



## Research Paper

# Relative contribution of uncertainties to standardized drought index calculation using a linear mixture model

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## ABSTRACT

Standardized Precipitation Index (SPI) is widely used for monitoring drought due to its simplicity and effectiveness. However, various uncertainties arise from multiple factors in SPI calculation including the length of precipitation data, accumulation periods, probability distributions, and parameter estimation methods. This study aims to quantify the relative contribution of these factors to SPI uncertainty using a linear mixed model (LMM). In this study, various SPI calculation scenarios were considered by combining three data lengths (20, 30, and 50 years), four accumulation periods (1, 3, 6, and 12 months), five probability distributions (gamma, normal, log-normal, logistic, and generalized extreme value), and two parameter estimation methods (maximum likelihood estimation and L-moment). In our study, reference precipitation was defined as the amount of precipitation corresponding to a target SPI value (e.g.,  $-1.0$  or  $-2.0$ ), determined by inverting the standard SPI calculation process. The uncertainty was quantified by calculating the root mean square error (RMSE) between the reference SPI and calculated SPI from various SPI calculation scenarios. The results showed that uncertainty decreased with longer accumulation periods and data lengths, while the RMSE was substantially higher and more variable under SPI =  $-2.0$  than SPI =  $-1.0$ . The LMM was then used to assess the contribution of each uncertainty factor. The results revealed that for moderate drought conditions (SPI =  $-1.0$ ), the primary contributors to uncertainty were sample size and accumulation period. However, under extreme drought conditions (SPI =  $-2.0$ ), probability distribution accounted for over 50% of the total variance, reaching up to 84% in some cases. The impact of parameter estimation methods was relatively nonsignificant under all conditions, consistently accounting for less than 3% of the total variance. These findings suggest that selecting an appropriate distribution and using long-term precipitation data are critical for improving the reliability of SPI-based drought assessments. This study highlights the critical need for long-term precipitation records (at least 50 years), appropriate accumulation periods, and rigorous selection of probability distributions, particularly under extreme drought conditions.

## 1. Introduction

Drought is an insidious natural hazard that occurs in all climatic regimes around the world and affects human society and natural ecosystems at different spatial and temporal scales. Drought is a phenomenon that begins with a lack of precipitation but is further influenced by a decrease in soil moisture, an increase in evapotranspiration, geological characteristics, and human activities (such as the use of surface water and groundwater). It is classified into meteorological, agricultural, hydrological, and socio-economic drought (Wilhite and Glantz, 1985). A

drought index is a numerical representation of drought phenomena using various hydro-meteorological variables such as precipitation, temperature, streamflow, and water level. Using a drought index, we can identify the occurrence of drought and quantify duration and severity of drought. More than 100 drought indices have been developed for monitoring and assessing drought conditions (WMO and GWP, 2016). These indices are categorized into single, multiple, and hybrid indices, depending on the hydro-meteorological variables used to calculate them and the way they are calculated (Mishra and Singh, 2010; WMO and GWP, 2016).

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Among various drought indices, the most commonly used index is the Standardized Precipitation Index (SPI) developed by McKee et al. (1993). The World Meteorological Organization (WMO) has proposed utilizing SPI as the global standard drought index (Wilhite, 2006). The WMO stated that the SPI allows the user to confidently compare historical and current drought conditions between different climatic and geographic locations. The SPI has been widely adopted in climate analysis and drought monitoring worldwide (Vergni et al., 2017) due to its straightforward calculation and spatiotemporal comparability (Svoboda et al., 2002; Bae et al., 2012; Stahl et al., 2016). Despite its widespread use, the SPI involves several estimation uncertainties that may lead to inconsistencies in drought classification. These include the choice of probability distribution, parameter estimation method, accumulation period, and data record length (Guttman, 1999; Wu et al., 2005; Stagge et al., 2015; Beyaztas et al., 2018; Zhang and Li, 2020). Laimighofer and Laaha (2022) categorized the uncertainty components in SPI calculation into five major factors: record length, observation period, probability distribution, parameter estimation method, and goodness-of-fit (GoF) test applied to the fitted distribution. The objective of our study is to enhance understanding of drought index reliability and monitoring accuracy through a quantitative assessment of the uncertainties inherent to SPI calculation.

Variations in SPI values arise depending on the length of the record period. McKee et al. (1993) recommended using at least 30 years of precipitation data, while Guttman (1999) suggested a minimum of 50 years for more stable estimates. Trustworthy estimation in the tail of the probability distribution function may require 70 to 80 years or more of data (Guttman, 1994; Zhang and Li, 2020). While increasing the record length improves the stability of SPI calculation, it may also exacerbate nonstationarity in the precipitation data (Wang et al., 2021). Therefore, it is necessary to examine the uncertainty associated with the length of the data used for SPI calculation.

The SPI can be calculated at different time scales by accumulating precipitation data. It is primarily used in drought studies of one to 24 months, and different time scales reflect the impact of drought on the availability of different water resources (Wang et al., 2022). For example, a 1- or 2-month SPI is used for meteorological drought, from 1-month to 6-month SPI for agricultural drought, and from 6-month to 24-month SPI or more for hydrological drought (Svoboda et al., 2012). Recently, a daily data-based SPI has been calculated (Wang et al., 2022; Zhang et al., 2023). Therefore, it is essential to determine the most appropriate accumulation period and evaluate its subsequent impact on drought index calculation.

The selection of probability distribution models and parameter estimation methods applied in SPI calculation can also contribute to uncertainty. McKee et al. (1993) proposed the SPI under the assumption that cumulative precipitation follows a gamma distribution. Since then, the gamma distribution has been widely applied across various precipitation accumulation periods and at different spatiotemporal scales, including regions such as Europe, China, Brazil, and Africa (Stagge et al., 2015; Okpara et al., 2017; Blain et al., 2018).

However, depending on the accumulation period of the time series and the climatic characteristics of the region, other probability distribution functions may be more appropriate. For example, Guttman (1999) suggested using Pearson Type III distribution when calculating SPI across various time scales in the United States. In addition, according to Sienz et al. (2012), gamma distribution tends to underestimate or overestimate SPI values under extreme events in Europe and the United States, and their analysis based on the Akaike Information Criterion (AIC) indicated that Weibull distribution provides a significantly better fit than the gamma distribution. In South Korea, gamma distribution has been widely adopted for SPI calculation, particularly by the Korea Meteorological Administration (KMA) and many researchers. The parameter estimation method used in SPI calculation also contributes to overall uncertainty. Thai et al. (2013) compared the maximum likelihood estimation (MLE) and restricted MLE (RMLE) and found that RMLE

is preferable when data are limited. Moreover, Carbone et al. (2018) investigated the correlation between parameter estimators and data length, demonstrating that the stability of parameter estimation increases nonlinearly with increasing sample sizes. Therefore, selecting an appropriate probability distribution and parameter estimation method that best reflects the characteristics of the underlying data is essential to ensure the reliability of SPI-based drought assessments.

Numerous studies have investigated the uncertainties associated with SPI calculation, including those arising from precipitation record length, accumulation periods, probability distribution models, and parameter estimation methods (Zhang and Li, 2020; Wang et al., 2021; Laimighofer and Laaha, 2022). To quantify these uncertainties, many researchers have applied bootstrap-based procedures (Naumann et al., 2012; Hu et al., 2015; Zhang and Li, 2020; Wang et al., 2021). Naumann et al. (2012) conducted a comparative analysis of SPI confidence bands obtained from datasets of varying lengths. Hu et al. (2015) focused on interval estimation of SPI in relation to the timescale. Wang et al. (2021) compared the uncertainty of parameter estimation according to data length using bootstrap and Monte Carlo methods. Zhang and Li (2020) examined the uncertainty in selecting the probability distribution by applying seven probability distributions for characterizing drought duration, severity, intensity, and frequency.

Most studies on the uncertainty of SPI calculation have primarily focused on individual factors and have not quantified multiple uncertainty components simultaneously within a unified analytical framework. Only a limited number of studies have examined the comparison of uncertainty influencing factors using the linear mixed model (LMM) (Laimighofer and Laaha, 2022), and few have extended this framework to regional or operational drought monitoring contexts. Notably, in South Korea, because the SPI is widely used for drought monitoring by various governmental organizations, systematically evaluating the relative contribution of multiple uncertainty sources in SPI estimation remains a challenge. Therefore, this study identifies and quantifies the major uncertainty factors affecting SPI calculation using observational precipitation data and compares their relative impacts through a comprehensive LMM-based approach. Building on the methodological framework proposed by Laimighofer and Laaha (2022), this study further examines how the relative contribution of each uncertainty factor varies with drought severity, thereby providing new insight into the sensitivity of uncertainty components under moderate ( $SPI = -1.0$ ) and extreme ( $SPI = -2.0$ ) drought conditions.

## 2. Study area and data

South Korea is in the mid-latitude temperate climate zone, which gives rise to distinctive seasonal climate characteristics. Seasonality is a prominent feature of Korea's monsoon climate; over 50% of annual precipitation occurs during the flood season from June to early September. In this study, we used precipitation data from 36 weather stations (Fig. 1) that have collected continuous precipitation data for more than 50 years since 1973. The data used in this study can be obtained from the KMA Weather Data Service (<https://data.kma.go.kr/>). Monthly precipitation data were aggregated from daily data and SPIs were calculated on different time scales, i.e., 1, 3, 6 and 12 months.

## 3. Methodology

### 3.1. SPI calculation

The SPI has been extensively used in drought analysis due to several key advantages (Vergni et al., 2017): (1) it is standardized, allowing for spatial and seasonal comparisons; (2) it offers flexibility, as it can be applied over various time scales; (3) it involves relatively simple computations compared to other drought indices; and (4) it is easy to implement, as it requires only precipitation data. In this study, the SPI was calculated through a four-step process: (1) accumulating monthly

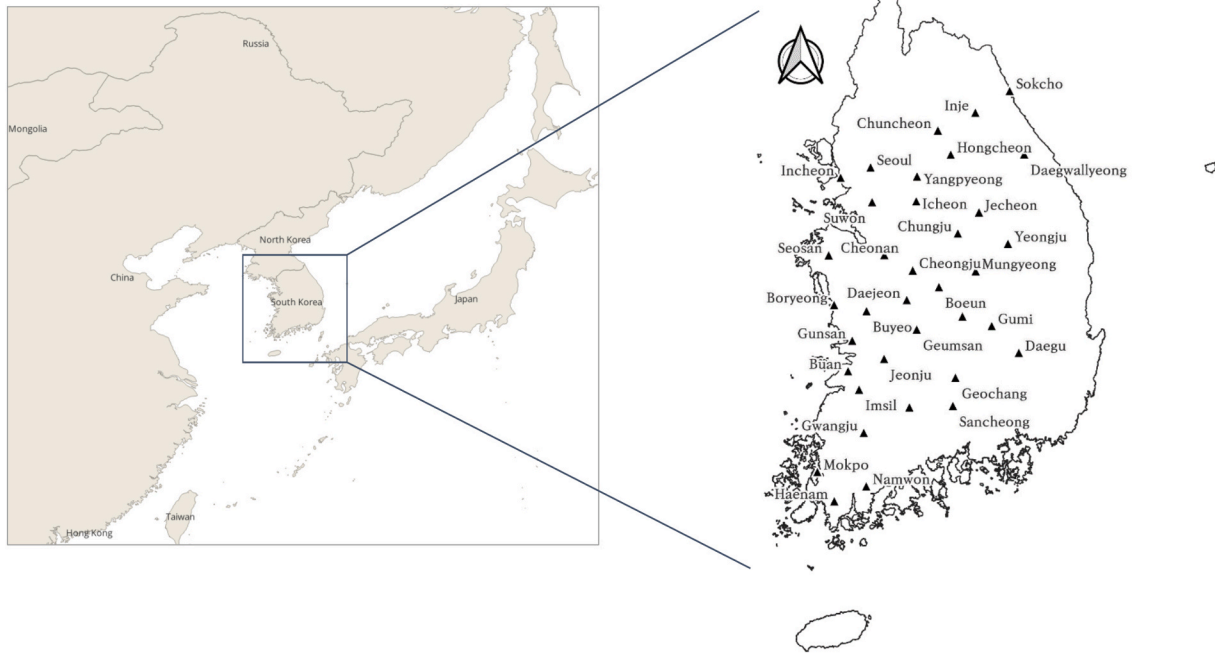


Fig. 1. KMA weather stations used in this study.

precipitation data over 1-, 3-, 6-, and 12-month periods; (2) partitioning the accumulated precipitation data into 12 annual time series (one for each month); (3) fitting each time series by a univariate parametric distribution; and (4) transforming the resulting probabilities into standard normal distribution quantiles. This process yields standardized values with a mean of 0 and a variance of 1.

SPI calculation can vary significantly depending on the selected distribution, the data length, and the accumulation period of the precipitation data. In this study, we estimated the uncertainty in the SPI calculation based on the concept of reference precipitation used by Laimighofer and Laaha (2022) for uncertainty analysis. Reference precipitation is the amount of precipitation corresponding to a fixed SPI value (e.g.,  $-1.0$  or  $-2.0$ ), obtained by inverting the SPI calculation procedure. In our study, reference precipitation was used as an input for an ensemble of SPI estimates based on various combinations of probability distributions and parameter estimation methods. As a baseline for comparison, we used the SPI computed with a 3-month accumulation

period, gamma distribution, and MLE over a 50-year record, following KMA guidelines for SPI calculation. The procedure is illustrated in Fig. 2.

The left panel of Fig. 2 shows a cumulative gamma distribution, using 3-month cumulative precipitation, with parameters estimated by MLE. The right panel of Fig. 2 is the cumulative standard normal distribution. Here, the SPI is calculated by standardizing the cumulative gamma distribution along the gray dashed lines (a)-(c). The calculation of the reference precipitation is the inverse of the SPI calculation process along the red solid line in Fig. 2. The reference precipitation is obtained through the inverse transformation of the SPI calculation process (red arrow in Fig. 2). For example, when  $SPI = -1.0$ , the corresponding 3-month cumulative precipitation in Fig. 2 was approximately 70.4 mm, which represented the precipitation amount associated with the onset of a moderate drought. The analysis in this study focuses on two SPI thresholds ( $SPI = -1.0$  for moderate drought and  $SPI = -2.0$  for extreme drought) for all accumulation periods and calendar months.

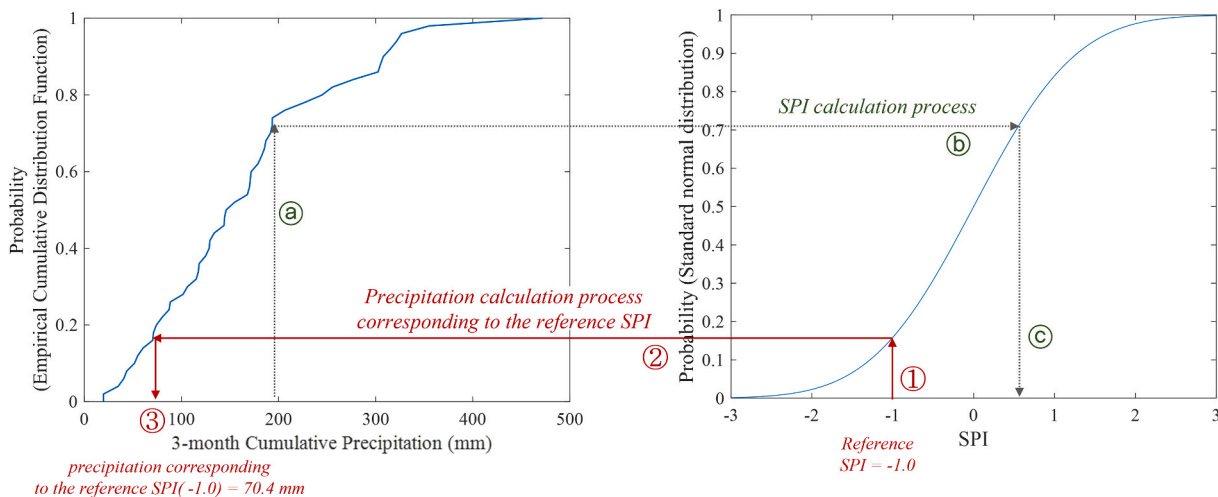


Fig. 2. Conceptual diagram illustrating the SPI calculation (gray line) and precipitation calculation of reference SPI (red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

### 3.2. Uncertainty assessment

The uncertainty assessment in this study consisted of several steps which are summarized in Fig. 3. To evaluate SPI uncertainty, we analyzed 36 stations and constructed possible scenarios by combining multiple uncertainty factors.

Prior studies identified several factors that influence the uncertainty associated with SPI calculations (Hu et al., 2015; Zhang and Li, 2020; Wang et al., 2021; Laimighofer and Laaha, 2022), including the accumulation period of precipitation (1, 3, 6, 12 months), the length of the data record (i.e., 20, 30, 50 years), the selection of the probability distribution (gamma, normal, log-normal, logistic), the parameter estimation method (MLE, and L-moments (LM)), and the application of Gof test. This study aims to quantify and compare these sources of uncertainty across different drought severity levels, using methods that are practically applicable and numerically stable. A range of parameter estimation methods have been developed, including the MLE, probability weighted moments, and method of moments, along with more advanced approaches such as Bayesian and robust estimators. According to Stagge et al. (2015), the MLE and LM were employed in this study because they are widely used, computationally efficient, and have proven reliability in monthly-scale drought analysis. Similarly, the probability distribution models adopted in this study were chosen for their simplicity, stability, and proven applicability in SPI estimation. The Gof test was excluded from analysis, as Laimighofer and Laaha (2022) demonstrated that its contribution to total uncertainty is minimal. Therefore, four key factors—accumulation period, record length, probability distribution, and parameter estimation method—were retained for the uncertainty assessment (Table 1).

In the study, the first source of uncertainty is the accumulation period (M) and the second is the sample size (Y), which are statistically dependent on each other (Laimighofer and Laaha, 2022). In addition, four distinct accumulation periods (1, 3, 6, and 12 months) and three sample sizes (20, 30, and 50 years) are included in the source of uncertainty.

According to the SPI calculation method, the first year of data is offset due to the precipitation accumulation process. Therefore, 21 years of precipitation data were used to calculate the SPI for a sample size of 20 years, and the sample size was defined as the SPI estimation period in this study. This study employed sets of sample sizes, comprising a total of six time series, for the comparison of uncertainty due to sample size: four 20-year periods (1973 to 1993, 1983 to 2003, 1993 to 2013 and 2003 to 2023), three 30-year periods (1973 to 2003, 1983 to 2013, and 1993 to 2023), and one 50-year period (1973 to 2023). It was difficult to secure data for more than 50 years, so we set the longest data period to 50 years. If more data becomes available, it will be possible to compare the results with longer data periods. Each of the precipitation time series

**Table 1**

Factors that affect SPI uncertainty in this study.

Influence factor	Model setups
Accumulation period (M)	1, 3, 6, 12 months
Sample size (Y)	50 years (1973 ~ 2023) 30 years (1973 ~ 1993, 1983 ~ 2013, 1993 ~ 2023) 20 years (1973 ~ 1993, 1983 ~ 2003, 1993 ~ 2013, 2003 ~ 2023)
Parameter estimation (P)	Maximum likelihood estimation (MLE) L-Moment (LM)
Probability distribution (D)	Gamma, Normal, Log-Normal, Generalized Extreme Value and Logistic

was aggregated within a moving window of 1, 3, 6, and 12 months. The third uncertainty component was defined by the selection of the distribution (D) used to fit the precipitation data. In this study, five distributions (gamma, normal, log-normal, generalized extreme value, and logistic) were employed for SPI calculation. The last source of uncertainty was the parameter estimation method (P). Two different approaches for estimating the parameters of the distributions were considered: MLE and LM.

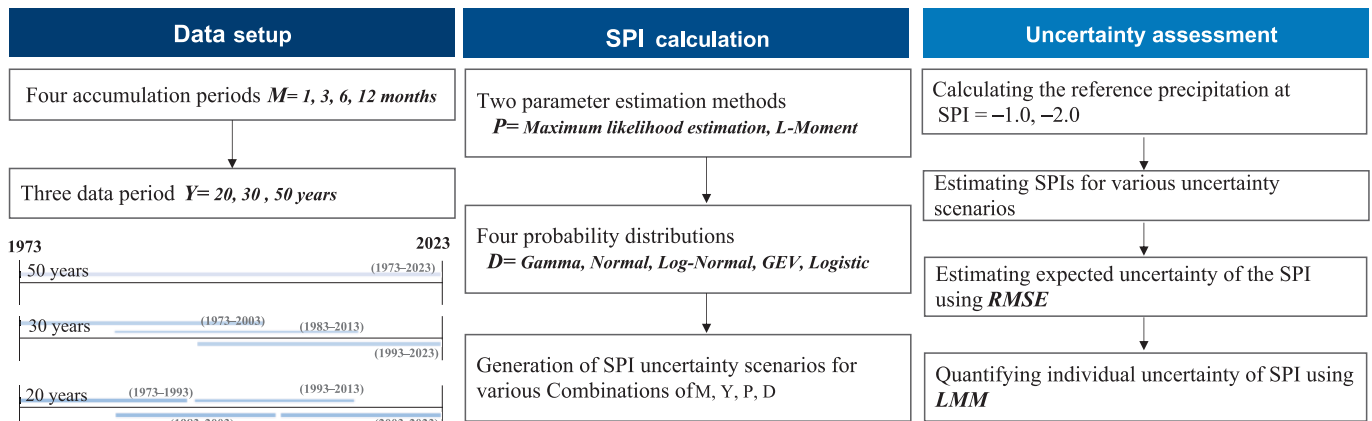
In this study, 320 ( $M \times Y \times D \times P = 4 \times 8 \times 5 \times 2 = 320$ ) distinct SPI time series were generated by combining four key components of the SPI calculation: accumulation period (M), sample size (Y), probability distribution (D), and parameter estimation method (P). These combinations are hereafter referred to as uncertainty scenarios, following the framework proposed by Laimighofer and Laaha (2022). The uncertainty scenarios serve as the basis for evaluating how each individual factor contributes to the variability in SPI calculation.

This study quantified the uncertainty of SPI values using two different approaches. First, we calculated the root mean square error (RMSE) of all possible variations SPI values for a given reference precipitation, calculated by the uncertainty scenarios.

$$y_{err} = y_t - y_{ref} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_i^I y_{err,i}^2}{I}}, \quad i = 1, 2, \dots, 12 \tag{2}$$

where  $y_{err}$  is the error term representing the difference between the SPI value ( $y_t$ ) and the reference SPI value ( $y_{ref}$ ).  $y_t$  is the SPI value computed by applying the reference precipitation to each uncertainty scenario.  $y_{ref}$  is the SPI value corresponding to the predefined reference precipitation, which in this study is set to  $-1.0$  and  $-2.0$ . The RMSE is a comprehensive measure of the inherent uncertainties associated with the calculation of the SPI.



**Fig. 3.** Overview of the uncertainty assessment performed in this study.

For example, Fig. 4 illustrates the procedure for calculating SPI values corresponding to a reference precipitation of 50.9 mm, which represents the 3-month cumulative precipitation associated with SPI = -1.0 in Seoul (January). This calculation was performed using four different probability distribution functions: gamma, normal, lognormal, and logistic. In accordance with the probability distribution model applied in the calculation of the SPI, the SPI value ( $y_t$ ) is -0.931 for the normal distribution, -1.011 for the lognormal distribution, and -0.942 for the logistic distribution. The value  $y_{err}$  is subtracted from the computed values derived from the reference SPI (value of -1.0). Subsequently, the RMSE was calculated based on the  $y_{err}$ . For example, at the Seoul station, using the 3-month accumulated precipitation time series from 1973 to 1993, the SPI was computed with a normal distribution fitted using the MLE. When applying the monthly reference precipitation values corresponding to SPI = -1.0 across all months from January to December, the resulting RMSE was 0.5645.

### 3.3. Relative contribution of uncertainty

The next step was to quantify the contribution of each source of uncertainty to individual uncertainties. This analysis utilized two additional metrics, relative uncertainty and total uncertainty, calculated through the LMM. The LMM is widely used in various fields such as ecology, psychology, and social sciences due to its flexibility in managing data with complex dependency structures (Pinheiro and Bates, 2000; West et al., 2014). The LMM extends simple linear models by incorporating both fixed and random effects, making it particularly useful for handling data with hierarchical structures or non-independent observations. In the LMM, fixed effects represent consistent, repeatable influences across the entire dataset, while random effects capture variability specific to individual groups within the data.

The LMM also allows comparison of SPI calculation uncertainty of each uncertainty component; each source of uncertainty is modeled as a random effect, with only the overall mean of the model considered as a fixed effect. Based on this, the error ( $y_{err}$ ) of the SPI, as presented in Eq. (1), was assumed to arise from the influence of four sources of uncertainty. This assumption allows us to establish the LMM for random effects, expressed as follows:

$$y_{err, t} = b_0 + Z_1 b_1 + \dots + Z_s b_s + \epsilon \quad (3)$$

where  $b_0$  is the intercept of the LMM representing a fixed effect.  $Z_1 b_1, \dots, Z_s b_s$  are the design matrices of each random effect with the random effect, parameters  $b_1, \dots, b_s$ , each of them normally distributed with zero mean and variance  $\sigma_s^2$ . The term  $\epsilon$  is the error term, also with a mean of

zero, and residual variance  $\sigma_\epsilon^2$ . In our study, the random effects correspond to four sources of uncertainty (with  $S = 4$ ). The variance of each random effect reflects the between-variance of these effects, while the residual variance  $\sigma_\epsilon^2$  captures the within-group variance.

The variance components in the LMM are typically estimated using restricted maximum likelihood, a method that is particularly effective for separating fixed and random effects to provide accurate variance component estimates (Laimighofer and Laaha, 2022; Pinheiro and Bates, 2000). The total variance components  $\sigma_s^2$  of the s-th random effect were employed to quantify each source of uncertainty using the linear mixed-effects model and we can denote the total variance by

$$\sigma^2 = \sum_{s=1}^S \sigma_s^2 + \sigma_\epsilon^2 + \sigma_d^2 \quad (4)$$

where  $\sigma_s^2$  is the variance component of the s-th effect, corresponding to the four sources of uncertainty: accumulation period, sample size, distribution selection, and parameter estimation method.  $\sigma_\epsilon^2$  is the residual variance, which can be further expressed as the sum of additive dispersion ( $\sigma_d^2$ ) and distribution specific variance ( $\sigma_s^2$ ). The individual relative uncertainty components ( $\eta_s$ ) can then be obtained by

$$\eta_s = \frac{\sigma_s^2}{\sigma^2} \quad (5)$$

This approach enabled us to isolate the contribution of individual uncertainty sources, identifying the predominant factors in the SPI calculation through relative and total uncertainty analysis.

## 4. Results

### 4.1. Reference precipitations and their errors

Monthly reference precipitation values corresponding to SPI thresholds of -1.0 and -2.0 were estimated using an empirical distribution approach. For each station, the precipitation amount associated with the target SPI values was computed by inverting the standard SPI calculation process. These values served as the baseline inputs for generating reference SPI time series across different months and accumulation periods.

To evaluate the deviation of SPI values calculated under different scenarios, SPI error ( $y_{err, t}$ ) was computed as the difference between the SPI value estimated from each uncertainty scenario ( $y_t$ ) and the corresponding reference SPI value ( $y_{ref}$ ), as defined in Eq. (1). The reference SPI values used in this study were -1.0 and -2.0. Fig. 5 presents boxplots

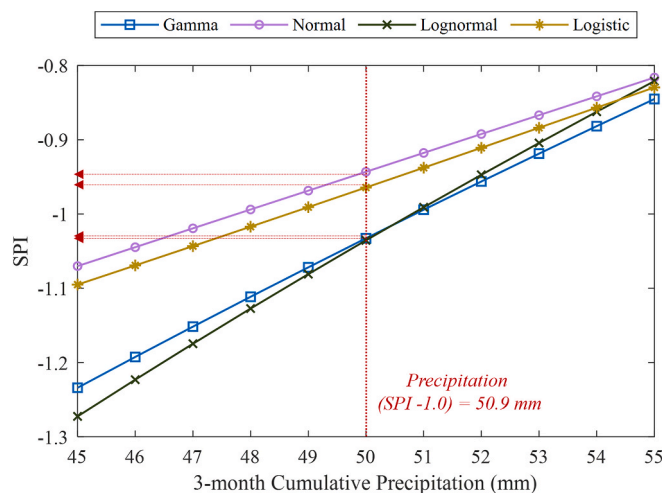
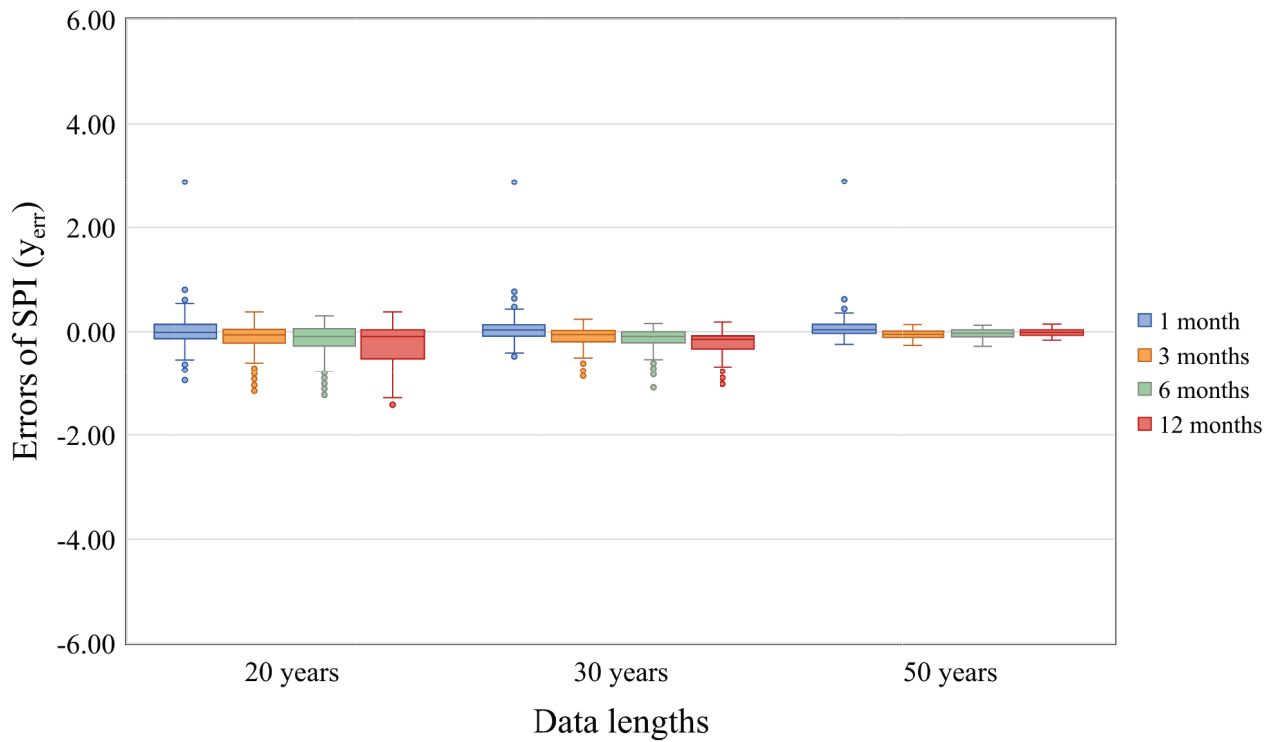
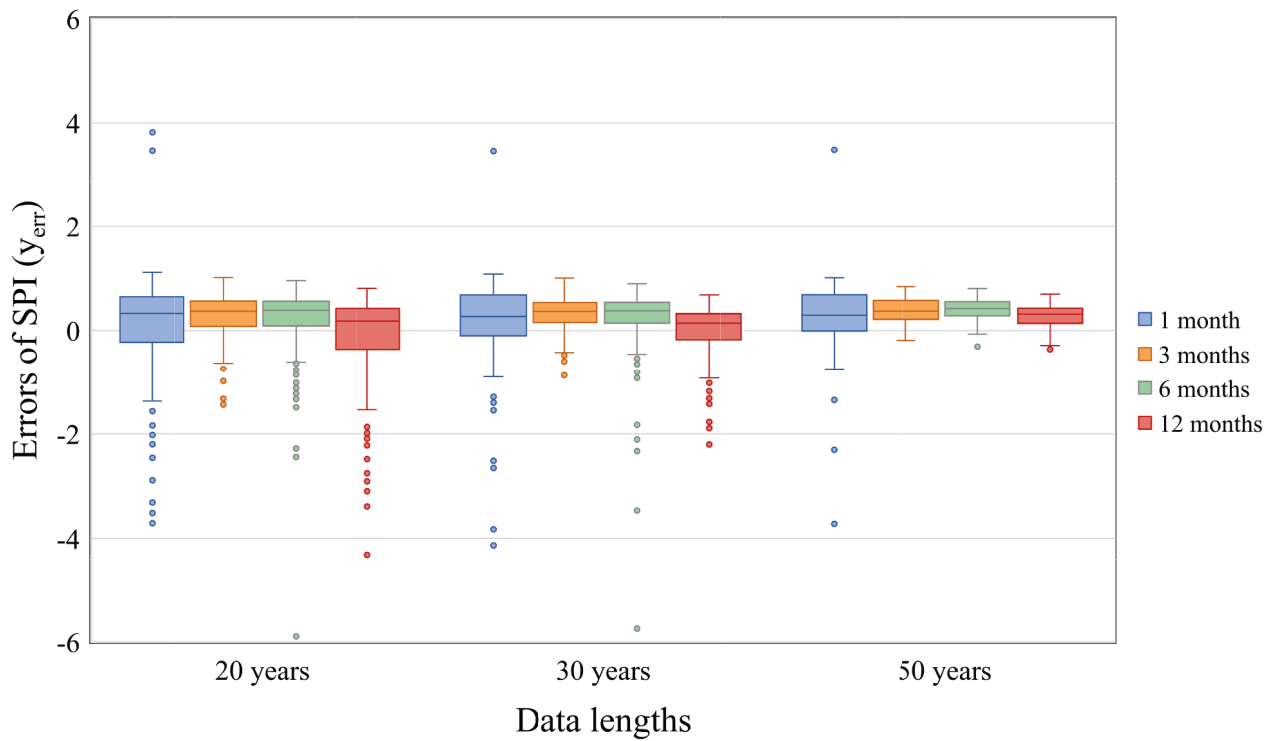


Fig. 4. SPI values derived from different probability distributions for a fixed reference precipitation of 50.9 mm corresponding to SPI = -1.0.



(a) Reference SPI = -1.0



(b) Reference SPI = -2.0

Fig. 5. Boxplots of SPI estimation errors by accumulation period and sample size.

of SPI estimation errors in Seoul station for reference SPI values of  $-1.0$  and  $-2.0$  for four accumulation periods (1, 3, 6, and 12 months). For SPI =  $-1.0$  (Fig. 5(a)), the errors are relatively narrow and centered around zero, with few outliers and small interquartile ranges. In contrast, for SPI =  $-2.0$  (Fig. 5(b)), the error distributions are more dispersed. In both Fig. 5(a) and Fig. 5(b), the error spread tends to be wider when the precipitation record length is limited to 20 years. The interquartile ranges are generally skewed toward negative errors, with the lower whiskers extending farther below the median. Fig. 5(b), which represents SPI =  $-2.0$  conditions, exhibits a significantly larger number of outliers, especially under shorter accumulation periods. When the threshold is set to  $-2.0$ , the SPI value lies in the extreme tail of the fitted probability distribution, where small deviations in the fitted model can lead to disproportionately large estimation errors.

To ensure robust evaluation of uncertainty, only SPI error values within the 95% confidence-based tolerance interval were retained for RMSE calculation. To reduce the impact of extreme errors caused by poor model fitting or unstable results, we removed about 5% of the SPI error values that were outside the 95% confidence interval. This approach is consistent with Laimighofer and Laaha (2022), who calculated RMSE based only on SPI values that fall within the tolerance interval. These filtered error values were used in the subsequent analysis to estimate the magnitude and structure of uncertainty in SPI calculations.

#### 4.2. Assessment of uncertainty using RMSE

RMSE was employed to provide a comprehensive estimate of uncertainty in the SPI calculation. Fig. 6 shows the distribution of RMSE values calculated after excluding outliers based on the 95% confidence interval. For SPI =  $-1.0$ , the RMSE values range between 0.063 and 0.600, while for SPI =  $-2.0$ , they range from 0.167 to 1.477, indicating that the estimation becomes less stable under more extreme drought conditions.

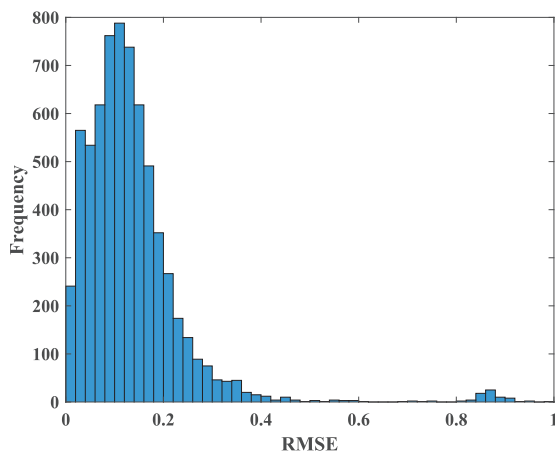
To examine the differences in RMSE in detail, we evaluated the overall trend across different accumulation periods (1, 3, 6, and 12 months) and sample sizes (20, 30, and 50 years), as illustrated in Figs. 7 and 8. Both figures clearly demonstrate that the RMSE distributions progressively shift to the left as the accumulation period increases and the sample size becomes larger. This indicates a general decrease in estimation uncertainty with more data and longer aggregation. Additionally, for SPI =  $-2.0$ , the RMSE distribution is noticeably wider than that for SPI =  $-1.0$ , suggesting greater uncertainty under more severe drought conditions.

When the sample size is fixed, the RMSE tends to decrease consistently as the accumulation period increases. For SPI =  $-1.0$  (Table 2), the mean RMSE decreases from 0.222 (20 years) to 0.133 (50 years) at the 1-month accumulation period, and from 0.226 to 0.125 at the 12-month period. For SPI =  $-2.0$  (Table 3), the same pattern holds but with larger absolute RMSE values and higher variances. For example, at the 1-month accumulation period, mean RMSE drops from 0.665 to 0.538 as the sample size increases from 20 to 50 years. At 12 months, the RMSE decreases from 0.355 to 0.310 over the same range. A comparison between SPI =  $-1.0$  and SPI =  $-2.0$  shows that the sensitivity of RMSE to changes in sample size and accumulation period is greater in the SPI =  $-2.0$  condition.

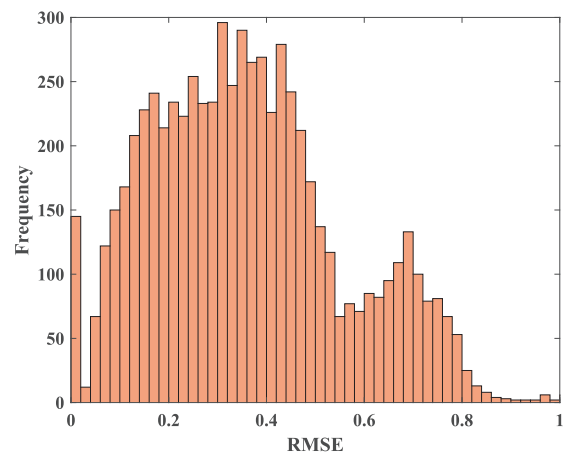
Among all combinations, the 12-month accumulation and 50-year sample size scenario consistently yielded the most stable results, with the lowest RMSE and variance observed for both SPI thresholds: 0.125 (0.002) for SPI =  $-1.0$  and 0.310 (0.008) for SPI =  $-2.0$ . These findings suggest that the uncertainty in SPI estimation increases under more severe drought conditions, highlighting the importance of sufficient sample sizes and longer accumulation periods in improving the reliability of drought assessment.

#### 4.3. Relative contribution of uncertainty using LMMs

It was challenging to quantify the uncertainty contributions of the four sources in this study. The LMM defined in Eq. (3) was applied to SPI values of  $-1.0$  and  $-2.0$ . Furthermore, the four sources of uncertainty described in this study were quantified using Eq. (4) and (5). Figs. 9 and 10 illustrate the relative uncertainty for the four uncertainty influence factors which are divided by the different sample sizes and the different accumulation periods. Under the condition of SPI =  $-1.0$  (Fig. 9), the relative contributions of uncertainty were primarily attributed to the sample size and accumulation period, especially at the 1-month accumulation scale. However, as the accumulation period increased to 12 months, the influence of these two factors gradually decreased, while the contribution of distribution selection showed a consistent upward trend. A similar pattern was observed in Fig. 10, which represents the results for SPI =  $-2.0$ . As the sample size increased from 20 to 50 years, the contributions of accumulation period and sample size generally declined, whereas the role of distribution selection increased steadily. Notably, under the 50-year sample size condition, the contribution of distribution selection exceeded 50% across most accumulation periods (1, 3, 6, and 12 months), reaching as high as 84% in the case of 12-month and 50-year. In contrast, under SPI =  $-1.0$ , the contribution of distribution selection remained within a relatively low range of 1–10%,



(a) Reference SPI =  $-1.0$



(b) Reference SPI =  $-2.0$

Fig. 6. Histogram of the RMSEs of SPI estimation errors.

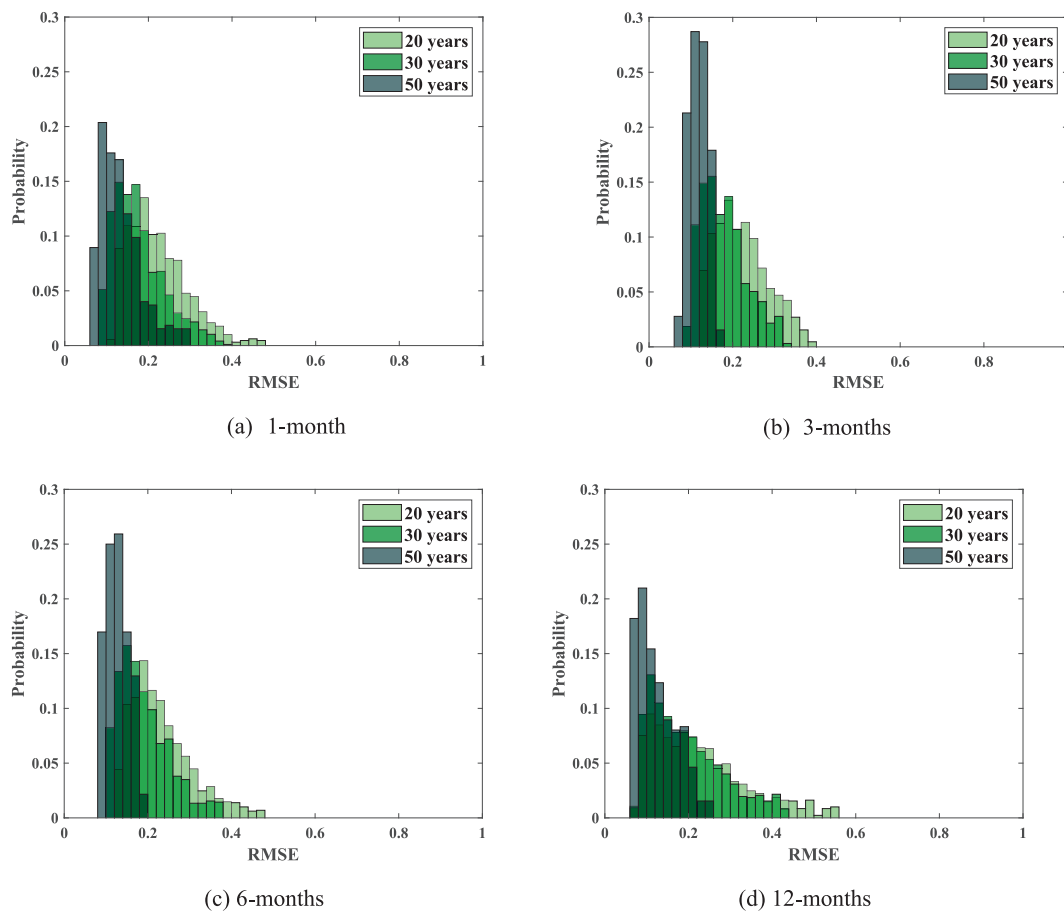


Fig. 7. Histogram of the RMSEs divided by different sample sizes and different accumulation periods for a reference SPI value of  $-1.0$ .

highlighting a substantial increase in influence under more extreme drought conditions.

These results suggest that in the early stages of drought, the uncertainty in SPI estimation is primarily driven by structural factors such as sample size and accumulation period. However, as the drought intensifies, the influence of statistical distribution selection becomes increasingly dominant. Particularly under extreme drought scenarios, the uncertainty becomes highly sensitive to the choice of distribution model, indicating that accurate distribution selection is a critical component in reliable SPI-based drought assessment.

## 5. Discussion

The results of the LMM analysis in this study revealed how the dominant factors contributing to uncertainty in SPI calculation vary according to drought severity. The findings provide important insight into the dynamic nature of uncertainty in drought assessment and its implications for improving operational drought monitoring.

The analysis confirmed that the dominant sources of uncertainty shift with drought severity. For moderate droughts ( $SPI = -1.0$ ), the main contributors to uncertainty were sample size and accumulation period. This implies that ensuring a sufficiently long and stable precipitation record, as well as selecting an appropriate accumulation period tailored to the drought impact being assessed (e.g., 3–6 months for agricultural drought), are critical for reliable drought evaluation. In contrast, for extreme droughts ( $SPI = -2.0$ ), the probability distribution choice accounted for over 50%—and up to 84%—of the total variance, emerging as the overwhelmingly dominant source of uncertainty. This occurs because extreme droughts correspond to the tail region of the fitted distribution, where small variations in tail shape can result in large differences in SPI values. Therefore, when assessing severe or record-

breaking droughts, the assumption of the statistical model (i.e., the choice of probability distribution) becomes the most sensitive and critical factor. Based on this, it is recommended that the optimal distribution for a specific region and time scale be determined through statistical GoF tests—including AIC, Bayesian Information Criterion, and Kolmogorov–Smirnov test—rather than adopting a single default distribution across all spatial and temporal scales. Applying an appropriate distribution is expected to reduce classification errors and enhance the reliability of extreme drought assessments. In contrast, parameter estimation method contributed less than 3% to overall uncertainty across all scenarios, indicating a negligible effect. This result is consistent with Laimighofer and Laaha (2022) and suggests that although computational approaches differ, the choice between standard estimation methods (e.g., MLE and LM) is not a major source of uncertainty compared with data length or distribution selection.

Although this study focused on the SPI, the analytical framework and findings are extendable to other standardized drought indices based on probability distribution fitting, such as the Standardized Streamflow Index and Standardized Precipitation–Evapotranspiration Index. These indices are likely to exhibit similar patterns, where uncertainty is primarily driven by data length and accumulation period during moderate droughts but dominated by distribution choice under extreme conditions.

This study has several limitations. First, while the proposed framework effectively quantified and compared the relative contributions of multiple uncertainty factors, it did not identify the optimal combination of parameters (e.g., the most appropriate distribution model or accumulation period) to minimize total uncertainty. Second, although 50 years of data were used, the analysis assumed stationary climatic conditions. As noted by Wang et al. (2021), long-term datasets may be affected by non-stationarity due to climate change, which introduces an

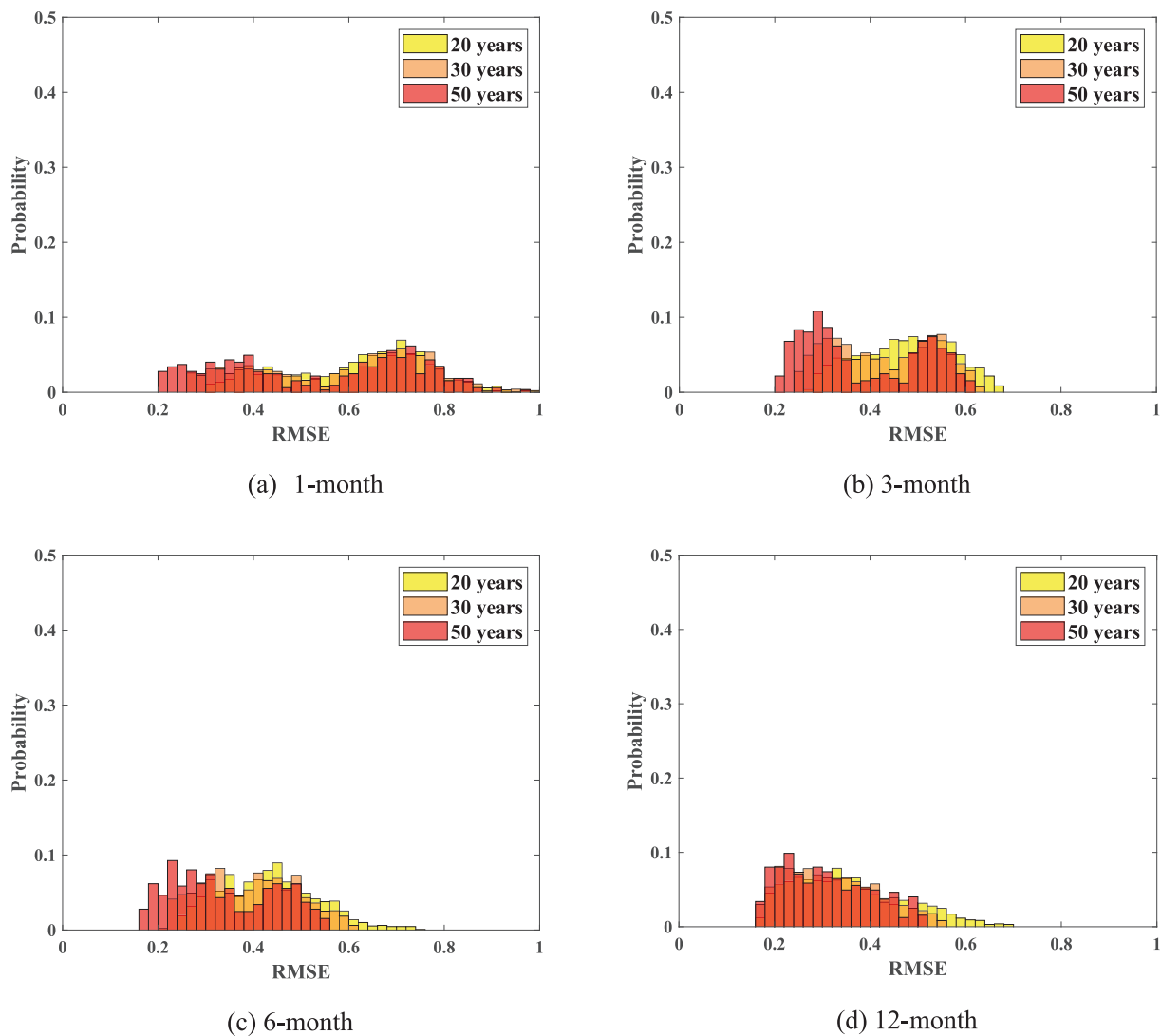


Fig. 8. Histogram of the RMSEs divided by different sample sizes and different accumulation periods for a reference SPI value of  $-2.0$ .

**Table 2**  
Mean and variance of RMSE for different accumulation periods and sample sizes (SPI =  $-1.0$ ).

Accumulation period (M) Sample size (Y)	1 month		3 months		6 months		12 months	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
20 years	0.222	0.005	0.223	0.004	0.232	0.005	0.226	0.012
30 years	0.177	0.004	0.179	0.003	0.190	0.004	0.195	0.008
50 years	0.133	0.002	0.118	0.00	0.128	0.001	0.125	0.002

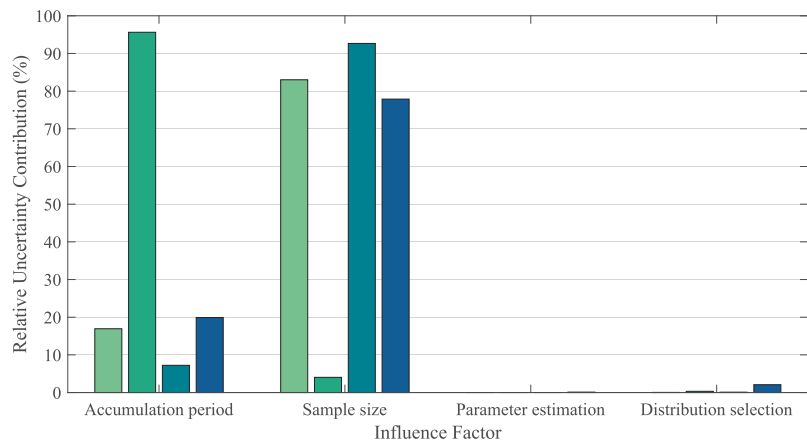
**Table 3**  
Mean and variance of RMSE for different accumulation periods and sample sizes (SPI =  $-2.0$ ).

Accumulation period (M) Sample size (Y)	1 month		3 months		6 months		12 months	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
20 years	0.665	0.048	0.474	0.009	0.431	0.010	0.355	0.013
30 years	0.611	0.040	0.428	0.012	0.394	0.009	0.322	0.009
50 years	0.538	0.041	0.385	0.01	0.340	0.012	0.310	0.008

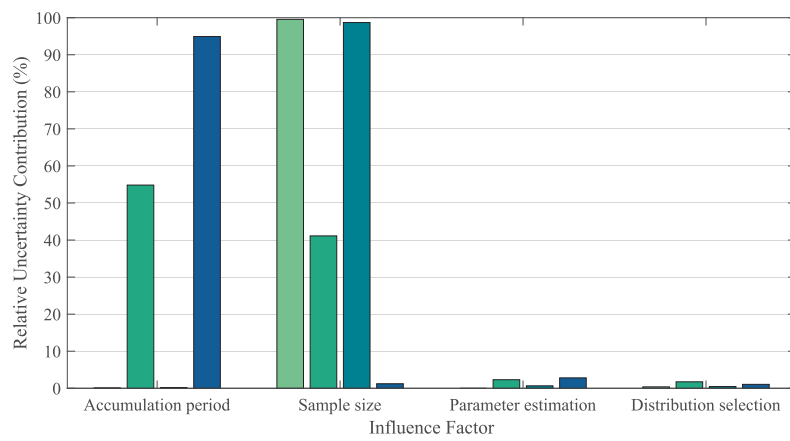
additional source of uncertainty not addressed within the present LMM framework.

Future studies should therefore consider integrating non-stationarity or time-varying parameter approaches to quantify such effects more explicitly. Furthermore, future research should expand this uncertainty

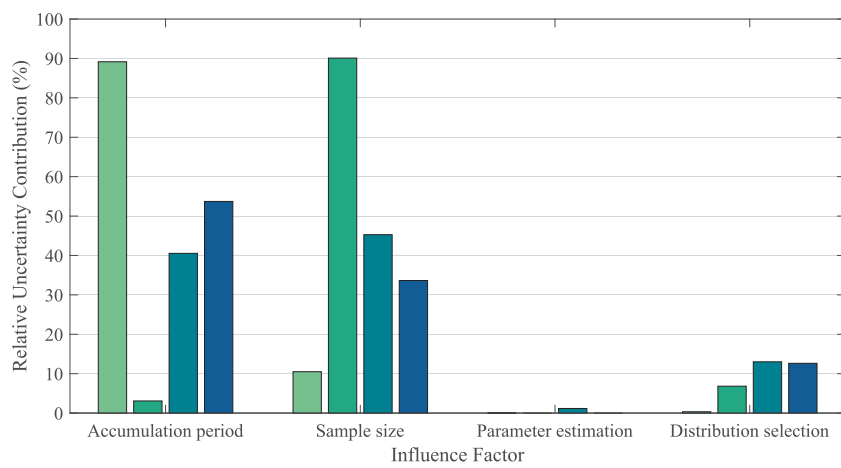
assessment framework to hydrological drought indices and develop tailored optimization techniques. These efforts should focus on minimizing total uncertainty by targeting the specific factors that exert the most significant influence at various drought severity levels. Such advancements would improve the robustness of SPI-based drought



(a) 20 years



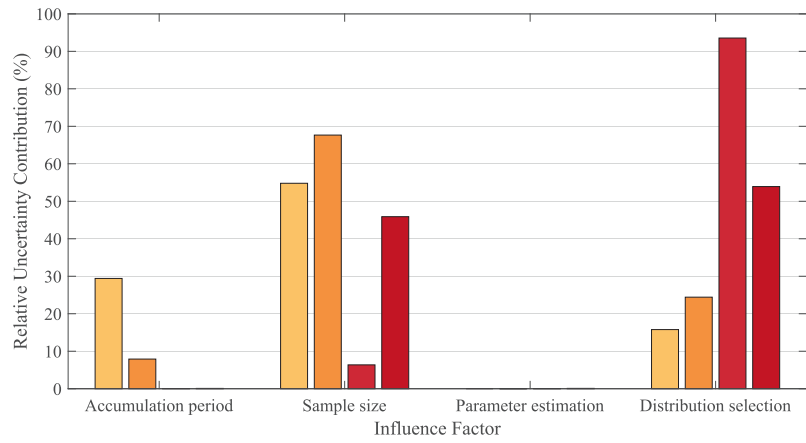
(b) 30 years



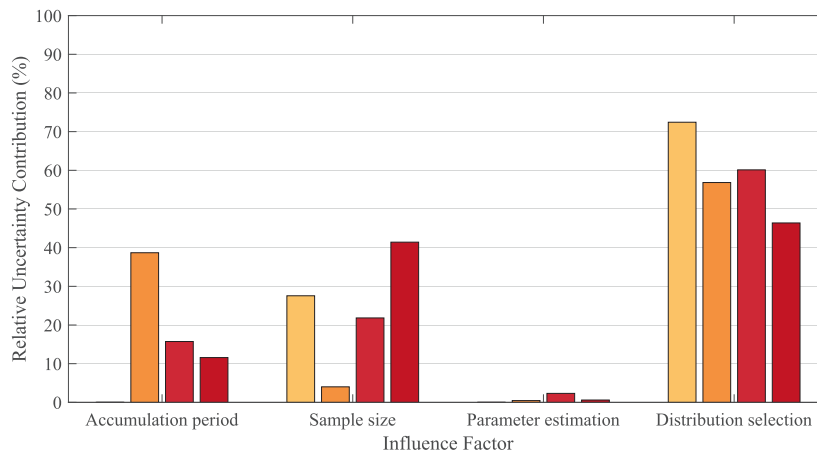
(c) 50 years



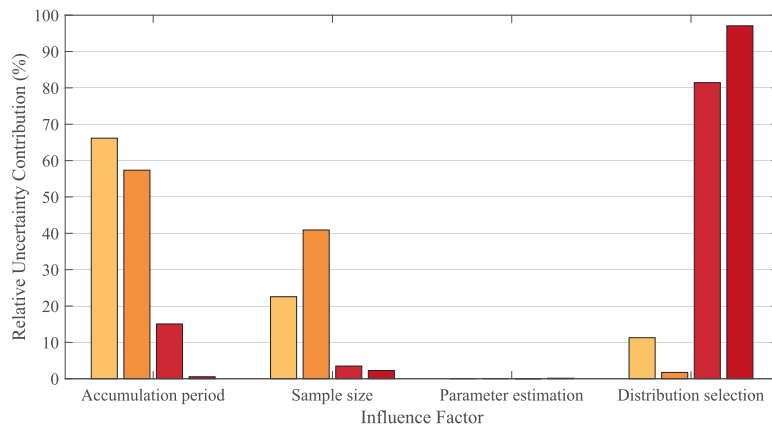
Fig. 9. Relative uncertainty contributions for a reference SPI value of  $-1.0$ .



(a) 20 years



(b) 30 years



(c) 50 years



Fig. 10. Relative uncertainty contributions for a reference SPI value of -2.0.

monitoring and drought management decision-making systems.

## 6. Conclusion

This study conducted a comprehensive evaluation of uncertainties inherent to SPI calculation, which is widely used for drought monitoring and early warning. Four key sources of uncertainty—accumulation period, sample size, distribution selection, and parameter estimation method—were assessed through a combination of RMSE analysis and an LMM framework.

The RMSE results showed that, regardless of drought severity, increasing the accumulation period and expanding the sample size consistently led to reduced uncertainty in SPI calculation. In particular, RMSE values associated with SPI = -2.0, which represents more severe drought conditions, were larger and more variable than those for SPI = -1.0, indicating heightened sensitivity under extreme conditions. Furthermore, the results confirmed that using long-term precipitation records (e.g., 50 years vs. 20 years in this study) significantly reduced estimation uncertainty for all drought scenarios. This finding concurs with prior recommendations advocating for the use of extended datasets; however, as addressed in the discussion, the potential influence of non-stationarity in long-term records warrants careful consideration.

LMM analysis revealed that the dominant sources of uncertainty varied with drought severity. For moderate drought (SPI = -1.0), sample size and accumulation period were the main contributors to overall uncertainty. In contrast, for extreme drought (SPI = -2.0), distribution selection contributed over 50% of the total variance in many scenarios. This finding emphasizes the need for careful selection of probability distributions when evaluating extreme droughts. Our findings are consistent with previous research. Wang et al. (2021) showed that shorter precipitation records decrease the stability of SPI estimates and result in higher misclassification rates, particularly under extreme drought conditions—observations directly supported by our RMSE and LMM-based results. Zhang and Li (2020) also emphasized the growing influence of distribution selection under severe drought, aligning with our finding that distribution-driven uncertainty dominates at SPI = -2.0. Additionally, the contribution of the parameter estimation method to SPI uncertainty was consistently minor, accounting for less than 2% of the total variance under SPI = -1.0 and less than 3% under SPI = -2.0. Its influence was negligible compared to that of accumulation period, sample size, and particularly distribution selection, which corroborates the findings of Laimighofer and Laaha (2022).

In conclusion, this study quantified the relative contribution of four major uncertainty sources in SPI calculation, demonstrating that their significance shifts according to drought severity. A key finding reveals a distinct divergence in uncertainty drivers: for moderate droughts (SPI = -1.0), uncertainty is primarily dictated by sample size and accumulation period; however, for extreme droughts (SPI = -2.0), the selection of the probability distribution becomes the most critical factor. Consequently, reliable assessment of extreme droughts necessitates a rigorous, data-driven approach to distribution selection, whereas stable monitoring of moderate droughts depends more heavily on the availability of long-term datasets. A systematic understanding of these SPI-related uncertainties is indispensable for enhancing drought risk assessments and informing more resilient water resource management and policy strategies.

## CRedit authorship contribution statement

**Ji Yae Shin:** Writing – original draft, Methodology, Formal analysis, Data curation. **Jeongwoo Han:** Visualization, Validation, Investigation. **Hyun-Han Kwon:** Validation, Investigation. **Tae-Woong Kim:** Writing – review & editing, Supervision, Project administration, Conceptualization.

## Declaration of competing interest

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

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jher.2026.100697>.

## Data availability

The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

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