

TRACKING DROUGHT PROPAGATION AND IRRIGATION RESPONSE LAGS USING SATELLITE OBSERVATIONS

SUIVI DE LA PROPAGATION DE LA SÉCHERESSE ET DES DÉCALAGES DE LA RÉPONSE DE L'IRRIGATION À L'AIDE D'OBSERVATIONS SATELLITAIRES

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ABSTRACT

Agricultural drought exhibits complex temporal relationships between hydroclimatic conditions and observed drought impacts, making lag analysis essential for effective drought monitoring and early warning. In this study, satellite-based precipitation data from the Climate Hazards Group InfraRed Precipitation with Station data Version 3.0 (CHIRPS V3.0) and climate and soil moisture variables from TerraClimate were used to derive drought indices, including the Standardized Precipitation Evapotranspiration Index (SPEI) at 3-, 6-, and 12-month accumulation scales and the Soil Moisture Index (SMI). Agricultural drought occurrence and damage records from 2018 to 2023 were analyzed using receiver operating characteristic (ROC) curves and area under the curve (AUC)-based lag analysis to evaluate the temporal response characteristics of the drought indices. The results demonstrated that all indices showed sufficient skill in explaining agricultural drought occurrence, although their temporal response characteristics differed substantially according to index type and accumulation period. Grid-based analysis revealed distinct spatial lag patterns, with SMI and SPEI-12 showing dominant leading responses, whereas SPEI-3 and SPEI-6 exhibited concurrent or mixed responses relative to observed drought impacts. These findings indicate that drought indices reflect different components of the drought propagation process and respond to agricultural drought conditions at different timescales. The study highlights the importance of selecting drought indices according to monitoring objectives and response timing, providing practical insights for satellite-based agricultural drought monitoring, irrigation management, and early warning systems under intensifying hydroclimatic stress.

Keywords: Agricultural drought; CHIRPS V3.0; Drought index; Lag analysis; Satellite-based precipitation; Soil moisture.

RÉSUMÉ

La sécheresse agricole présente des relations temporelles complexes entre les conditions hydroclimatiques et les impacts observés de la sécheresse, ce qui rend l'analyse des décalages temporels essentielle à un suivi efficace de la sécheresse et à l'alerte précoce. Dans cette étude, les données de précipitations satellitaires Climate Hazards Group InfraRed Precipitation with Station data Version 3.0 (CHIRPS V3.0), ainsi que les variables climatiques et d'humidité du sol de TerraClimate, ont servi à calculer des indices de sécheresse, notamment l'indice standardisé de précipitations et d'évapotranspiration (SPEI) à des échelles d'accumulation de 3, 6 et 12 mois et l'indice d'humidité du sol (SMI). Les relevés d'occurrence et de dommages liés à la sécheresse agricole entre 2018 et 2023 ont été analysés au moyen de courbes ROC (caractéristique de fonctionnement du récepteur) et d'une analyse des décalages fondée sur l'aire sous la courbe (AUC), afin d'évaluer les caractéristiques de réponse temporelle des indices de sécheresse. Les résultats ont montré que tous les indices possédaient une capacité suffisante pour expliquer l'occurrence de la sécheresse agricole,

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bien que leurs caractéristiques de réponse temporelle diffèrent sensiblement selon le type d'indice et la période d'accumulation. L'analyse par grille a révélé des schémas spatiaux de décalage distincts : le SMI et le SPEI-12 présentaient principalement des réponses anticipées, tandis que le SPEI-3 et le SPEI-6 affichaient des réponses simultanées ou mixtes par rapport aux impacts observés de la sécheresse. Ces résultats indiquent que les indices de sécheresse reflètent différentes composantes du processus de propagation de la sécheresse et réagissent aux conditions de sécheresse agricole à des échelles temporelles différentes. L'étude souligne l'importance de sélectionner les indices de sécheresse en fonction des objectifs de suivi et du calendrier de réponse, et fournit des indications pratiques pour le suivi satellitaire de la sécheresse agricole, la gestion de l'irrigation et les systèmes d'alerte précoce dans un contexte d'intensification des contraintes hydroclimatiques.

Mots clés : Sécheresse agricole; CHIRPS V3.0; Indice de sécheresse; Analyse Lag; Précipitations satellitaires; Humidité du sol.

INTRODUCTION

Agricultural drought is fundamentally distinguished from meteorological drought by its dependence not only on precipitation deficits but also on soil moisture storage conditions and the structure of irrigation water supply systems, including reservoirs and conveyance infrastructure (Jeon et al., 2022). Increasing climate variability has modified the spatiotemporal characteristics of drought, with recent events exhibiting more rapid onset and greater spatial heterogeneity than historical patterns (Otkin et al., 2018; Lee et al., 2024). Whereas large-scale rainfall deficits once drove gradual, regionally coherent drought development, current conditions increasingly produce severe agricultural drought impacts in geographically limited areas under identical precipitation anomalies, reflecting the growing complexity of drought propagation pathways (Kim and Yun, 2015).

A critical implication of this complexity is that agricultural drought impacts do not necessarily coincide in time with precipitation deficits. In the Republic of Korea, agricultural water supply depends heavily on reservoirs and irrigation facilities, and the distinct soil moisture storage characteristics of different regions mean that agricultural activities may continue for a period following rainfall deficits (Shin et al., 2021). Conversely, when reservoir storage declines below critical thresholds or cumulative soil moisture deficits reach a tipping point, agricultural impacts may materialize at a substantially later time than the initial meteorological trigger. This temporal delay between precipitation anomalies and agricultural drought occurrence—commonly described as a lag relationship—constitutes a structural feature of drought propagation that has critical implications for monitoring and early warning system design (Nam et al., 2013; Yang et al., 2017; Do et al., 2023).

Quantifying this lag structure at the regional scale requires spatially continuous and temporally consistent data on both precipitation and related hydroclimatic variables. Ground-based rainfall gauge networks, which have historically served as the primary basis for drought monitoring in Korea, are characterized by uneven spatial distribution and limited coverage in areas with sparse gauge density, constraining the ability to capture the full spatial variability of drought signals (Cha et al., 2025). Satellite-based precipitation products provide a spatially continuous and spatially uniform alternative that enables grid-level assessment of drought indices without dependence on gauge density (Jang et al., 2018; Jeon et al., 2020; Mun et al., 2024). Among current products, CHIRPS V3.0 has demonstrated superior performance relative to other satellite products in terms of spatial resolution, temporal coverage, and gauge integration quality (Cha et al., 2025), making it particularly suitable for long-term drought monitoring applications.

Despite the growing literature on satellite-based drought index computation, studies that systematically quantify the temporal lag between drought indices and agricultural drought occurrence at the grid scale remain limited. Existing research has largely focused on distributional characteristics or static correlations between index values and drought events, without explicitly evaluating the time offset that governs how drought indices respond to agricultural drought development (Won and Chung, 2016). The inherently event-based and low-frequency nature of agricultural drought records

further constrains the applicability of conventional cross-correlation approaches, which assume continuous time series relationships (Seo et al., 2009; Lee et al., 2021).

This study addresses these limitations by proposing a ROC-AUC based lag analysis framework that systematically characterizes the temporal response of multiple satellite-derived drought indices relative to agricultural drought occurrence and damage records across the Korean mainland. The framework evaluates lag offsets ranging from -6 to +6 months using AUC as the performance metric, enabling differentiation of leading, concurrent, and lagging response patterns by index type. Applied to 4,012 grid cells at 5 km resolution across the Korean mainland for the period 2018–2023, the proposed framework provides a spatially explicit basis for understanding how different drought indices respond to agricultural drought under intensifying hydroclimatic stress.

DATA AND METHODS

Study Area and Irrigation System Characteristics

The study area encompasses the mainland of the Republic of Korea, situated between approximately 34°N–38°N latitude and 126°E–130°E longitude. Korea is characterized by a temperate monsoon climate with a pronounced wet season from June to September, during which approximately 60–70% of annual precipitation is concentrated. Mean annual precipitation varies substantially across the peninsula, ranging from approximately 800 mm in leeward inland areas to over 1,800 mm in windward coastal and mountainous zones. Interannual variability is high, with drought years commonly exhibiting precipitation totals 30–50% below the long-term mean. Agriculture is predominantly rain-fed and irrigated paddy rice cultivation, which depends heavily on reservoir-based irrigation systems managed by the Korea Rural Community Corporation (KRC). The drought monitoring framework is applied to 4,012 grid cells at 5 km spatial resolution covering the entire Korean mainland.

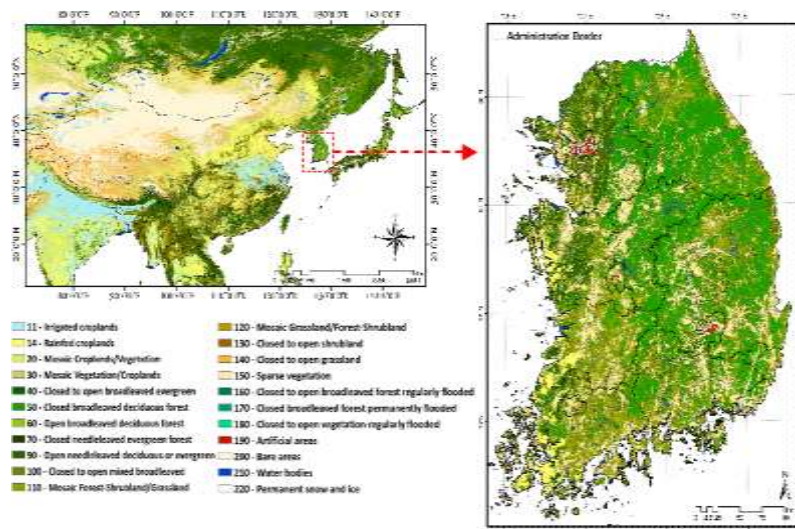


Figure 1. Geographic location and land cover distribution of the study area

Satellite-Derived Hydroclimatic Data

Satellite-based precipitation data were obtained from CHIRPS V3.0, developed by the Climate Hazards Group (Funk et al., 2015). CHIRPS V3.0 provides daily and monthly precipitation data at 0.05° spatial resolution from 1981 to the present with global terrestrial coverage. Compared with earlier versions, CHIRPS V3.0 incorporates an updated gauge integration scheme and improved climatological baseline, enabling more consistent representation of recent hydroclimatic conditions. Owing to its high spatial resolution, long-term temporal continuity, and enhanced gauge correction

performance, CHIRPS V3.0 was selected as the primary precipitation dataset for drought index computation in this study (Table 1).

Climate and soil moisture variables required for SPEI and SMI computation were obtained from TerraClimate (Abatzoglou et al., 2018), a global gridded monthly climate dataset with approximately 4 km spatial resolution. Key variables extracted include potential evapotranspiration (PET) and soil moisture. TerraClimate provides continuous monthly climate records from 1958 to the present, enabling computation of long-term baseline distributions for standardized drought index calculation. All TerraClimate variables were resampled to the CHIRPS V3.0 grid (0.05°) using nearest-neighbor spatial resampling.

Table 1. Characteristics of satellite-based precipitation products commonly used for agricultural drought assessment

Product	Data source	Spatial resolution	Temporal resolution	Period
GPM IMERG	Multi-satellite	0.1°	Daily	2000–present
PERSIANN-CDR	IR-based	0.25°	Daily	1983–present
CMORPH	Microwave-based	0.25°	Daily	1998–present
CHIRPS V2.0	IR and gauge blended	0.05°	Daily	1981–present
CHIRPS V3.0 (this study)	IR with updated gauge observations	0.05°	Daily	1981– present

Agricultural Drought Occurrence and Damage Records

Agricultural drought occurrence and damage records were compiled from two independent official sources. Agricultural drought damage records, published by the Korea Rural Community Corporation (KRC), document the timing and spatial extent of agricultural drought impacts where actual damage has been recorded. Damage records from August 2018 and June 2022—representing the two most spatially extensive documented drought events within the analysis period—were used as event-based reference points for lag analysis ($t = 0$).

Agricultural drought early-warning records, published monthly by official agencies, reflect the operational recognition of drought conditions based on reservoir storage ratios and supply-demand assessments. Early-warning stage classifications (Caution, Advisory, Warning, Severe) from 2018 to 2023 were used to construct a binary monthly drought occurrence time series for each grid cell, where any early-warning stage activation in a given month was coded as 1 (drought) and no activation as 0 (non-drought). This formulation enables quantitative ROC-AUC based temporal lag analysis across all 4,012 grid cells.

Computation of Satellite-Derived Drought Indices

The Standardized Precipitation Evapotranspiration Index (SPEI) integrates precipitation and potential evapotranspiration to reflect soil water balance conditions, enabling detection of drought driven by both precipitation deficits and elevated evaporative demand (Vicente-Serrano et al., 2010). The climatic water balance at time t is defined as $D_t = P_t - PET_t$, where P is monthly precipitation (from CHIRPS V3.0) and PET is potential evapotranspiration (from TerraClimate). Cumulative water balance series are computed over 3-, 6-, and 12-month accumulation periods, fitted to a log-logistic probability distribution, and transformed to standard normal deviates following established protocols.

The Soil Moisture Index (SMI) directly represents standardized subsurface water storage conditions, reflecting the actual soil moisture state rather than the atmospheric water balance approximated by SPEI. SMI is computed from TerraClimate near-surface soil moisture (SM_t), fitted by month to an appropriate probability distribution $F(SM_t)$, and transformed to standard normal deviates as $SMI_t = \Phi^{-1}[F(SM_t)]$, where Φ^{-1} is the inverse standard normal cumulative distribution function. By separating

analysis by calendar month, the seasonal cycle in soil moisture is removed. Four drought indices (SPEI-3, SPEI-6, SPEI-12, SMI) were computed at 5 km resolution across all 4,012 grid cells for the full analysis period.

ROC-AUC Framework for Temporal Lag Analysis

To quantify the temporal response of each drought index to agricultural drought, a ROC-AUC based lag evaluation framework was applied. Conventional cross-correlation analysis assumes continuous linear time series relationships and is constrained by the typically short and episodic nature of agricultural drought records. The ROC-AUC approach overcomes these limitations by evaluating the discriminatory performance of each index at a given lag, without assuming a linear relationship structure and with stability even when drought occurrence records are limited in length.

For event-based agricultural drought analysis, a ± 6 -month temporal window was constructed around the two major agricultural drought damage events (August 2018 and June 2022). Temporal drought response profiles were characterized using the median and interquartile range (IQR) of drought index values across all drought-affected grid cells. This approach enabled evaluation of the onset, persistence, and recovery characteristics of each drought index relative to observed agricultural drought damage.

For grid-scale drought occurrence analysis, a binary monthly drought occurrence series was constructed for each grid cell using agricultural drought early-warning records. Receiver operating characteristic (ROC) curves were then computed for each drought index at lag offsets ranging from -6 to $+6$ months. Negative lag values indicate that drought index anomalies preceded observed agricultural drought occurrence (leading responses), whereas positive lag values indicate delayed responses following drought occurrence. The area under the curve (AUC) was calculated at each lag offset, and the optimal lag was defined as the lag maximizing AUC for each grid cell. Based on the optimal lag, grid cells were classified into leading (optimal lag < 0), concurrent (optimal lag $= 0$), and lagging (optimal lag > 0) response categories.

RESULTS AND DISCUSSION

Spatiotemporal Evolution of Drought Conditions

To characterize the spatiotemporal distribution of grid-scale drought indices, the four-month period from May to August 2022—spanning the onset of record low precipitation through the peak of the southern drought—was selected as the primary case study period. This period brackets the June 2022 agricultural drought damage event and allows examination of how different indices capture the evolving spatial structure of drought development.

SPEI-3 exhibited moderate drought conditions concentrated in eastern coastal areas in May 2022, rapidly intensifying to extreme drought across southern regions by June and July, with partial recovery by August as summer monsoon precipitation arrived. SPEI-6 showed widespread extreme and severe drought across the entire peninsula as early as May 2022, reflecting accumulated deficits from the preceding winter and spring dry period, with considerably slower recovery than SPEI-3. SPEI-12, capturing long-term water balance conditions, showed severe drought concentrated in central and northern areas in May before re-intensifying across southern areas by July and August. SMI exhibited a markedly different temporal trajectory, reflecting the buffering effect of soil moisture storage; northern and Gangwon province areas showed severe to extreme soil moisture drought in May, followed by partial recovery in June before severe soil moisture drought re-emerged in Jeollanam-do province by July and August.

The distinctly different spatiotemporal signals underscore the dependence of drought signal structure on index accumulation period and physical basis. Short-term indices capture rapid transitions, while long-term accumulation indices reflect sustained background moisture deficits. SMI's divergence from

the precipitation-based SPEI indices reflects the additional role of soil moisture storage in buffering precipitation variability—particularly relevant to irrigation system management where soil conditions govern crop water stress onset.

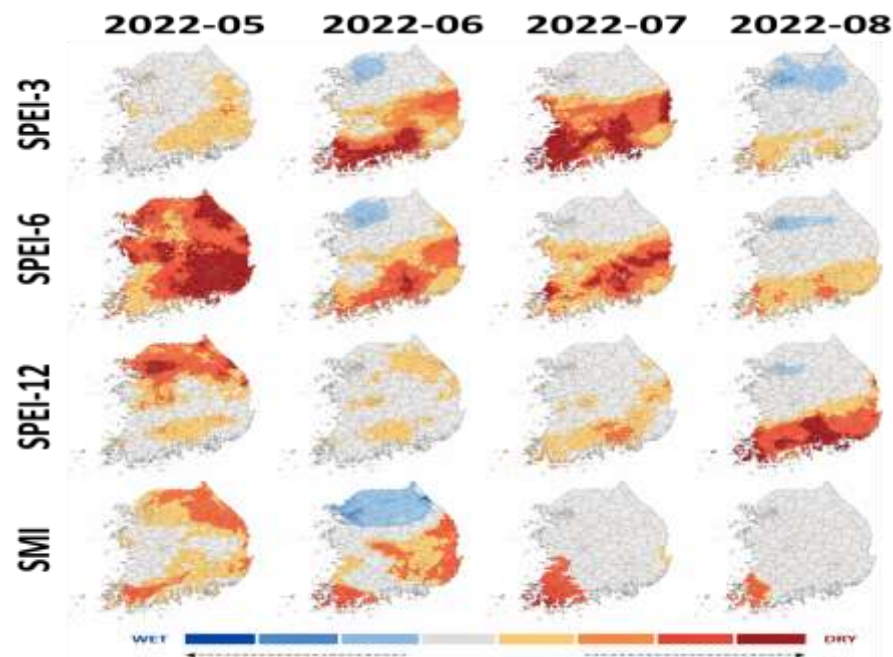


Figure 2. Spatial progression of drought severity at different accumulation timescales, illustrating contrasting temporal responses among SPEI and SMI during the 2022 drought even

Event-Based Temporal Response Characteristics of Drought Indices

The temporal profiles of drought indices around the two agricultural drought damage events (August 2018, June 2022) were examined over a ± 6 -month window centered on each damage event ($t = 0$). SPEI-3 showed a consistent pattern across both events, with index values declining progressively from approximately two months before the damage event (lag -2), reaching minimum values near the damage month, and exhibiting partial recovery by lag +2 months—consistent with a leading response. SPEI-6 showed a declining trend beginning approximately two months before the damage event, but negative values persisted for an extended period after the damage event, reflecting the carry-forward effect of accumulated precipitation deficits. SPEI-12 exhibited broad and gradual index evolution with wide interquartile ranges reflecting substantial spatial heterogeneity across the Korean mainland. SMI showed a leading response relative to both damage events, with index values beginning to decline approximately two months before each event, consistent with progressive depletion of soil moisture reserves prior to formal damage recognition.

Grid-Scale Temporal Lag Response Patterns

Prior to lag analysis, ROC curves were computed at the grid level to verify that the four indices possessed sufficient discriminatory skill. All four indices showed AUC values exceeding 0.7 across all representative locations, confirming that the indices reliably differentiate drought occurrence from non-drought conditions above random classification levels. SPEI indices generally showed high AUC values across most locations, while SMI also demonstrated acceptable discriminatory skill in reflecting soil moisture-driven agricultural drought.

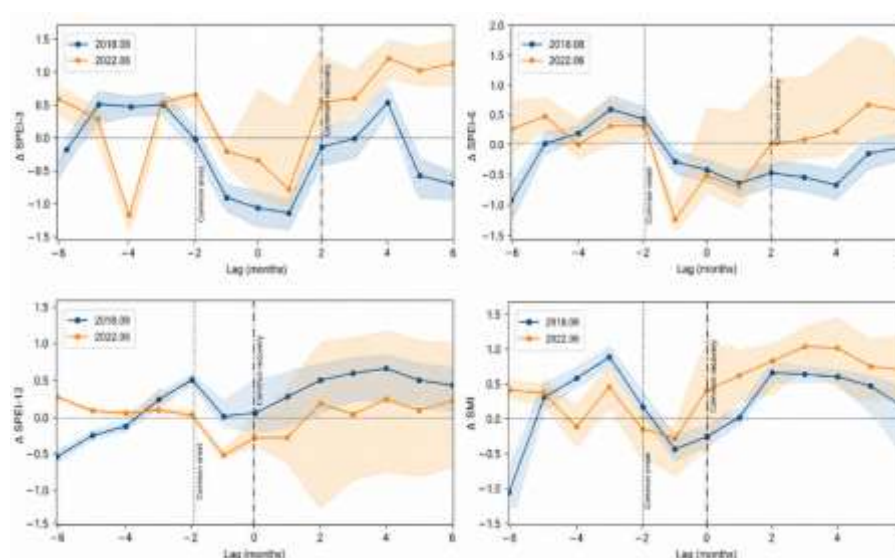


Figure 3. Comparative temporal lag characteristics of satellite-derived drought indices relative to observed agricultural drought damage events, illustrating differences in onset and recovery responses across accumulation timescales

Grid-level optimal lag distributions revealed distinct patterns by index type. SMI showed the most concentrated distribution with the highest proportion of grid cells classified at lag -1 month, indicating a predominantly one-month leading response. SPEI-3 showed mixed distributions concentrated at lags -1 and 0, indicating approximately equal leading and concurrent responses. SPEI-6 exhibited its largest grid count at lag -2 months with a broader distribution extending into positive lags. SPEI-12 showed the most extreme leading pattern with the highest proportion of grid cells concentrated at lag -6 months.

The quantitative lag summary (Table 3) indicates that SPEI-12 has the largest mean lag of -2.97 months and the highest mean absolute lag of 3.97 months, confirming its role as the index most strongly and consistently preceding agricultural drought occurrence. SMI has a mean lag of -1.00 months with a mean absolute lag of 2.81 months, reflecting its consistent one-month leading signal. SPEI-3 shows a mean lag of +0.95 months, reflecting its mixed leading and lagging character, while SPEI-6 has a near-zero mean lag (+0.08 months) but a mean absolute lag of 2.04 months, indicating substantial bidirectional spread.

Table 2. Classification of grid cells according to temporal drought response characteristics

Drought Index	Leading response	Concurrent response	Lagging response	Dominant response
SMI	383 (73.7%)	0 (0.0%)	137 (26.3%)	Leading
SPEI-3	209 (40.2%)	148 (28.5%)	163 (31.3%)	Mixed
SPEI-6	232 (44.6%)	60 (11.5%)	228 (43.9%)	Mixed
SPEI-12	346 (66.5%)	24 (4.6%)	150 (28.9%)	Leading

Note: Leading responses indicate that drought indices responded prior to observed agricultural drought occurrence, whereas lagging responses indicate delayed responses following drought occurrence. Concurrent responses represent drought responses occurring near the timing of observed agricultural drought events.

Table 3. Summary statistics of temporal lag characteristics for drought indices

Drought index	Peak damage lag (month)	Peak occurrence lag (month)	Mean lag (month)	Mean absolute lag (month)
SMI	-2	-1	-1.00	2.81
SPEI-3	-2	-1, 0	+0.95	1.98
SPEI-6	-2	-2	+0.08	2.04
SPEI-12	-1	-6	-2.97	3.97

CONCLUSIONS

This study proposed a ROC-AUC based lag analysis framework for characterizing the temporal response of satellite-derived drought indices to agricultural drought occurrence and damage across the Korean mainland. The temporal lag relationships identified are both systematic and physically interpretable. The distinct lag patterns exhibited by SMI, SPEI-3, SPEI-6, and SPEI-12 reflect the different physical mechanisms by which each index captures moisture deficits: SMI directly represents the soil moisture state governing crop water availability, while SPEI indices capture the cumulative atmospheric water deficit over different time scales. The strong leading response of SMI (mean lag -1.00 months) is consistent with the expectation that soil moisture depletion typically precedes the operational recognition of agricultural drought impacts. The markedly stronger leading response of SPEI-12 (mean lag -2.97 months) reflects the tendency of long-term cumulative indices to capture background climate conditions that predispose agricultural systems to drought well before formal recognition.

These findings have direct implications for the design of adaptive monitoring of irrigation system responses under intensifying hydroclimatic stress. Long-term accumulation indices such as SPEI-12 appear best suited for background drought risk assessment and strategic irrigation water resource planning, providing advance warning of elevated drought risk up to three months before agricultural impacts materialize. Short-term and soil moisture-based indices (SPEI-3, SMI) are more appropriate for near-event monitoring and operational irrigation scheduling. This differentiation suggests that a multi-index monitoring framework—combining long-term indices for risk signal identification and short-term indices for operational irrigation response—would provide more complete characterization of agricultural drought dynamics than any single index applied uniformly.

The finding that all four indices demonstrated AUC values consistently above 0.7 across the Korean mainland confirms the viability of ROC-AUC-based lag analysis as a robust tool for characterizing drought temporal dynamics even when agricultural drought records are limited in number and temporal extent. This methodological contribution extends the applicability of satellite-based drought monitoring frameworks to operational settings where long continuous records of agricultural impacts are unavailable.

The key findings are summarized as follows: (1) All four drought indices demonstrated AUC values exceeding 0.7 across all evaluated grid cells, confirming their adequacy for discriminating agricultural drought occurrence in Korea. (2) Grid-level lag analysis revealed distinct temporal response patterns: SMI exhibited a dominant leading response (73.7% of grids, mean lag -1.00 months) and SPEI-12 showed the strongest leading tendency (66.5% of grids, mean lag -2.97 months), while SPEI-3 and SPEI-6 showed concurrent or mixed patterns. (3) These response differences reflect the physical meaning and accumulation period of each index, underscoring the necessity of purpose-driven index selection.

Several limitations should be noted. Agricultural drought occurrence times defined by early-warning issuance reflect operational and administrative recognition rather than the actual physical onset of crop water stress, introducing a systematic offset between the index signal and the physiological drought state. Additionally, the ROC-AUC based lag evaluation quantifies discriminatory performance

but does not directly characterize the relationship between index magnitude and drought severity or damage extent.

Building on these findings, future research should extend the lag-based monitoring framework toward operational adaptive monitoring of irrigation system responses under intensifying hydroclimatic stress. The grid-scale lag structure identified here provides the quantitative foundation needed to link satellite-derived drought signals to the operational thresholds and response timelines of Korea's reservoir-based irrigation infrastructure.

Future work should integrate the lag-adjusted drought signal timing with reservoir storage dynamics and irrigation water release records to evaluate how irrigation systems buffer or amplify drought propagation, and under what hydroclimatic conditions that buffering capacity is overwhelmed. As climate change continues to intensify the frequency and severity of drought events—particularly rapid-onset flash droughts that compress available lead time for irrigation response—the ability to anticipate irrigation system stress through spatially explicit, lag-corrected satellite-derived indices will become increasingly critical. An adaptive monitoring framework that dynamically updates lag parameters in response to shifting hydroclimatic regimes represents the next step toward drought-resilient irrigation management across the Korean mainland.

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