchewan, Lower North Saskatchewan, Upper South Saskatchewan, Lower South Saskatchewan, Saskatchewan, Battle, Qu'Appelle, Souris, Assiniboine, Missouri, and Central North Saskatchewan. The region has a strongly continental climate, with cold winters, warm summers, and large seasonal and interannual variability in precipitation and temperature. Precipitation is strongly seasonal, with the highest monthly precipitation generally occurring in late spring and summer, especially June and July [20]. The domain is also heterogeneous. Aridity decreases from the semi-arid southwest, dominated by Brown and Dark Brown Chernozemic soils and extensive rangeland, to the more humid Black and Gray soil zones of the north and east. Cropland, mainly spring wheat, canola, barley, and pulses, dominates the Central and Eastern Prairies, and most irrigation is concentrated in Southern Alberta. The eastern sub-basins also contain many depositional wetlands that store spring runoff. To account for these differences, we standardized SMDI separately for each HRU and month against its own historical distribution and calculated all propagation metrics at the sub-basin scale.

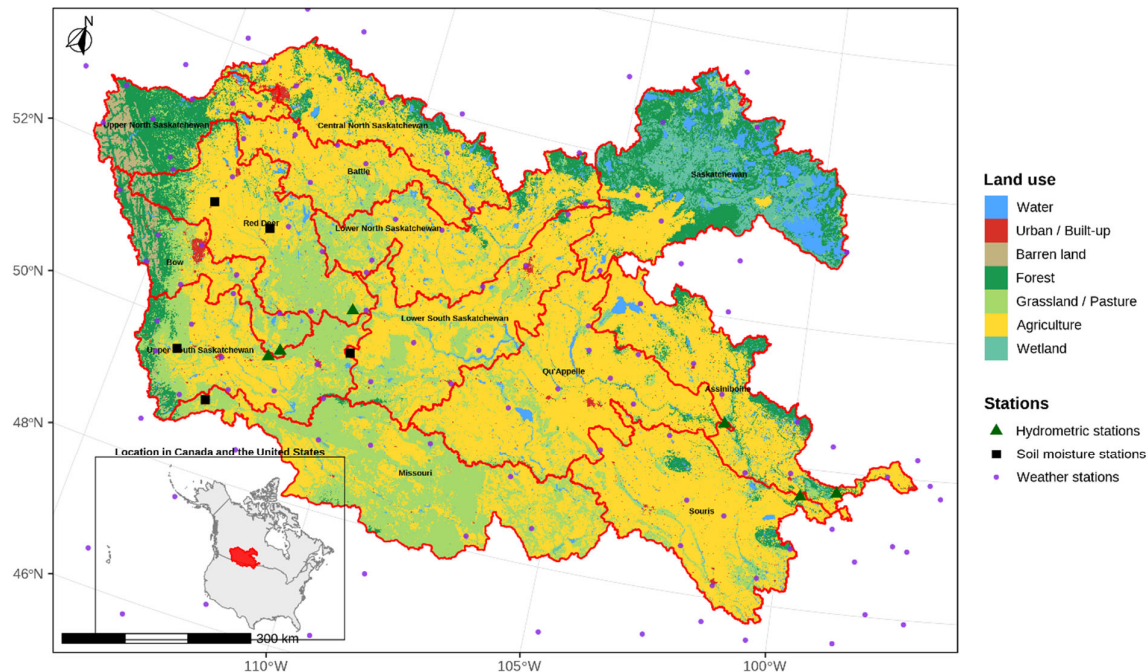


Figure 1. Location and sub-basins of the North American Prairie.

2.2. Datasets

We compiled daily meteorological observations for 1950–2024 from 140 stations across the study domain. Data for 100 Canadian stations were obtained from Environment and Climate Change Canada (ECCC), including daily precipitation, as well as minimum and maximum temperatures. The remaining 40 stations were selected from the U.S. portion of the domain using the NOAA National Centers for Environmental Information (NCEI) Global Historical Climatology Network Daily dataset (GHCN-Daily/GHCNd). GHCN-Daily is a quality-controlled daily land–surface climate dataset maintained by NOAA/NCEI. We used monthly streamflow data from five regulated hydrometric stations for SWAT model calibration and validation. The calibration and validation periods were 1985–2001 and 2002–2014, respectively. The selected streamflow stations were Oldman River near the Mouth (05AG006), Bow River near the Mouth (05BN012), Red Deer River near Bindloss (05CK004), Assiniboine River near Holland (05MH005), and Qu’Appelle River near Welby (05JM001). Since all five calibration stations are located on regulated rivers, naturalized streamflow was estimated using a Multiple-donor stations Drainage Area Ratio (MDAR) method incorporating a runoff depth correction factor [24]:

$$Q_{net} = Q_{proxy} \times \frac{A_{target}}{A_{proxy}} \times \frac{R_{target}}{R_{proxy}} \quad (1)$$

where Q_{proxy} is the observed monthly mean discharge at an upstream unregulated proxy gauge (m^3/s), A is drainage area (km^2), and R is mean annual runoff depth (mm/yr) computed from HYDAT daily records over 1985–2001. The correction factor R_{target}/R_{proxy} accounts for hydroclimatic differences in runoff generation between Rocky Mountain headwater proxy gauges and Prairie outlet target stations. We selected proxy stations as the nearest upstream unregulated WSC gauge on the same river system with at least 75% data completeness. In addition, daily measured soil moisture data from five ACIS stations, including Brocket AGDM (HRU = 5280), Schuler AGDM (HRU = 3718), Morrin AGDM (HRU = 3074), Del Bonita AGDM (HRU = 6104), and Olds College AGDM (HRU = 3054), were used to calibrate soil water content in the SWAT model during the warm season from April 2005 to September 2024. Land-use data for 2015 were retrieved from land-use

classification databases, whereas topographic data were derived from a 30 m resolution Digital Elevation Model (SRTM) for watershed delineation. Soil data were obtained from the FAO-UNESCO Digital Soil Map of the World, as provided in the ArcSWAT global soil database. The study domain contains 104 soil mapping units, each described by up to two layers (0–30 cm and 30–100 cm). For each layer, SWAT used the layer depth, moist bulk density, available water capacity, saturated hydraulic conductivity, organic carbon content, and clay, silt, sand, and rock fractions. Table 1 summarizes the input data used for hydrological modeling in the ArcSWAT interface.

Table 1. Input data used in SWAT model.

Data Type	Description	Information	Source
Digital Elevation Model	Watershed delineation	Raster, 30 m	https://srtm.csi.cgiar.org/ (accessed on 5 October 2026)
Land use (Canada)	Land-use classification	Raster, 30 m	http://geogratis.gc.ca (accessed on 5 October 2026)
Land use (US)	Land-use classification	Raster, 30 m	https://www.mrlc.gov/ (accessed on 5 October 2026)
Soil type	Soil properties	Vector	https://www.fao.org/soils-portal (accessed on 5 October 2026)
Weather (Canada)	Precipitation and temperature	Daily	https://weather.gc.ca (accessed on 5 October 2026)
Weather (US)	Precipitation and temperature	Daily	https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily (accessed on 5 October 2026)
Streamflow measured	Calibration and validation	Monthly	https://wateroffice.ec.gc.ca (accessed on 5 October 2026)
Soil moisture measured	Calibration model	Daily	https://acis.alberta.ca (accessed on 5 October 2026)

We obtained daily precipitation and temperature projections from the Ouranos CRCM5-CMIP6 ensemble, a dynamically downscaled dataset produced with the Canadian Regional Climate Model version 5 (CRCM5) driven by multiple CMIP6 Earth system models at 11 km resolution [25]. The ensemble spans the historical period (1950–2014) and future projections (2015–2100) under multiple SSP scenarios: SSP2-4.5, SSP3-7.0, and SSP5-8.5. Dynamical downscaling improves the representation of near-surface temperature, precipitation, and extreme climate indices relative to raw GCM output by explicitly resolving regional atmospheric processes and land–atmosphere interactions (Table 2). We used simulations driven by CanESM5, CNRM-ESM2-1, MPI-ESM1-2-LR, and NorESM2-MM. To correct for systematic biases in the raw simulations, three bias-correction methods were applied at a monthly scale: Linear Scaling (LS), Equidistant Quantile Mapping (EQM), and Quantile Delta Mapping (QDM), using station-based observations as reference data. All four driving models available in the CRCM5-CMIP6 ensemble for the study domain were used; SSP5-8.5 is available only for CanESM5. The models span an equilibrium climate sensitivity of about 2.5 °C (NorESM2-MM) to 5.6 °C (CanESM5). We selected QDM because it corrects the full distribution while preserving the relative change projected by each model in every quantile. Quantile-based corrections can still modify the magnitude of projected precipitation change, particularly where wet-day frequency changes, and this remains a source of uncertainty in the drought projections.

Table 2. Availability of CRCM5-CMIP6 simulations by driving Earth system model and emission scenario.

Driving ESM	Historical	SSP2-4.5	SSP3-7.0	SSP5-8.5
CanESM5	✓	✓	✓	✓
CNRM-ESM2-1	✓	✓	✓	—
MPI-ESM1-2-LR	✓	✓	✓	—

NorESM2-MM	✓	✓	✓	—
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2.3. Hydrological Modeling

The Soil and Water Assessment Tool (SWAT) was employed as the hydrological modeling framework. SWAT is a spatially distributed, temporally continuous, semi-distributed, and physically based catchment model that simulates physical processes, including climate, soil moisture, plant growth, nutrients, and soil management at daily, monthly, and yearly time steps [26]. Sub-basins are delineated based on land use, soil type, and slope inputs, which are then discretized into hydrologic response units (HRUs). Hydrological simulation in SWAT is governed by the water balance equation [26]:

$$SW_t = SW_o + \sum_{i=1}^t (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw})_{i\#} \quad (2)$$

where, SW_t is final soil water content (mm), SW_o is initial soil water content (mm), t is time (days), R_{day} is the amount of precipitation on day i (mm), Q_{surf} is the amount of surface runoff on day i (mm), E_a is actual evapotranspiration (mm), W_{seep} is the amount of percolation and bypass flow exiting the soil profile (mm), and Q_{gw} is the amount of return flow on day i (mm).

Model calibration and validation were performed using monthly observed streamflow data obtained from the Water Survey of Canada gauging stations. We used SWAT-CUP with the Sequential Uncertainty Fitting algorithm (SUFI-2) [27] for sensitivity analysis, calibration, and uncertainty quantification. Monthly simulated and observed streamflow during the calibration period (1985–2001) and validation period (2002–2014) were evaluated using three goodness-of-fit criteria: the Nash–Sutcliffe efficiency (NSE) [28]; the percent bias (PBIAS) [29]; and the Coefficient of Determination (R^2) [30]. SWAT was calibrated in two steps. Streamflow was calibrated first to constrain the overall water balance, and soil moisture was then calibrated at a second level to constrain root-zone dynamics, using daily warm-season (April–September) observations from five ACIS stations (Brocket AGDM, Schuler AGDM, Morrin AGDM, Del Bonita AGDM, and Olds College AGDM) for 2005–2024. We used all soil-moisture observations for calibration and did not hold out an independent soil-moisture validation period because of the limited number of stations. Given that the study domain has a cold-region hydrology where spring snowmelt is a dominant streamflow generation mechanism, the standard SWAT snow routine was modified following Zare et al. [31]. Specifically, a physically based soil temperature module replaced the default empirical module, and an energy budget equation was incorporated to account for rain-on-snow (ROS) events, which are frequently observed across the transboundary prairie watershed during winter and spring. These modifications improved the representation of non-homogeneous snowmelt runoff at the catchment scale and reduced uncertainty in model performance under cold region conditions [31,32].

Simulated soil moisture from SWAT was post-processed to enable direct comparison with field observations. Two adjustments were applied. First, SWAT was configured to print per-layer soil water content, and 0–30 cm root-zone soil water was extracted as the sum of the simulated surface skin and the first user-defined soil layer to match the field observations sensor depth. Second, because SWAT reports plant-available water (i.e., water held between the wilting point and field capacity), while soil moisture probes measure total volumetric water content, wilting-point water was added back to the simulated values. The wilting point was computed for each HRU and soil layer with the equation used internally by SWAT [33]: $\theta_{WP} = 0.40 \times (m_c \times \rho_b)/100$, where θ_{WP} is the volumetric water content at wilting point (mm mm^{-1}), m_c is the clay content (%), and ρ_b is the moist bulk density (Mg m^{-3}). Since SWAT uses the same equation to separate plant-available water from total soil water, adding θ_{WP} back to the simulated values recovers the

total water content implied by the model. The wilting-point depth ($\theta_{WP} \times$ layer thickness, mm) was added to the simulated soil water (mm), and the result was divided by the layer thickness to obtain volumetric water content (%).

2.4. Drought Indices

To characterize drought conditions across the study domain under historical (1950–2014) and projected (2015–2100) climates, we computed meteorological and agricultural drought indices using the Ouranos CRCM5-CMIP6 regional climate projections and SWAT model outputs. Drought classification follows the widely adopted threshold system of McKee et al. [34] and Vicente-Serrano et al. [35], summarized in Table 3.

Table 3. Drought classification thresholds applied in this study.

Category	SMDI/SPEI	Condition
Extreme drought	≤ -2.0	Exceptional water deficit
Severe drought	-1.5 to -1.99	Significant crop/streamflow stress
Moderate drought	-1.0 to -1.49	Developing moisture deficit
Near normal	-0.99 to 0.99	No significant drought
Moderately wet	1.0 to 1.99	Above-normal moisture

2.4.1. Meteorological Drought Indices

The Standardized Precipitation Evapotranspiration Index (SPEI) [35] was calculated at 3-, 6-, and 12-month accumulation timescales using the monthly climatic water balance $D_i = P_i - PET_i$, where PET was estimated using the Hargreaves method [36]. The accumulated water-balance series was fitted to a three-parameter log-logistic distribution, and the resulting probabilities were transformed to standard normal variates [35]:

$$SPEI = \Phi^{-1}[F(D_i^k)] \quad (3)$$

where D_i^k is the water balance accumulated over k months, F is the fitted log-logistic cumulative distribution function, and Φ^{-1} is the inverse standard-normal distribution. SPEI-12 was used as the primary indicator to characterize long-term meteorological drought and to extract drought events using run theory [37]. For the propagation analysis, SPEI-3 was used to identify short-term meteorological trigger events, while SPEI-3, SPEI-6, and SPEI-12 were evaluated to determine the accumulation timescale.

Adopting a truncation level of zero, a drought event was defined as a spell of consecutive months during which the index remained negative and reached at least the moderate-drought threshold of Table 3 ($SPEI \leq -1.0$), consistent with the event criterion of McKee et al. [34]; the event was considered terminated when the index returned to a non-negative value. For each identified event, we extracted two characteristics: drought duration (DD), the number of months from onset to termination, and drought severity (DS), the absolute value of the cumulative index accumulated over the event (dimensionless). Following common practice, events shorter than 3 months were excluded, as their hydrological and agricultural impact are small [38]. The two characteristics were computed independently for each climate model (CanESM5, CNRM-ESM2-1, MPI-ESM1-2-LR, NorESM2-MM), emission scenario (SSP2-4.5, SSP3-7.0, SSP5-8.5), and time period (historical, 1985–2014; near future, 2015–2040; mid future, 2041–2070; and far future, 2071–2100), with each event assigned to a period according to its month of onset, enabling changes in drought duration and severity to be compared across models, scenarios, and future horizons.

2.4.2. Agricultural Drought

Agricultural drought was characterized using the Soil Moisture Deficit Index (SMDI) [39], calculated from SWAT-simulated soil-water content for soil-bearing HRUs (land-use

classes AGRC, PAST, RNGE, RNGB, FRSD, FRSE, FRST, URHD, URML, URLD, and UTRN). HRUs classified as water (WATR), wetland (WETN), and barren land (BARR) were excluded. For each HRU and calendar month, the soil–water deficit was standardized relative to the historical median and minimum or maximum soil–water content [39]:

$$SD_{i,j} = \frac{SW_{i,j} - MSW_j}{MSW_j - minSW_j} \times 100, \text{ if } SW_{i,j} \leq MSW_j,$$

$$SD_{i,j} = \frac{SW_{i,j} - MSW_j}{maxSW_j - MSW_j} \times 100, \text{ if } SW_{i,j} > MSW_j, \quad (4)$$

$$SMDI_j = 0.5SMDI_{j-1} + \frac{SD_j}{50} \quad (5)$$

where $SD_{i,j}$ is the soil–water deficit (%), $SW_{i,j}$ is the mean monthly SWC in the soil profile (mm), MSW_j is the long-term median SWC in the soil profile (mm), $minSW_j$ and $maxSW_j$ are the long-term minimum and maximum SWC in the soil profile (mm), i is the year, and j is the month. Because SMDI is derived from monthly anomalies standardized by the median and range of each HRU's own record, it is not affected by constant or proportional biases in simulated soil water and depends mainly on the timing of wetting and drying.

Monthly SMDI values for the warm season (April–September) were retained and aggregated from HRUs to sub-basins using HRU-area weighting. No additional 3-month accumulation was applied to SMDI. In the propagation analysis, monthly SMDI was compared with SPEI at 3-, 6-, and 12-month timescales, while SPEI-3 was used to identify short-term meteorological drought events preceding agricultural drought. In this study, SMDI is used as an indicator of soil–moisture drought hazard. It does not account for crop type, growth stage, rooting depth, or management practices and therefore does not directly measure crop yield loss or economic impact.

2.5. Drought Propagation Framework

Because SPEI was grid-based and SMDI was calculated for individual agricultural HRUs, we harmonized the two indices at the sub-basin scale. SMDI was aggregated using HRU-area weights, while each SPEI grid cell was weighted by the total area of retained agricultural HRUs assigned to that cell. Open-water, wetland, and barren-land HRUs were excluded during SMDI construction. To limit spatial extrapolation, only HRUs located within 15 km of an SPEI grid-cell center were retained, and a sub-basin was included when these HRUs represented at least 90% of its agricultural HRU area. The analysis covered the historical period (1985–2014) and the near- (2015–2040), mid- (2041–2070), and far-future (2071–2100) periods under SSP2-4.5, SSP3-7.0, and SSP5-8.5 emission scenarios where available. Following the multiscale propagation framework of Dai et al. [21], Spearman rank correlations were calculated between warm-season SMDI and SPEI accumulated over 3-, 6-, and 12-month timescales for each model–scenario–period–sub-basin combination. The SPEI timescale producing the largest correlation coefficient was designated the dominant meteorological accumulation timescale. The separation between the two highest correlations was calculated as $\Delta\rho = \rho_{max} - \rho_{second}$. Scale selection was operationally classified as fragile when $\Delta\rho < 0.05$, indicating that the two leading timescales were weakly separated. We adopted this threshold as a study-defined robustness criterion rather than a formal significance test. The Spearman-based selection was further compared with the timescales that maximized the empirical and Clayton-copula conditional probabilities:

$$P(SMDI \leq -1 \mid SPEI-k \leq -1), k \in \{3, 6, 12\} \quad (6)$$

Agreement among the Spearman, empirical-probability, and Clayton-probability selections provided an additional assessment of the robustness of the identified meteorological response timescale. We then applied an event-based analysis adapted from Xu et al. [22]. Meteorological events were extracted from full-year SPEI-3, whereas agricultural events were extracted from April–September SMDI. An event was a continuous run of negative index values lasting at least two months and containing at least one value at or below -1.0 . Its onset was the first month at which the index crossed -1.0 , its duration was the length of the complete negative run. For the primary event-matching analysis, agricultural events were processed chronologically and matched to all meteorological droughts whose threshold-crossing onsets occurred between 0 and 6 months before the agricultural-drought onset. Meteorological events beginning after agricultural-drought onset were excluded, and each meteorological event could be assigned only once. The primary propagation lag was calculated as the number of months between agricultural onset and the earliest matched meteorological onset, representing the full antecedent development period. We retained a lag based on the closest preceding meteorological onset as a sensitivity measure. The translation rate quantified the percentage of detected meteorological drought events associated with a subsequent agricultural drought event:

$$TR = 100 \times N(\text{matched meteorological events})/N(\text{all meteorological events}).$$

2.6. Copula-Based Dependence and Lower-Tail Linkage

We used copulas to characterize warm-season monthly dependence between SPEI-3 and SMDI beyond correlation and event matching. For spatial conditional-probability analysis, we converted the paired indices to rank-based pseudo-observations separately for each model–scenario–period–sub-basin group with at least 80 observations. One-parameter Clayton, Frank, Gumbel, and Joe copulas were fitted by maximum likelihood, and the family with the lowest Akaike information criterion was selected [40,41]. For nested thresholds, the fitted conditional probability was calculated as

$$P(Y \leq y \mid X \leq x) = C[F_X(x), F_Y(y)]/F_X(x) \quad (7)$$

where X and Y denote SPEI-3 and SMDI, respectively. For the copula-based conditional-probability analysis, SPEI-3 and SMDI were divided into four mutually exclusive dry-condition classes: abnormally dry ($-1.0, -0.5$], moderate drought ($-1.5, -1.0$], severe drought ($-2.0, -1.5$], and extreme drought ($-\infty, -2.0$]. Values greater than -0.5 were classified as non-dry. The abnormally dry class subdivides the lower half of the near-normal range in Table 3 to resolve the onset of dryness below the drought threshold; the three drought classes follow Table 2. This class was used only in the categorical probability analysis, whereas drought-event detection retained the threshold of index ≤ -1.0 . The conditional probability for each cell of the resulting 4×4 matrix was obtained from the corresponding copula-rectangle probability divided by the probability of its meteorological category. Available climate models were weighted equally within each sub-basin, and sub-basin probabilities were then weighted by their soil-HRU areas to obtain scenario–period domain means. Because AIC measures fit over the full distribution, we evaluated lower-tail dependence separately using pooled sub-basin records within each model–scenario–period member. The nonparametric lower-tail dependence function was calculated as

$$\chi L(u) = \hat{C}(u, u)/u = P(V \leq u \mid U \leq u) \quad (8)$$

at $u = 0.05, 0.10$, and 0.15 . Under independence, $\chi L(u)$ equals u ; values exceeding u therefore indicate amplified lower-tail co-occurrence. Uncertainty was quantified using 1000 cluster-bootstrap repetitions in which whole sub-basins were resampled within each

model–scenario member, preserving the monthly records within each sampled sub-basin [42]. A Clayton copula was also fitted as a parametric lower-tail reference, with $\lambda L = 2^{-(1/\theta)}$ [41]. For period-level summaries, scenarios were first averaged within each model, and the resulting model estimates were then equally weighted.

3. Results

3.1. Performance of the Bias Correction

We compared the three bias-correction methods against station observations using Taylor diagrams, quantile–quantile plots, monthly percentile biases, probability density functions, and spatial bias maps (Figure 2). Raw CRCM5-CMIP6 simulations showed only moderate agreement with observations, with correlation coefficients of approximately 0.4–0.6 for precipitation and 0.7–0.8 for temperature. Modelled precipitation overestimated observed variability and exhibited a drizzle effect at low quantiles together with overestimation of summer extremes, while both temperature variables carried a pervasive cold bias and underestimated variability.

All three methods improved on the raw simulations, but the distribution-based approaches were consistently superior. EQM and QDM raised correlations to approximately 0.85–0.95, brought standard deviations close to unity, and reduced biases to within about ± 1 mm/day for precipitation and ± 1 – 2 °C for temperature across months and sub-basins. Linear Scaling corrected the mean but not the shape of the distribution: residual curvature persisted in the upper quantiles, and precipitation extremes were overcorrected, producing a negative bias in the 95th percentile. The improvement from bias correction was largest for precipitation, where correlation increased by roughly 0.2–0.3, and the excess variability was effectively removed.

This pattern is summarised in the Taylor diagram for precipitation (Figure 2). The raw simulations lie far from the reference point, with low correlation and inflated variability. Linear Scaling moves the points toward the reference but leaves a visible residual offset. EQM and QDM cluster tightly around the reference point, indicating near-optimal agreement in both correlation and variability. EQM and QDM performed comparably across all diagnostics; QDM was selected for this study because it additionally preserves the projected change signal in quantiles.

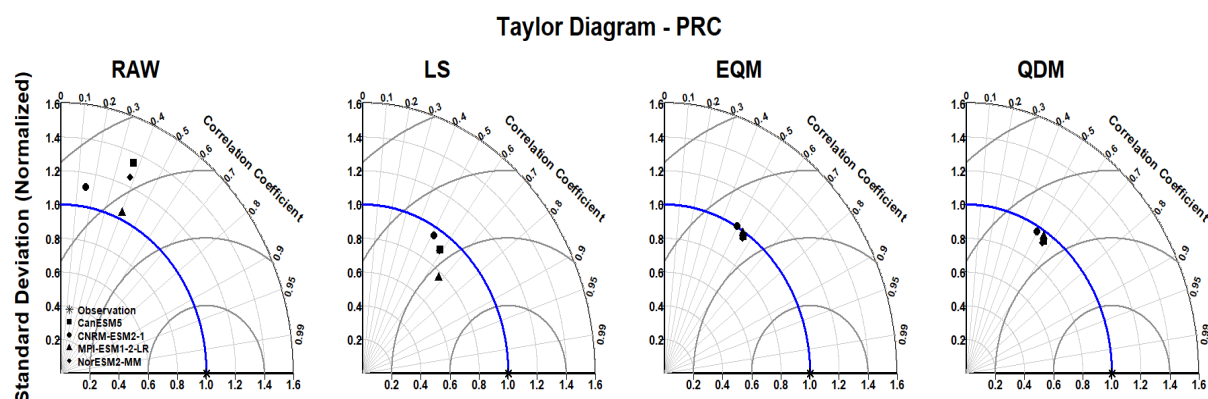


Figure 2. Taylor diagram comparing observed and simulated monthly precipitation (1998–2014) for the raw CRCM5-CMIP6 simulations and the three bias-correction methods (LS, EQM, QDM).

3.2. SWAT Parameter Sensitivity and Streamflow Calibration

The global sensitivity of the 15 SWAT parameters was analysed using the SUFI-2 algorithm of SWAT-CUP and the t-Stat and p-Value as ranking criteria, where a larger ab-

solute *t*-Stat and a smaller *p*-Value indicate higher parameter sensitivity [43]. Table 4 presents the results, with parameters ranked from most to least sensitive. Five parameters were identified as significantly sensitive ($p < 0.10$), namely the snowmelt base temperature (SMTMP), the SCS curve number for moisture condition II (CN2), the snowfall temperature (SFTMP), the threshold water depth in the shallow aquifer required for return flow to occur (GWQMN), and the soil evaporation compensation factor (ESCO). Among these, SMTMP ($t = -6.82$, $p < 0.001$), CN2 ($t = -4.34$, $p < 0.001$), and SFTMP ($t = -2.95$, $p = 0.006$) were statistically significant at the 99% confidence level and emerged as the most influential parameters controlling streamflow simulation in the study watershed. The remaining 10 parameters, including ALPHA_BF, EPCO, and GW_DELAY, showed comparatively low sensitivity ($p > 0.10$) and exerted negligible influence on the model output during calibration.

Table 4. Sensitivity analysis of SWAT model in the NGP.

Rank	Parameter	Description	Change Type	Default Range	Final Range	<i>t</i> -Stat	<i>p</i> -Value
1	V__SMTMP.bsn	Snow melt base temperature (°C)	Replace	−5 to 5	−2 to 3	−6.8160	0.0000
2	R__CN2.mgt	SCS runoff curve number (moisture condition II)	Relative	−0.2 to 0.2	−0.1 to 0.1	−4.3433	0.0001
3	V__SFTMP.bsn	Snowfall temperature (°C)	Replace	−5 to 5	−2 to 3	−2.9540	0.0057
4	V__GWQMN.gw	Threshold water depth in shallow aquifer for return flow (mm)	Replace	0 to 5000	500 to 4000	2.0076	0.0526
5	R__ESCO.hru	Soil evaporation compensation factor	Relative	0 to 1	0.5 to 0.95	1.9110	0.0645
6	V__REVAPMN.gw	Threshold depth for revap to occur (mm)	Replace	0 to 500	120 to 250	1.4087	0.1670
7	R__TIMP.bsn	Snow pack temperature lag factor	Relative	0 to 1	0.5 to 1	1.3787	0.1768
8	R__SMFMN.bsn	Min melt rate for snow on Dec 21 (mm/°C·day)	Relative	0 to 10	1.4 to 4	1.1646	0.2523
9	R__SOL_K().sol	Saturated hydraulic conductivity (mm/h)	Relative	−0.8 to 0.8	−0.3 to 0.1	1.0319	0.3094
10	R__SOL_AWC().sol	Available water capacity of soil layer	Relative	−0.25 to 0.25	0 to 0.4	−0.8647	0.3933
11	V__SMFMX.bsn	Max melt rate for snow on June 21 (mm/°C·day)	Replace	0 to 20	2 to 6	−0.8496	0.4015
12	V__SURLAG.bsn	Surface runoff lag coefficient	Replace	0.05 to 24	2 to 12	0.8072	0.4252
13	V__ALPHA_BF.gw	Baseflow alpha factor (1/days)	Replace	0 to 1	0.05 to 0.5	−0.2809	0.7805
14	V__EPCO.hru	Plant uptake compensation factor	Replace	0 to 1	0.5 to 1	−0.2322	0.8178
15	V__GW_DELAY.gw	Groundwater delay time (days)	Replace	0 to 500	100 to 400	−0.0460	0.9636

The calibrated SWAT model reproduced observed monthly streamflow satisfactorily to well at most stations across the study domain (Table 5). Following the performance criteria of Moriasi et al. [44], the Bow River near the Mouth achieved the strongest agreement between simulated and naturalized flows, with good model efficiency and negligible bias in both periods, while the Oldman and Red Deer rivers performed satisfactorily to

well. At these mountain-fed stations, the validation efficiency equalled or exceeded that of calibration, indicating that the calibrated parameter set was temporally robust and not overfit. Performance declined eastward across the plains. The Qu'Appelle River near Welby remained satisfactory but exhibited a pronounced positive bias during calibration that largely disappeared in validation, whereas the Assiniboine River near Holland did not meet the performance criteria of Moriasi et al. [44] during calibration ($NSE = 0.15$, $PBIAS = +41.8\%$), improving to marginally satisfactory in validation ($NSE = 0.41$, $PBIAS = -11.2\%$). Results for the Assiniboine and, to a lesser degree, the Qu'Appelle sub-basins should therefore be interpreted with lower confidence than those for the mountain-fed western basins. The observed–simulated hydrographs (Figure 3) confirmed these statistics, showing that the model captured the magnitude, timing, and recession of monthly flows well at the Bow, Oldman, and Red Deer stations, reproduced the lower-flow Qu'Appelle regime reasonably while missing several peaks, and systematically over-generated flow while mistiming the episodic high-flow events at the Assiniboine.



Figure 3. Monthly simulated and observed flows during the calibration period (1985–2001) and validation (2002–2014) for SWAT-M.

Table 5. Performance statistics of the SWAT model for monthly streamflow simulation at the calibration (1985–2001) and validation (2002–2014) stations across the North American Prairie domain.

Station	Period	Mean Obs (m ³ /s)	Mean Sim (m ³ /s)	R ²	RMSE	MAE	NSE	KGE	PBIAS (%)
Oldman River near the Mouth	Calibration	65.22	71.74	0.609	55.30	36.43	0.593	0.732	9.99
Oldman River near the Mouth	Validation	83.53	72.12	0.714	65.01	39.91	0.686	0.642	−13.66
Bow River near the Mouth	Calibration	91.10	88.66	0.706	50.89	37.46	0.705	0.777	−2.68
Bow River near the Mouth	Validation	89.94	83.58	0.735	49.71	35.25	0.726	0.736	−7.07
Red Deer River near Bindloss	Calibration	56.73	55.58	0.617	36.58	26.31	0.608	0.753	−2.03
Red Deer River near Bindloss	Validation	63.61	60.07	0.552	53.19	33.15	0.547	0.594	−5.56
Qu'Appelle River near Welby	Calibration	12.25	15.16	0.603	15.67	11.14	0.575	0.656	23.75
Qu'Appelle River near Welby	Validation	15.30	15.65	0.608	21.19	12.16	0.587	0.571	2.31
Assiniboine River near Holland	Calibration	54.34	77.07	0.463	74.82	55.49	0.152	0.449	41.82
Assiniboine River near Holland	Validation	115.18	102.25	0.416	125.02	76.71	0.410	0.497	−11.23

3.3. Soil Moisture Calibration Performance

We compared daily warm-season soil moisture simulated by SWAT with ACIS observations at the five ACIS stations used in soil–water calibration across the southern NGP domain over 2005–2024 (Figure 4; Table 6). The model reproduced both the magnitude and the day-to-day dynamics of observed root-zone soil moisture, including the characteristic spring wet-up following snowmelt, the response to convective rainfall events, and the progressive summer dry-down driven by evapotranspiration. Performance varied among stations. NSE was positive at Brocket, Morrin, and Schuler (0.26–0.47) but negative at Del Bonita (−0.08) and Olds College (−0.68), while KGE ranged from 0.58 to 0.73 and R² from 0.42 to 0.57 at all five stations, indicating that the simulation captured about half of the daily variance in observed soil moisture. Mean simulated and observed soil moisture across the five stations agreed within approximately 2 percentage points (volumetric), with the smallest bias at Brocket and the largest underestimation at Olds College. Negative NSE values at Del Bonita and Olds College were driven by systematic underestimation of growing-season peak values rather than by phase or timing errors, as indicated by the positive KGE and moderate R² at the same stations. The depth-matched and wilting-point-corrected extraction therefore provides a defensible representation of daily root-zone soil moisture dynamics, supporting the application of SWAT soil–water output to the agricultural drought indices (SMDI) subsequently analyzed.

Table 6. Daily soil-moisture calibration statistics (2005–2024, April–September) for SWAT-M at the five ACIS stations.

Station	Mean.Obs	Mean.Sim	R2	RMSE	MAE	NSE	KGE	PBIAS
Brocket	30.379	30.575	0.535	3.943	3.174	0.47	0.731	0.646
Del_Bonita	23.973	19.894	0.538	6.179	5.493	−0.081	0.662	−17.014
Morrin	16.402	18.31	0.488	4.685	3.569	0.361	0.641	11.634
Olds_College	29.685	23.131	0.424	8.315	7.389	−0.678	0.575	−22.077
Schuler	20.365	18.303	0.568	4.562	3.941	0.257	0.693	−10.126

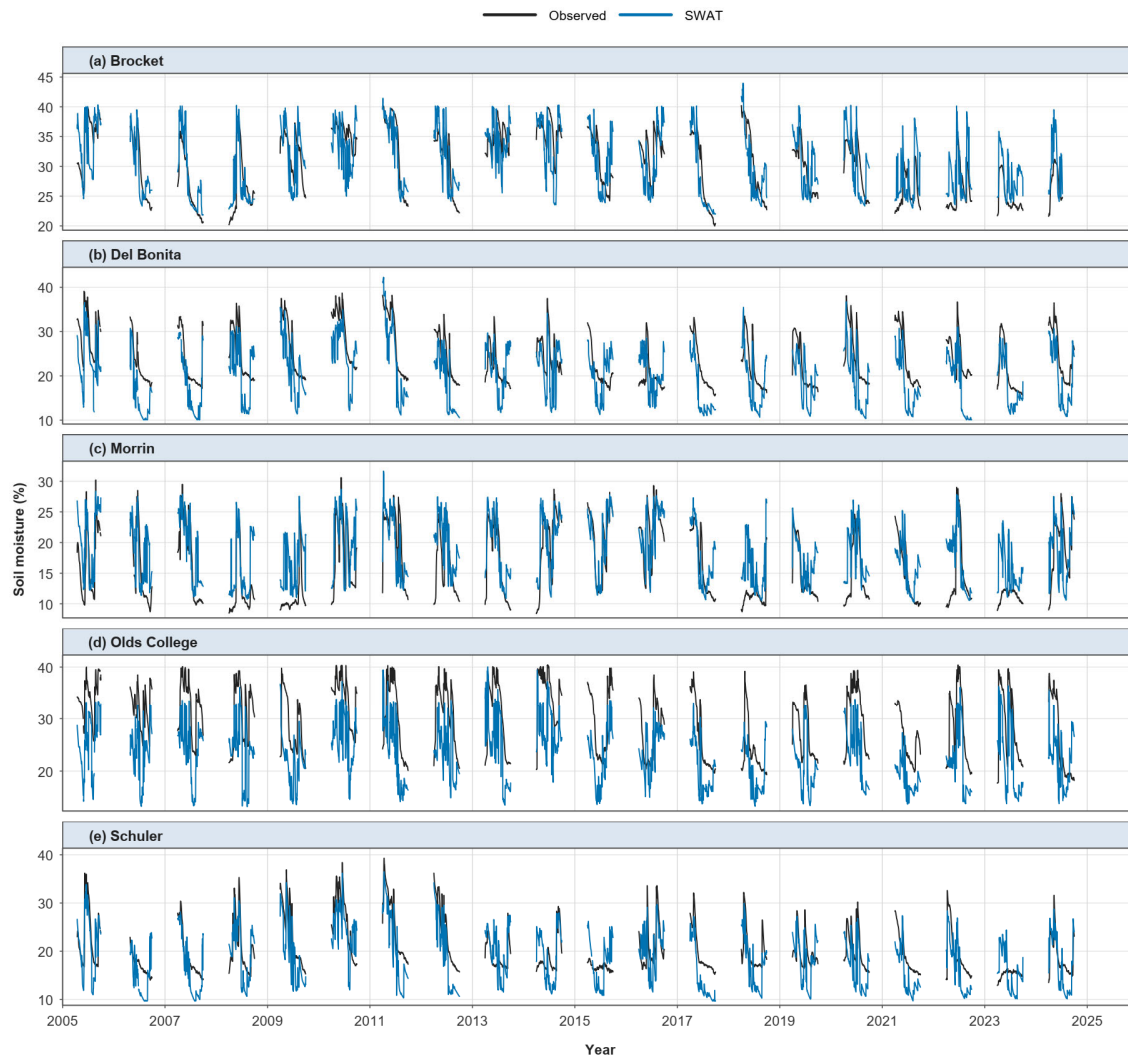


Figure 4. Observed and SWAT daily warm-season soil moisture for all stations.

3.4. Projected Changes in Meteorological Drought Duration and Severity

The ensemble mean both the duration and severity of SPEI-12 meteorological droughts increased relative to the 1985–2014 baseline across the Canadian Prairies, and the increases scaled strongly with emissions and time (Figures 5 and 6). Under SSP2-4.5, changes remained modest through all three future periods, with drought-severity increases largely confined to the lower end of the legend range (Δ severity $\lesssim 10$) and only small duration changes (Δ duration of a few months). Under SSP3-7.0, intensification became more pronounced by the far-future period, particularly across the Southern Prairies. The most severe changes occurred under SSP5-8.5, where far-future drought severity increased by ~ 60 – 67 (dimensionless), and drought duration lengthened by ~ 20 – 22 months in the most affected areas, with a clear west-to-east and time-progressive darkening of the maps from near to far. In every scenario, the far-future period showed the largest departures, and the severity and duration fields were spatially coherent: regions of longer droughts were also regions of more severe droughts.

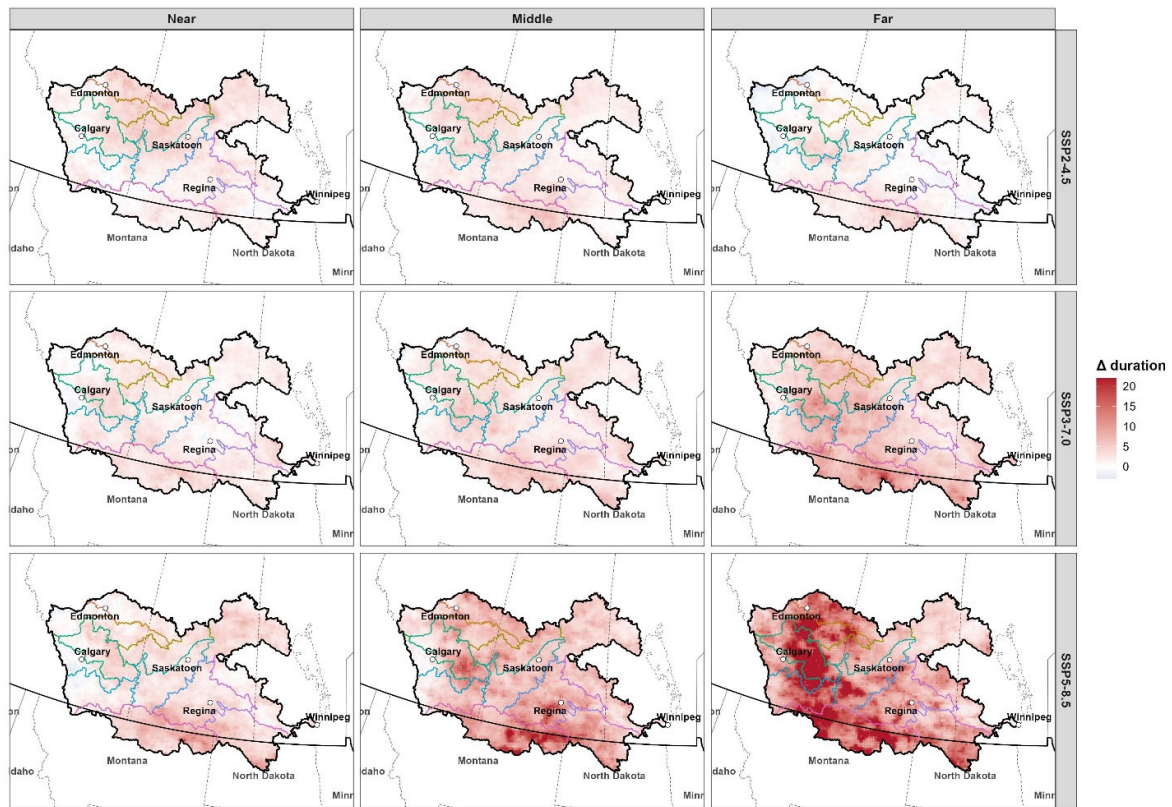


Figure 5. Ensemble-mean SPEI-12 Duration change relative to historical.

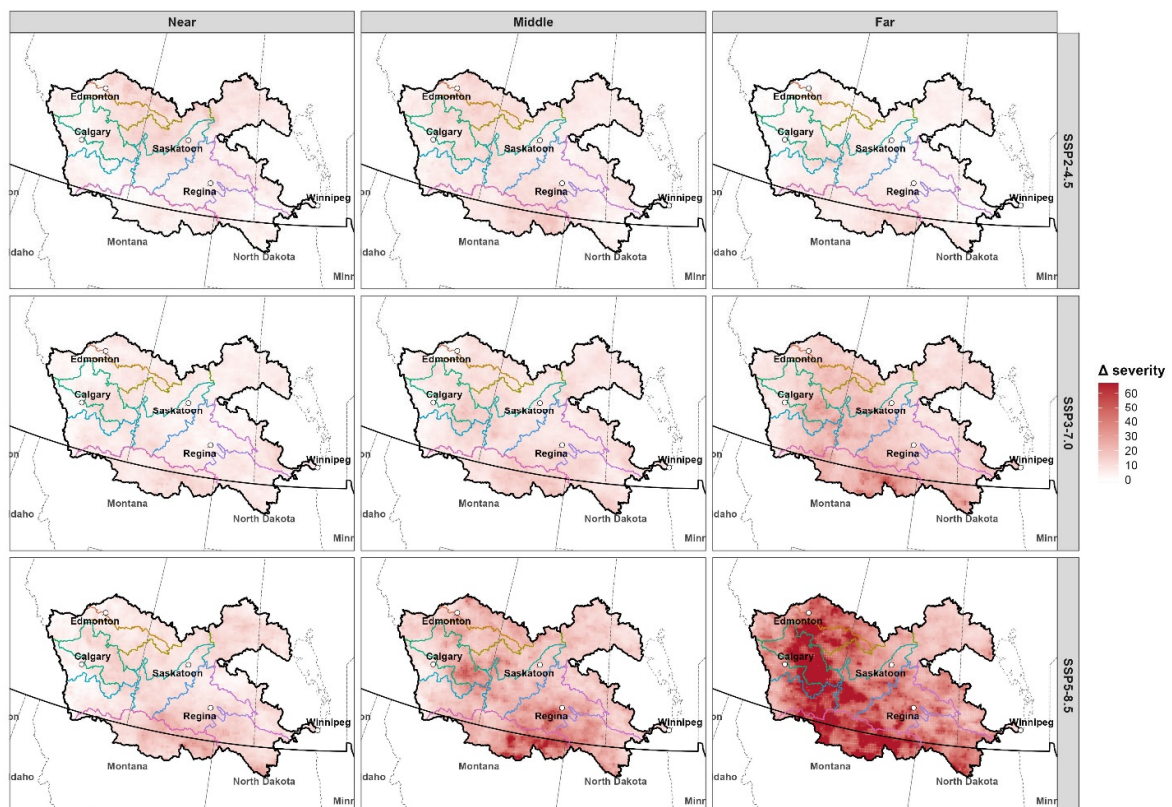


Figure 6. Ensemble-mean SPEI-12 severity change relative to historical.

3.5. Projected Changes in Agricultural Drought

Ensemble-mean SMDI indicated a progressive intensification of warm-season soil-moisture drought across the Canadian Prairies under all three scenarios, deepening from the near- to the far-future period (Figure 7). Relative to the 1985–2014 baseline (basin-mean SMDI ≈ 0), the basin-averaged SMDI declined to -0.40 , -0.60 , and -0.69 under SSP2-4.5 and to -0.74 , -0.92 , and -1.08 under SSP5-8.5 for the near- (2015–2040), mid- (2041–2070), and far-future (2071–2100) periods, respectively. SSP5-8.5 produced the strongest and most spatially extensive drying, with the semi-arid Southern and Southeastern Prairies emerging as the primary drought hotspot. Drought conditions were near-ubiquitous by the far-future period: fewer than 2% of soil HRUs showed a positive SMDI change relative to historical under any scenario. SSP3-7.0 yielded drying of comparable magnitude to SSP2-4.5 (basin-mean SMDI of -0.36 , -0.40 , and -0.63 for the three periods), and at mid-century, it was marginally less negative than SSP2-4.5, indicating that the two intermediate scenarios do not diverge appreciably before the late century.

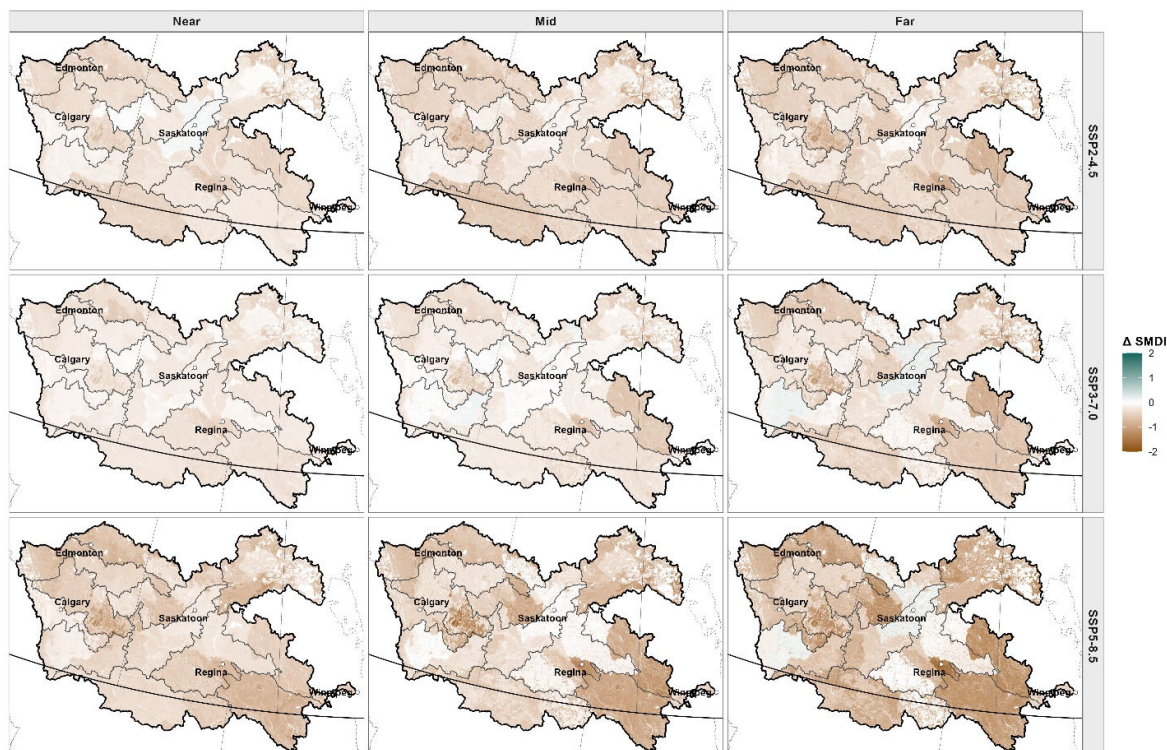


Figure 7. Ensemble mean of SMDI change relative to historical.

3.6. Meteorological–Agricultural Coupling and Propagation Time

Warm-season coupling between meteorological and agricultural drought, quantified using the SPEI-3–SMDI Spearman rank correlation, was moderate and spatially variable across the North American Prairie (Figure 8). The model-balanced domain-mean correlations were approximately 0.62, 0.61, and 0.57 in the near-, mid-, and far-future periods, respectively. The multiscale analysis showed a pronounced future shift toward SPEI-3 as the dominant meteorological drought timescale, accompanied by fewer fragile scale selections. Agreement between the Spearman-based selection and the empirical and Clayton-copula probability-based selections also generally increased or remained high, indicating that multiple dependence measures supported the growing dominance of SPEI-3 (Table 7).

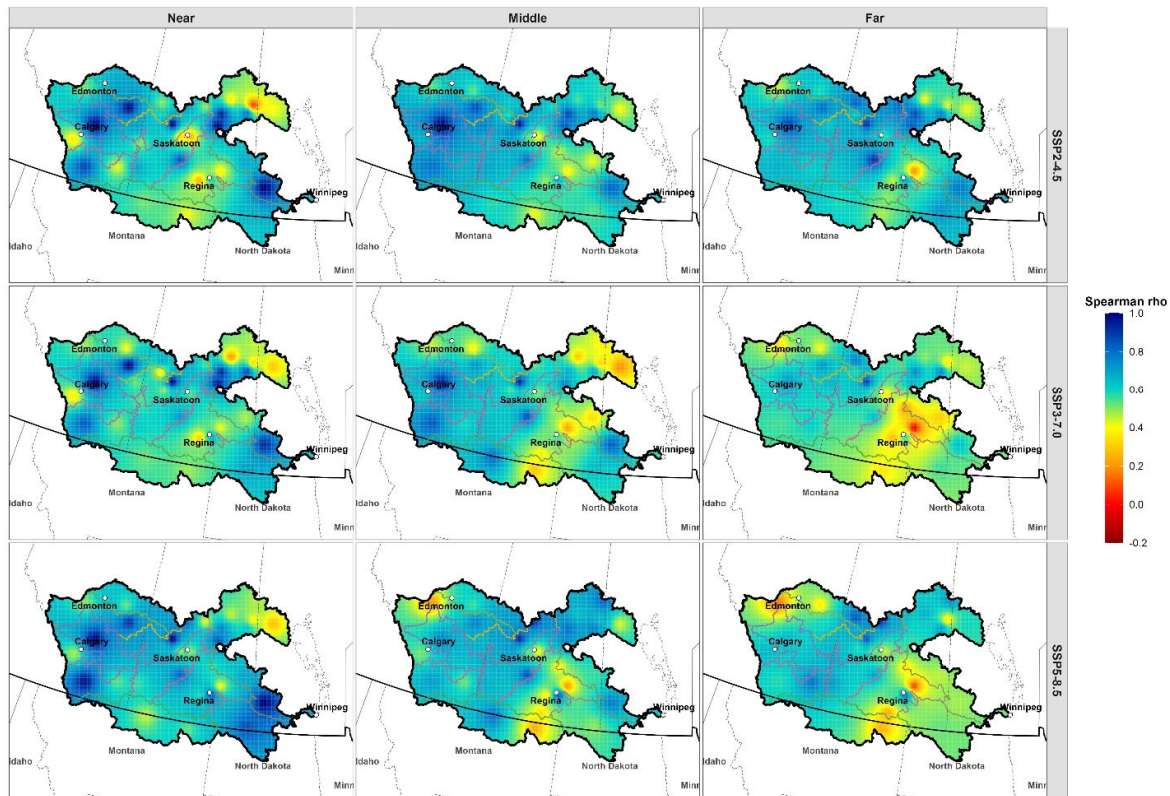


Figure 8. Spearman rank correlation between SPEI-3 and SMDI in the NGP.

Table 7. Dominant meteorological accumulation timescale, scale fragility, and agreement among selection methods.

Period	SPEI-3 Dominant (%)	SPEI-6 Dominant (%)	SPEI-12 Dominant (%)	Fragile Selection (%)	Spearman–Empirical Agreement (%)	Spearman–Clayton Agreement (%)
Historical	56.9	40.3	2.8	70.8	50	86.1
Near	81.7	14.8	3.5	33.8	74.5	88
Mid	85.6	13	1.4	32.4	79.4	94.9
Far	73.8	14.6	11.6	27.5	82.6	88.4

Meteorological drought generally propagated into agricultural drought within 1–3 months, although propagation time varied spatially among sub-basins and scenarios (Figure 9). The model-balanced mean propagation time decreased from 2.37 months in the near future to 2.23 months in the mid future and 1.81 months in the far future. The strongest acceleration occurred under SSP5-8.5, for which the mean lag declined from 2.47 months in the near future to 1.80 months in the mid future and 1.04 months in the far future. Spatially, the shortest propagation times were concentrated across the Southern and South-Central Prairies. By the far-future period under SSP5-8.5, propagation times approached approximately 1 month across much of the study domain.

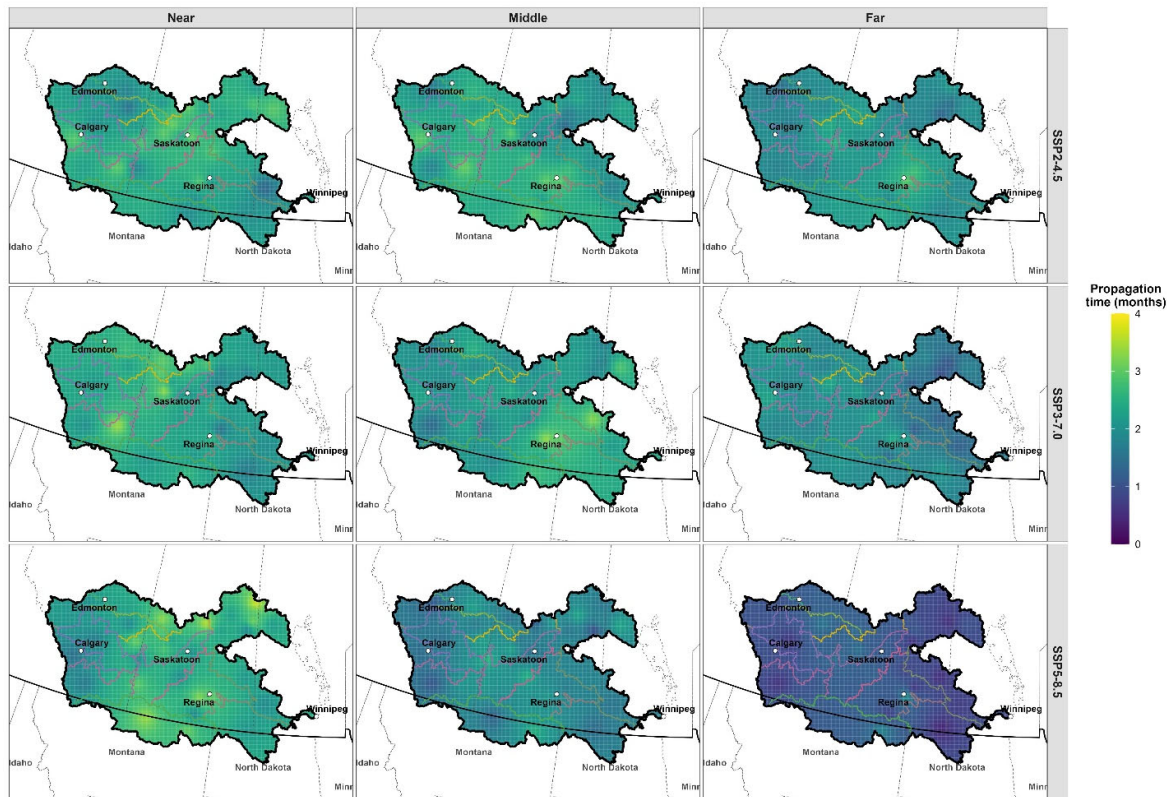


Figure 9. Meteorological-to-agricultural drought propagation time in the NGP.

3.7. Conditional Probability of Agricultural Drought

The conditional probability of agricultural drought increased consistently with meteorological drought intensity across all scenarios and periods (Table 8). Domain-mean probabilities ranged from 0.475–0.536 under abnormally dry meteorological drought, rising to 0.527–0.647 under moderate, 0.579–0.742 under severe, and 0.690–0.825 under extreme conditions. The gradient was monotonic in every scenario–period combination. The steepest response occurred under SSP5-8.5 in the near-future period, where 82.5% of extreme meteorological drought conditions coincided with agricultural drought and the increase from light to extreme conditions was largest (0.536 to 0.825). Temporal behaviour differed among scenarios: probabilities peaked in the mid-century period under SSP2-4.5 but were highest in the near future under SSP3-7.0 and SSP5-8.5, declining thereafter. The scenario spread also widened with meteorological severity, from approximately 0.06 under light drought to 0.14 under extreme drought, indicating that the pathways diverge most where the hazard is greatest.

Table 8. The regional mean occurrence probability of agricultural drought under the four levels of meteorological drought.

Scenario	Period	Abnormally Dry MD	Moderate MD	Severe MD	Extreme MD
SSP2-4.5	Near	0.507	0.597	0.670	0.746
SSP2-4.5	Mid	0.516	0.615	0.699	0.777
SSP2-4.5	Far	0.509	0.592	0.660	0.733
SSP3-7.0	Near	0.527	0.624	0.699	0.768

SSP3-7.0	Mid	0.487	0.566	0.635	0.709
SSP3-7.0	Far	0.492	0.545	0.599	0.690
SSP5-8.5	Near	0.536	0.647	0.742	0.825
SSP5-8.5	Mid	0.526	0.602	0.669	0.764
SSP5-8.5	Far	0.475	0.527	0.579	0.698

3.8. Matched Drought Events and Translation Rate

The number of matched meteorological-to-agricultural drought events and the translation rate showed coherent spatial and scenario patterns (Figures 10 and 11). Matched events increased with both emission intensity and time, from an area-weighted mean of 11.6 events under near-future SSP2-4.5 to 18.8 under far-future SSP5-8.5, with the highest counts concentrated in the Central and Eastern Prairies. The translation rate, the percentage of meteorological droughts propagating into agricultural drought, increased with emissions, from a domain mean near 54–58% under SSP2-4.5 to 63–68% under SSP5-8.5. Its temporal behaviour was non-monotonic: rather than rising continuously to the end of the century, translation increased from the near-to-mid-future and then plateaued or eased slightly, most clearly under SSP5-8.5 (63.8%, 67.9%, and 62.5% for the near, mid, and far periods). Importantly, this plateau in the rate coincided with a continued rise in the absolute number of matched events (15.7, 18.6, and 18.8 under SSP5-8.5), and the share of the domain with a translation rate $\geq 55\%$ remained high throughout (78%, 88%, and 71% under SSP5-8.5).

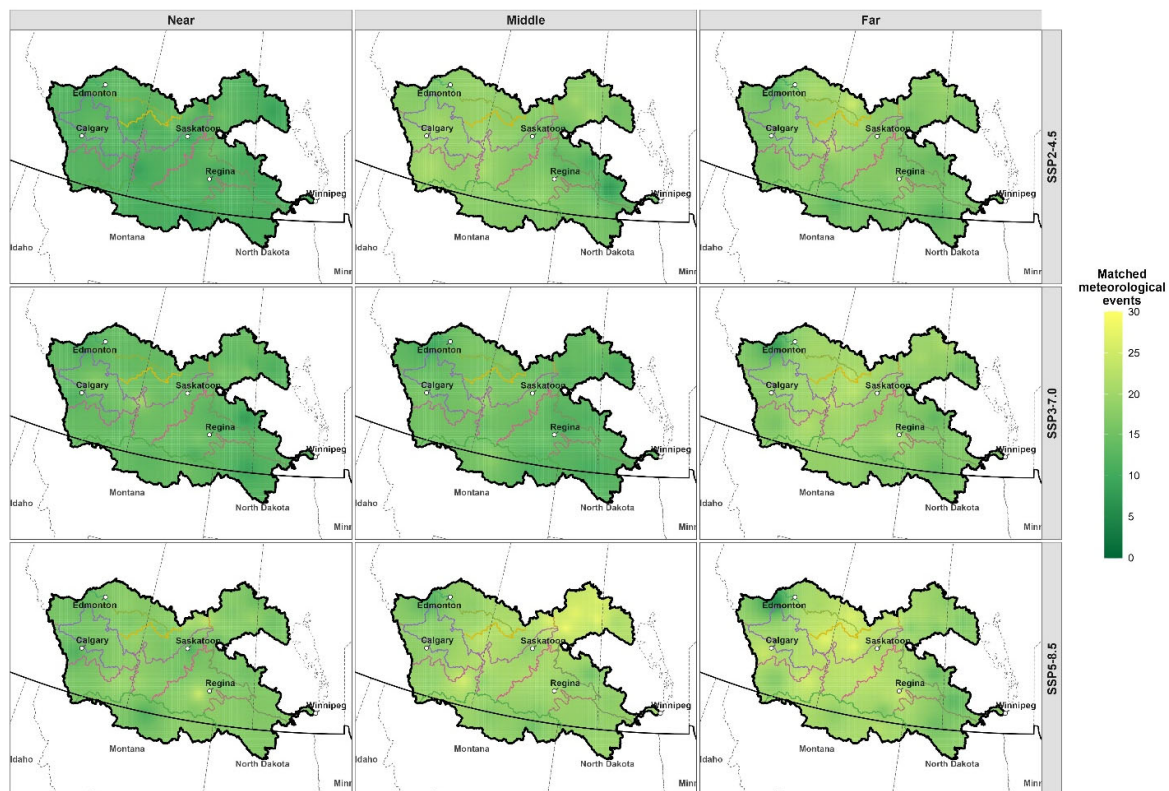


Figure 10. Matched meteorological-to-agricultural drought events across scenarios and future periods.

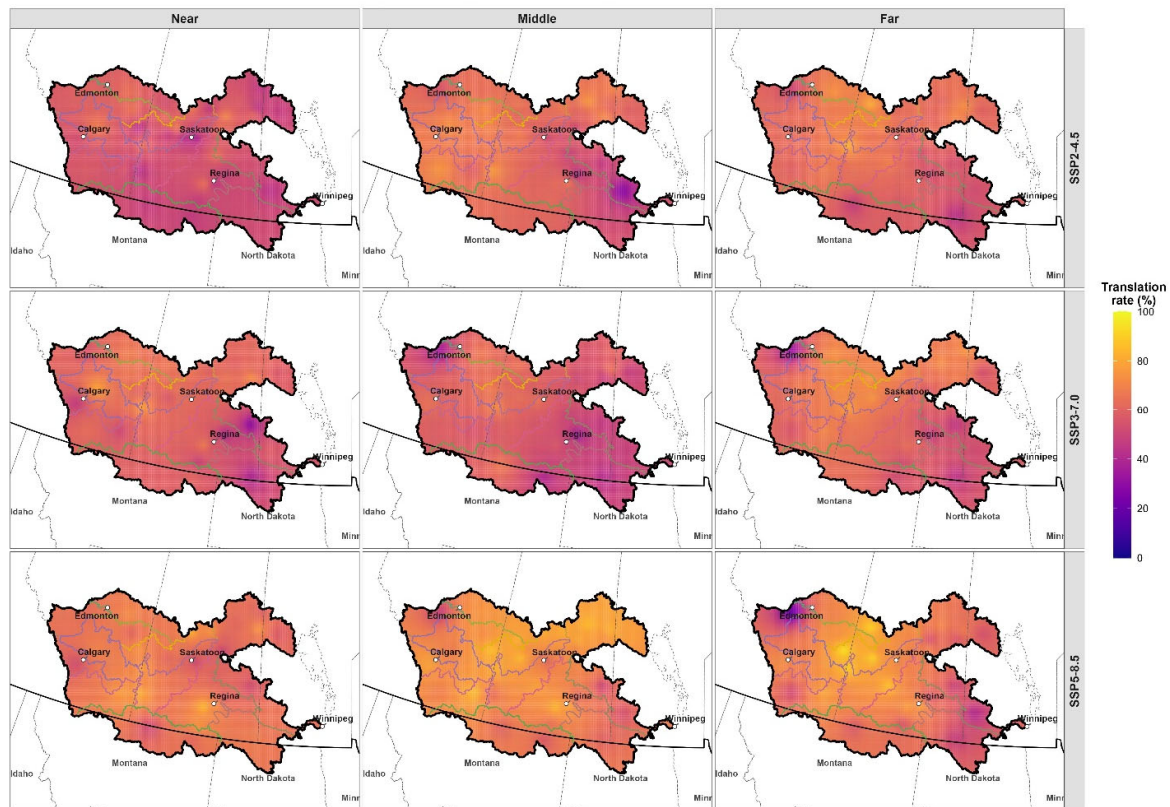


Figure 11. Meteorological-to-agricultural drought translation rates across scenarios and future periods.

3.9. Copula Selection and Lower-Tail Dependence

Copula selection varied across model–scenario–period–sub-basin groups. The Frank copula was selected most frequently (45.4%), followed by Gumbel (26.7%), Clayton (26.5%), and Joe (1.5%; Figure 12a). The finite-threshold lower-tail co-occurrence measure, $\chi_L(u)$, exceeded its independence benchmark at all three examined tail depths (Figure 12b). At $u = 0.10$, $\chi_L(u)$ increased from 0.264 historically to 0.304 in the near future before declining to 0.276 and 0.239 in the middle and far futures, respectively. Despite this decline, the far-future value remained substantially above the independence benchmark of 0.10, indicating persistent, although temporally variable, lower-tail association between meteorological and agricultural drought.

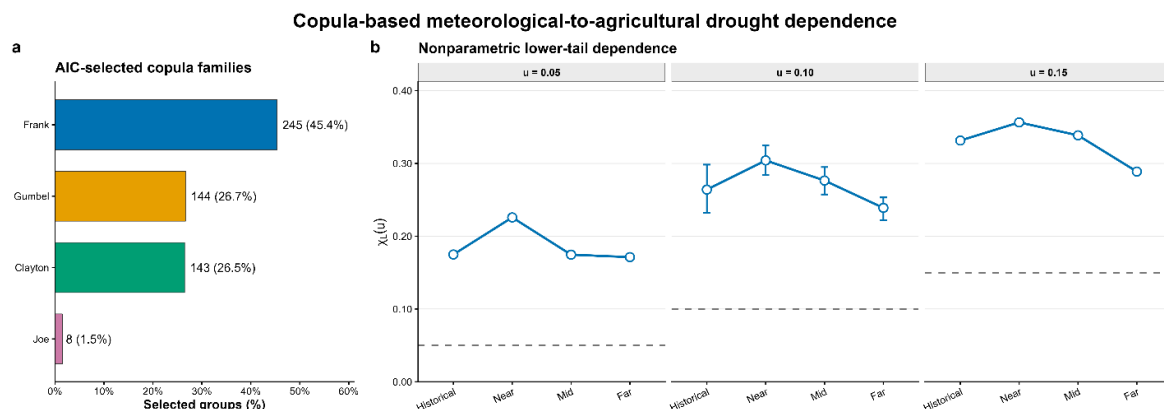


Figure 12. Copula-based meteorological-to-agricultural drought dependence: (a) selected copula families, and (b) lower-tail dependence across historical and future periods. The dashed lines in (b) show the independence benchmark ($\chi_L(u) = u$).

4. Discussion

The sensitivity and validation analyses provide a solid groundwork for assessing drought conditions. The strong influence of SMTMP, SFTMP, and CN2 confirms that snowfall–rainfall partitioning, snowmelt timing, and surface-runoff generation are important controls on the regional water balance, consistent with previous cold-region SWAT studies [45–47]. Model performance was less consistent in the Prairie Pothole Region, particularly within the Qu’Appelle and Assiniboine basins, where depressional storage and dynamically changing contributing areas generate threshold-dependent fill-and-spill runoff that standard SWAT does not explicitly represent [48,49]. Soil–moisture validation nevertheless revealed that the model successfully captured the key sequence of spring recharge, rainfall response, and growing-season depletion. Underestimation of wetter conditions at Olds College and Del Bonita likely reflects uncertainty in snowmelt infiltration and the difference between point measurements and HRU-average soil moisture. Although these limitations constrain the interpretation of individual events, the model reproduced the seasonal and interannual wet–dry variations required to derive SMDI and analyse meteorological-to-agricultural drought propagation [39].

The projected SMDI changes reveal a progressive intensification of warm-season soil moisture stress, but the response is spatially heterogeneous rather than uniform. The strongest drying occurs across the Southern and Southeastern Prairies, where low climatological precipitation coincides with high atmospheric water demand. In these areas, additional warming raises potential evapotranspiration and accelerates depletion of root-zone storage, meaning projected spring precipitation increases may be insufficient to prevent agricultural drying. This interpretation aligns with projections for Southern Saskatchewan, which show that soil water can decline despite increasing precipitation when stronger evaporative demand offsets the additional supply [20]. The central agricultural region exhibits a more variable response, possibly because deeper Chernozemic soils and greater antecedent storage can temporarily buffer short rainfall deficits. However, this protection diminishes as successive dry months exhaust available water. In the Eastern Prairies, fine-textured soils, wetlands, and depressional storage may retain spring moisture and delay the development of soil–water deficits. Poorly connected drainage and fill-and-spill processes create significant local variability. This variability is part of the reason why neighboring HRUs can react differently to the same meteorological forcing. Farther north, lower evaporative demand and later snowmelt generally provide greater buffering, although this advantage weakens under stronger warming. These explanations are based on known regional soil and landscape characteristics; this study did not directly analyze the effects of soil texture, depth, and storage capacity.

The apparently near-neutral areas in the SMDI maps should therefore not be interpreted as locations unaffected by climate change. The HRU-level diagnostic indicated that no agricultural HRU remained within ± 0.10 SMDI units across all nine SSP–period combinations, and only 34 HRUs remained within ± 0.20 . Under SSP2-4.5 and SSP3-7.0, many weak ensemble changes resulted from cancellation between climate models projecting changes of opposite signs. A pale ensemble-mean colour can consequently indicate model disagreement rather than physical stability. Soil depth alone was not a consistent explanation because depth does not necessarily represent plant-available storage, as a deep but coarse-textured soil may retain less accessible water than a shallower fine-textured soil. Similarly, blank areas on the maps represent excluded water, wetland, and barren HRUs, not areas experiencing zero change. These distinctions are important because visually

similar map patterns can arise from different mechanisms such as model cancellation, physical buffering, normalization, or exclusion and therefore require different interpretations.

The multiscale propagation results connect these spatial SMDI patterns to changes in meteorological control. SPEI-3 became the dominant water-balance timescale, while fragile scale selections became less frequent. Agreement among the Spearman, empirical-probability, and Clayton-copula selections further indicates that the shift toward SPEI-3 was not an artifact of a single statistical measure. This transition signifies a reduction in the climatic memory that influences agricultural drought conditions. Historically, soil moisture could integrate meteorological conditions over several months because antecedent storage, snowmelt recharge, and lower evaporative losses sustained the root zone through short dry intervals. Under warming, higher evaporative demand draws down this reserve more rapidly. As SPEI integrates precipitation and PET, the projected lengthening and intensification of SPEI drought (Figures 5 and 6) indicates that increases in evaporative demand are not offset by changes in precipitation, while SMDI declined progressively under all scenarios (Figure 7). As a result, a 3-month water-balance deficit is more relevant than longer accumulation periods. The partial re-emergence of SPEI-12 dominance in the far future does not contradict this general pattern. Instead, it suggests that some sub-basins remain sensitive to prolonged antecedent deficits, possibly where larger soil reservoirs or delayed snowmelt maintain a longer hydrological memory. Thus, short-term deficits increasingly control the typical response, while long-duration drought remains important where storage processes delay but do not prevent soil–water depletion. This shorter meteorological memory is consistent with the event-based propagation results. Model-balanced mean propagation time declined from approximately 2.37 months in the near future to 1.81 months in the far future, with the mean lag approaching 1 month under far-future SSP5-8.5. The fastest responses were concentrated in the Southern and South–Central Prairies, where high evaporative demand and limited moisture availability reduce the root zone’s capacity to buffer rainfall deficits. Longer response times elsewhere may reflect greater antecedent storage or snowmelt recharge. Similar reductions in meteorological-to-agricultural drought propagation time have been associated with warming and accelerated soil–water depletion in other semi-arid regions [21]. The dominant time-scale and event-lag results therefore describe complementary aspects of the same process: SPEI-3 dominance identifies the shorter climatic accumulation period most closely associated with SMDI, while propagation time measures how quickly a discrete meteorological event is followed by agricultural drought. Their convergence provides stronger evidence for an accelerated drought cascade than either metric alone.

The moderate SPEI-3–SMDI correlations do not imply that meteorological drought is an uninformative agricultural indicator. Correlation describes average rank correspondence across all warm-season conditions and can weaken with nonlinear responses, storage thresholds, crop water use, and spatial heterogeneity. The calculated future correlations of approximately 0.57–0.62 were lower than the value of approximately 0.71 reported for the more humid Yangtze River Basin by Xu et al. [22], but this contrast is physically plausible. The NGP analysis excludes the winter months, reducing common seasonal variation, and Prairie soil moisture is partly decoupled from concurrent climatic conditions by snowmelt, frozen ground, antecedent storage, and heterogeneous soils. The conditional-probability analysis nevertheless showed that agricultural dry conditions became progressively more likely as meteorological drought intensified. This means SPEI-3 may show only moderate correspondence with SMDI across the full distribution yet still provide useful information once a meteorological drought threshold is crossed. Average correlation and conditional drought probability therefore measure different properties: the

former describes general co-variation, whereas the latter evaluates agricultural risk under specified meteorological conditions.

The copula and lower-tail analyses extend this distinction by showing that the propagation pathway is nonlinear and spatially variable. Selecting Frank, Gumbel, Clayton, and Joe copulas across groups indicates that no single dependence structure characterizes the entire Prairie domain. This heterogeneity may reflect regional differences in soil texture, available water capacity, snowmelt contribution, land cover, and evaporative demand. Despite this variation, lower-tail co-occurrence remained above the independence benchmark at all examined tail depths. At $u = 0.10$, $\chi_L(u)$ increased in the near future and subsequently declined to 0.239 in the far future but remained substantially above the independence value of 0.10. The late-century decline should not be interpreted as a reduction in agricultural-drought hazard. The lower-tail statistic measures the synchronization of the worst relative SPEI-3 and SMDI conditions after accounting for changes in their marginal distributions. Agricultural drought can therefore become more frequent and severe even if its most extreme months become less precisely synchronized with the lowest SPEI-3 ranks. Increasing control by antecedent storage, evapotranspiration, snowmelt, vegetation water use, and soil properties offers a physically consistent explanation: meteorological drought remains important, but the exact agricultural response becomes increasingly mediated by land–surface conditions.

Translation rate provides an event-based expression of this threshold-controlled relationship. Approximately one-half to two-thirds of meteorological drought events were associated with agricultural drought, with generally higher rates under stronger forcing. However, the temporal pattern of these events does not follow a simple linear trajectory; translation rates often increase from the near to the mid future before stabilizing or even declining slightly. This decline should not be interpreted as a sign of weakening propagation. When meteorological droughts become more frequent, several meteorological events may contribute to one persistent agricultural event, while an already active SMDI drought cannot be counted repeatedly as a new event. Consequently, the denominator may grow more rapidly than the numerator, causing the conversion rate to level off despite widespread agricultural drought. Matched-event counts were generally higher than in the near-future but did not increase at every successive horizon, reinforcing the need to interpret event counts, translation rate, propagation lag, and drought severity together. The NGP translation rates were below the approximately 72% reported by Xu et al. [22], consistent with greater snowmelt and storage buffering in the Prairies.

These findings illustrate a cohesive shift in the behavior of drought in the Prairie regions. Increased demand for atmospheric water results in more pronounced negative climatic water balances, alongside a decreasing SMDI, especially in the southern and southeastern areas. As the buffering capacity of the root zone decreases, short-term SPEI-3 deficits play a more significant role. Consequently, the selection of scales becomes clearer, leading to a more rapid transition from meteorological drought to agricultural drought. Conditional probability and lower-tail dependence underscore the significance of the pathway, even when correlations across entire distributions are merely moderate. On the other hand, the concept of translation-rate saturation reveals that simply relying on event ratios fails to fully convey the intensification associated with persistent drought conditions. For effective drought monitoring, it is essential to assess SPEI-3 jointly with antecedent SMDI, snowmelt recharge, and local soil–water storage. A warning system that integrates meteorological severity with reduced antecedent soil moisture presents a more robust approach than relying on a single-index threshold. This consideration accounts not only for the atmospheric conditions that initiate events but also for the land's capacity to absorb the resulting moisture.

Shorter lead times are particularly consequential for rain-fed agriculture in the Southern and Southeastern Prairies. Farmers may need to decide on seeding, crop and cultivar selection, grazing pressure, supplemental irrigation, and water allocation before soil-moisture stress is fully established. Moisture-conserving tillage, residue retention, diversified rotations, and drought-tolerant cultivars can increase the effective buffering capacity of the root zone, whereas targeted irrigation may be most valuable where high translation rates coincide with short propagation times. Where irrigation water is available, its allocation under uncertain supply and demand scenarios can be optimized with stochastic and Monte Carlo-based approaches [50,51], and the propagation times and translation rates presented here could provide spatially explicit inputs to such frameworks. In central areas with greater storage, management should emphasize retaining spring moisture and avoiding its rapid depletion during critical crop stages. In eastern depression-dominated landscapes, adaptation must also consider drainage and wetland connectivity, as removing stored water may reduce resilience to subsequent summer drought, even when it improves spring field access. These regional differences show why a uniform Prairie-wide adaptation strategy would be inefficient: the most suitable response depends on whether drought sensitivity is controlled mainly by climatic aridity, limited storage, rapid depletion, or landscape connectivity.

5. Conclusions

This study assessed how meteorological drought propagates into agricultural drought across a large part of the Northern Great Plains under three CMIP6 emission pathways, combining bias-corrected regional climate projections with a calibrated SWAT model and a multi-method propagation framework. Three findings stand out. First, soil-moisture drought intensifies consistently through the century under every scenario, with the strongest and most spatially extensive drying over the semi-arid Southern and Southeastern Prairies, the region least able to absorb additional water stress. Second, the average statistical coupling between meteorological and agricultural drought is only moderate and does not strengthen under warming, yet propagation becomes markedly faster: mean lag shortens from roughly 2.4 to 1.8 months, approaching 1 month under the highest-emission pathway. Third, the probability that meteorological drought translates into agricultural drought rises monotonically with severity and remains elevated in the joint lower tail, indicating that severe compound events do not decouple even as mean correlation weakens.

Several limitations bound these conclusions. The propagation analysis of SSP5-8.5 is represented by a single model, so that pathway should be read as indicative rather than definitive. In fact, future changes are presented mainly as ensemble means of four climate models, and SSP5-8.5 is represented by CanESM5 only. Although all metrics were calculated separately for each model, the ensemble mean does not represent the full inter-model spread, and model disagreement contributes to weak ensemble changes in parts of the domain. The SWAT structure does not represent dynamic contributing areas or depression storage, which limits skill in the pothole-dominated eastern sub-basins. In addition, the lack of long-term root-zone soil-moisture observations across the Prairies limited validation to five stations, all located in Alberta, so results for the eastern sub-basins should be interpreted with lower confidence. Translating these hazard projections into agronomic and economic risk will require coupling to crop-growth and loss models, which we identify as the necessary next step.

Taken together, our results describe a shift from a relatively buffered system toward a shorter-memory response in which short-term atmospheric water-balance anomalies translate quickly into crop-water stress. The practical consequence is a contraction of the warning interval available to Prairie producers and water managers precisely as drought

severity increases. Effective early warning will therefore require joint triggers that combine meteorological severity with antecedent root-zone conditions rather than single-index thresholds.

A progressive intensification of warm-season soil moisture stress is a common and consistent climate change projection for the Northern Great Plains. Our work confirms this scenario and adds a key finding: the soil water balance responds more immediately to precipitation deficits as the climate warms. This finding further underscores the critical need for climate-resilient soil and water management and adaptation strategies. While best management practices have always differed among soil landscapes and agri-ecosystems, knowledge of climate-change impacts adds a new element to this geographic diversity: differences in the relative timing of precipitation and soil water deficits among landscapes and agri-ecosystems. This type of information will inform the design and implementation of climate-resilient agriculture.

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Data Availability Statement: The station observations used in this study are publicly available from Environment and Climate Change Canada (<https://weather.gc.ca>, accessed on 5 October 2026) and the NOAA Global Historical Climatology Network Daily dataset (<https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily>, accessed on 5 October 2026). Streamflow data are available from the Water Survey of Canada (<https://wateroffice.ec.gc.ca>, accessed on 5 October 2026), and soil-moisture observations from the Alberta Climate Information Service (<https://acis.alberta.ca>, accessed on 5 October 2026). The CRCM5-CMIP6 simulations are described in Paquin et al. [25]. The SWAT outputs and drought indices generated in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ACIS	Alberta Climate Information Service
AIC	Akaike Information Criterion
CanESM5	Canadian Earth System Model version 5
CMIP6	Coupled Model Intercomparison Project Phase 6
CNRM-ESM2-1	Centre National de Recherches Météorologiques Earth System Model version 2.1
CRCM5	Canadian Regional Climate Model version 5
CRCM5-CMIP6	CRCM5 simulations driven by CMIP6 Earth system models
DD	Drought Duration
DS	Drought Severity
ECCC	Environment and Climate Change Canada
EQM	Equidistant Quantile Mapping
ESM	Earth System Model
GCM	Global Climate Model
GDP	Gross Domestic Product
GHCN-Daily	Global Historical Climatology Network Daily
HRU	Hydrologic Response Unit
HYDAT	National Water Data Archive (Hydrometric Database)

KGE	Kling–Gupta Efficiency
LS	Linear Scaling
MAE	Mean Absolute Error
MD	Meteorological Drought
MDAR	Multiple-donor stations Drainage Area Ratio
MPI-ESM1-2-LR	Max Planck Institute Earth System Model version 1.2, low resolution
NCEI	National Centers for Environmental Information
NGP	Northern Great Plains
NOAA	National Oceanic and Atmospheric Administration
NorESM2-MM	Norwegian Earth System Model version 2, medium resolution
NSE	Nash–Sutcliffe Efficiency
PBIAS	Percent Bias
PDSI	Palmer Drought Severity Index
PET	Potential Evapotranspiration
PFRA	Prairie Farm Rehabilitation Administration
QDM	Quantile Delta Mapping
RCP	Representative Concentration Pathway
RMSE	Root Mean Square Error
ROS	Rain-on-Snow
SD	Soil Water Deficit
SMDI	Soil Moisture Deficit Index
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
SRTM	Shuttle Radar Topography Mission
SSP	Shared Socioeconomic Pathway
SSP2-4.5	Intermediate-emission SSP scenario (4.5 W m ⁻² by 2100)
SSP3-7.0	High-emission SSP scenario (7.0 W m ⁻² by 2100)
SSP5-8.5	Very high-emission SSP scenario (8.5 W m ⁻² by 2100)
SUFI-2	Sequential Uncertainty Fitting version 2
SWAT	Soil and Water Assessment Tool
SWAT-CUP	SWAT Calibration and Uncertainty Programs
SWAT-M	Modified Soil and Water Assessment Tool
SWC	Soil Water Content
TR	Translation Rate
WSC	Water Survey of Canada

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