OneMap Drought Monitoring Analysis Based on Statistical Models

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Abstract: As the effects of droughts on agriculture and industrial water availability intensify with climate change, developing suitable drought prevention and mitigation measures has become increasingly important. However, measuring drought conditions using different indices leads to disjointed drought management responses by ministries and agencies. Additionally, indices based on only one variable are insufficient to accurately assess drought conditions. Therefore, creating and adopting a OneMap drought index would be beneficial in the assessment of drought conditions and the implementation of appropriate measures. In this study, we used multivariate statistical modeling using Bayesian principal component analysis to develop a OneMap drought index that unifies existing measures of drought conditions, including meteorological, agricultural, and hydrological drought indices. After evaluating the accuracy of the corrected OneMap drought index based on the self-organizing migrating algorithm optimization technique, it was found that the applicability of the OneMap drought index and its ability to regenerate drought were excellent for ground and satellite data. Therefore, the authors recommend implementing step-by-step drought management action plans using the integrated index to generate drought forecasts and warnings, thus promoting concerted and effective responses of local governments and authorities.

Keywords: drought; drought assessment; drought management; OneMap drought monitoring index

1. Introduction

As a result of climate change caused by global warming, hydrological phenomena are changing dramatically. Distinct from other hydrological disasters such as floods, droughts occur over extended periods and in large areas [1–3]; therefore, technology is required to accurately monitor droughts and predict them spatiotemporally [4,5]. Drought monitoring requires a widely applicable and objective drought index [4,6–8]. The World Meteorological Organization [9] defined the drought index as “an index related to some cumulative effects of long-term and abnormal water deficiency”. Studies have been conducted to analyze drought conditions, particularly meteorological and hydrological droughts, based on several factors [10,11]. Ahn et al. [10] analyzed 2012 spring droughts and their spatiotemporal scales using the standardized precipitation index (SPI, a meteorological drought index [12]) and the water availability drought index (WADI, a hydrological drought index [13]), as well as the normalized difference vegetation index (NDVI, [14]) and the enhanced vegetation index (EVI, [14]), which are based on satellite images. They found that SPI and WADI expressed extreme spring drought characteristics well and that the vegetation index adequately reflected early summer drought situations. Sur et al. [11] analyzed drought situations in South Korea between 2004 and 2013 using the energy-based water deficit index (EWDI), which is based on satellite images. The results were compared with those obtained using the evaporative stress index (ESI); the effective drought index (EDI), an evaporation-based drought index; the soil moisture drought index (SSMI), a drought index...
reflecting soil moisture conditions; the aforementioned SPI; and the Palmer drought severity index (PDSI). For the severe drought scenarios that occurred in South Korea after 2010, ESI and EWDI showed high applicability, confirming high degrees of correlation between the drought indices.

Drought phenomena are related to several other variables; hence, drought analysis based on a single index may not suffice to monitor complex drought phenomena. Therefore, research is needed on the development of a OneMap drought index for accurate drought monitoring using information from various drought indices (meteorological, agricultural, hydrological) [15–17]. Hao and Aghkouchak [16] proposed a multivariate multi-drought monitoring framework using a non-parametric method. Hao [15] presented a global-based integrated drought monitoring and prediction system, integrated meteorological drought index, and soil moisture information using the multivariate standardized drought index (MSDI) for monitoring and measurement prediction. In previous studies, monthly drought conditions were analyzed using two drought indices (SPI and the standardized streamflow index, SSI), the MSDI index was calculated by applying an empirical or Copula-based joint distribution, seasonal predictions were made using univariate and multivariate drought indices, providing globally integrated drought monitoring information. While most of the drought studies deal with meteorological drought, a few recent studies [18,19] have been conducted for all major drought types (meteorological, hydrological, and agricultural droughts) using multivariate techniques to provide a comprehensive assessment of drought events.

In July 2004, South Korea introduced the “Basic Guidelines for National Crisis Management”, a crisis alert system for national crisis management. This system accurately determines the level of crisis and issues an alarm at the corresponding level (attention, caution, alert, or severe) when organizations in charge and related organizations detect signs of crisis. This system enables systematic crisis management by helping organizations to prevent and prepare for crises in advance. Analysis of the crisis response processes of the ministries and agencies concerned determines the crisis alert level and associated countermeasures. In addition, the Ministry of Public Administration Security issues an integrated forecast and warning for administrative districts through the information that can intuitively understand drought conditions. Operating a well-organized response process, such as preliminary preparation and emergency measures, is necessary.

Through reviewing previous studies, indices based on a single variable are insufficient to accurately assess drought conditions. Therefore, creating and adopting an integrated drought index based on multivariate analysis that can provide comprehensive, integrated drought information by maintaining its unique characteristics would be beneficial in assessing drought conditions and implementing appropriate measures. In addition, it is difficult to intuitively understand a drought situation, because various maps are provided depending on the division of ministry-specific business fields; technology is required to integrate the information available and assess the situation comprehensively. To this end, in this study, a OneMap drought index based on a multivariate statistical model was developed, and the ability of the drought index to reproduce drought based on ground and satellite data was evaluated.

2. Materials and Methods
2.1. Study Area and Data

To develop an OneMap drought index based on existing drought indices, the spatial range was targeted at data for 167 local governments (Figure 1), and the time range was set to 2017–2020 to comparatively analyze drought forecasts and warning data for each ministry. The ground- and satellite-based drought indices were corrected, and the application data were drought forecasts and warning operation data provided by ministries.
2.1.1. Ground Data

The SPI was calculated using ground-based precipitation data from 60 observation stations provided by the automated synoptic observing system (ASOS) of the Korea Meteorological Administration (KMA). Agricultural drought conditions were evaluated based on the nationwide water reserve rates of agricultural reservoirs. Although the data are divided based on the headquarters name, branch name, and facility name, in this study, the average value of the water reserve rate was calculated for 167 cities, municipalities, and districts. Of these 167 local governments, 135 had water reserve data and 32 did not. The first water source for each local government was used to calculate a hydrological drought index based on public water, and in the case of areas for which the first water source is a river rather than a dam or reservoir, river flow data at drought prediction, warning, and monitoring points for each major river were used. One hundred and twenty-two local governments could secure data on dam water levels and river flow to monitor hydrological drought; no data were available for the remaining twenty-two.

2.1.2. Remote Sensing Data

In this study, satellite data-based information, such as precipitation, evaporation, soil moisture, and vegetation data, were extracted to calculate various drought indices. The latest available MODIS, PERSIANN-CDR, TRMM, and GPM IMERG data from Aqua satellites were utilized (Table 1).

Table 1. Satellite data information used in this study.

| Product          | Resolution       | Time   |
|------------------|------------------|--------|
| MODIS MOD11A1    | Land Surface Temperature | 1 km–daily | 2001–2020 |
| MOD13A3          | Vegetation Indices | 1 km–monthly |        |
| MOD16A2          | Evapotranspiration | 0.5 km–8 days |        |
| MCD43B2          | Albedo            | 1 km–8 days |        |
| PERSIANN-CDR     | Precipitation     | 25°–daily | 1983–1997 |
| TRMM TRM3B42     | Precipitation     | 25°–3 h | 1998–2014 |
| GPM GPM IMERG    | Precipitation     | 10°–30 min | 2015–2020 |
2.2. Multi-Drought Indices

Just as there is no universal definition of drought, there is no single index or indicator that can explain and apply to all types of drought and climate systems affected by drought. In this study, the “Handbook of Drought Indicators and Indices” by Svoboda and Fuchs [20] was used as a reference in selecting an index for drought index convergence. This convergence index was calculated based on the drought index type, ease of use, data availability, and calculation feasibility. Drought indices calculated through synthesis or modeling were excluded.

2.2.1. Meteorological Drought Indices

Most drought indices based on meteorological factors have been developed and used for meteorological and agricultural monitoring. Among the meteorological drought indices available, the SPI was selected for use because data can be obtained to calculate it, it is easy to calculate, and it is monitored by government ministries. SPI, developed by Mckee et al. [12,21], the most widely used drought index, is based on the fact that drought begins with a decrease in precipitation that causes water shortages compared to relative water demand. SPI is calculated through a statistical analysis process, representing the effect of individual water sources on drought by setting the time unit as a cumulative series, such as 3, 6, 9, 12, and 24 months, and calculating the precipitation shortage per cumulative time unit. The SPI calculated for a specific time unit is used to monitor various drought conditions according to each time unit. For instance, short time units such as 1 and 3 months can be used to evaluate short-term drought, and longer time units such as 12 and 24 months can be used to assess long-term drought. Table 2 below shows a classification of drought conditions according to the SPI range.

Table 2. Classification of drought conditions according to the range of each drought index.

| SPI Range   | Moisture Condition   |
|-------------|----------------------|
| >2.00       | Extremely wet        |
| 1.50–1.99   | Very wet             |
| 1.00–1.49   | Moderately wet       |
| -0.99–0.99  | Near normal          |
| -1.00–1.49  | Moderately dry       |
| -1.50–1.99  | Severely dry         |
| <−2.00      | Extreme dry          |

2.2.2. Agricultural Drought Indices

Agricultural drought occurs when crops do not have enough water to start and maintain growth due to a lack of short-term rainfall, a lack of moisture in the ground surface and root areas, and an abnormality in the surface temperature. Drought indices representing the effects of the aforementioned variables were developed to quantify agricultural drought. The most commonly used vegetation data-based drought indices determined using satellite images include the vegetation health index (VHI, [22]), microwave integrated drought index (MIDI, [23]), and agricultural drought condition index (ADCI, [24]), as shown in Table 3.

Table 3. Classification of drought conditions according to VHI, ADCI, and MIDI ranges.

| VHI, ADCI, MIDI Range | Classification of Drought Conditions |
|-----------------------|-------------------------------------|
| >40                   | No drought                          |
| 30–40                 | Mild drought                         |
| 20–30                 | Moderate drought                     |
| 10–20                 | Severe drought                       |
| 0–10                  | Extreme drought                      |
2.2.3. Hydrological Drought Indices

Hydrological drought refers to a decrease in the amount of surface or underground water due to a lack of precipitation. The frequency and severity of drought are defined based on the size of the basin unit. In general, the time of occurrence of meteorological and agricultural drought has some time delay, and it takes more time for precipitation shortages to appear in hydrological systems, such as soil moisture, river flow, underground water, and reservoir water levels. Therefore, the various fields of water use have different water supply sources; hence, the timing of drought damage is different.

In this study, the streamflow drought index (SDI, [25]), which evaluates drought using river flow rates, the standardized reservoir supply index (SRSI, [26]), which is based on dam water storage, and the water budget-based drought index (WBDI, [27]), which evaluates hydrological drought using recent satellite data, were used. Table 4 presents the classification of drought conditions according to the range of each hydrological drought index.

Table 4. Classification of drought conditions according to SDI, SRSI, and WBDI ranges.

| SDI    | SRSI    | WBDI    | Classification of Drought Conditions |
|--------|---------|---------|--------------------------------------|
| >0     | > 0     | >0      | No drought                           |
| −1.0–0 | −1.0−0  | −0.5−0  | Mild drought                         |
| −1.5–1.0 | −1.0−1.5 | −1.5−1.0 | Moderate drought                     |
| −2.0–1.5 | −2.0−1.5 | −1.5−1.5 | Severe drought                       |
| <−2.0  | <−2.0   | <−1.5   | Extreme drought                      |

2.3. OneMap Drought Index Combining Meteorological, Agricultural, and Hydrological Drought Indices

2.3.1. Integration of Drought Indices by Statistical Methods

Drought phenomena are related to several other variables, and thus, drought analyses based on a single index are insufficient in monitoring complex drought phenomena. Therefore, an OneMap drought index for accurate drought monitoring was developed using a combination of information related to various types of drought indices (meteorological, agricultural, and hydrological). The OneMap drought index was based on ground and satellite data using multivariate statistical models. The OneMap drought index developed in this study was compared to and verified with a drought index calculated using drought history data, and the degree of the drought was expressed using the verified OneMap drought index. This study sought to evaluate the applicability of the OneMap drought index, determine the drought stage (attention, caution, alert, or severe), and evaluate the applicability of the drought index and drought reproduction ability based on ground and satellite data.

In this study, the drought index for each application method was evaluated by applying four linear models and two nonlinear models. The OneMap drought index was developed via multivariate statistical modeling applying Bayesian principal component analysis (BPCA), developed by Oba et al. [28], to estimate high-dimensional datasets with missing data. The modeling involved three procedures: principal component regression analysis, Bayesian estimation, and the expected value maximization algorithm. The first two procedures were conducted to derive and determine appropriate parameters, and the third was used to estimate missing values.

2.3.2. Accuracy Evaluation of Drought Monitoring by the Drought Index

A receiver operating characteristic (ROC) analysis based on a confusion matrix was conducted to review the applicability of the drought index. If a drought-affected area was identified as being affected by drought, it was classified as a Hit (H), and if the drought-affected area was not identified as being affected by drought, it was classified as False (F). If a drought area was not identified as exhibiting drought, it was classified as missing (M),
and if an area without drought was identified as not being affected by drought, it was classified as a negative hit (N). ROC values between 0 and 1 were calculated, with perfect predictions represented by a hit rate (HR) = 1 and a false alarm rate (FAR) = 0, implying that the closer the ROC is to 1, the better the prediction is (Table 5, [29]).

Table 5. Confusion matrix of ROC Analysis.

| Drought Indices          | Drought | Non-Drought |
|--------------------------|---------|-------------|
| Drought damaged area     | Hit (H) | False (F)   |
| Drought area             |         |             |
| Non-damaged area         | Missing (M) | Negative hit (N) |

The drought index, the drought forecast and the warning information did not match exactly. Therefore, the calculated drought index was therefore corrected and used to yield consistent forecast and warning information. ROC scores were utilized to evaluate the classification model and correct the drought index. Drought specificity and accuracy were considered in the performance evaluation. The self-organizing migrating algorithm (SOMA, [30]) optimization technique was used to determine the weight for drought index correction. The objective function estimated values with maximum drought specificity and overall accuracy. The application range of the weights was $-20\%$ to $+20\%$, adjusted and verified in increments of 1%.

3. Results and Discussion

3.1. Correction of the Drought Index through Analysis of Drought Forecast and Warning Data

The KMA produces meteorological drought forecasts and warnings based on cumulative precipitation information and SPI data over the previous six months. Nationwide warnings were issued 5.54 times per year on average from 2017 to 2020 (Figure 2). In the agricultural sector, drought forecast warnings at the attention, caution, alert, and severe levels are issued based on information about the average year water reserve rate and the effective water content in the soil. On average, such warnings were issued 0.74 times per year on average from 2017 to 2020. In the case of the hydrological field, forecasts and warnings are provided based on information about the water level and water storage volume of rivers and dam reservoirs that provide public water. On average, warnings were issued 3.61 times per year from 2017 to 2020.

![Figure 2](image-url)  
**Figure 2.** The number of monthly drought forecasts and warnings issued from 2017–2020.
The procedure for correcting the monitoring results of the meteorological, agricultural, and hydrological drought indices calculated in this study was performed based on the current status of the forecasts and warnings of the analyzed meteorological, agricultural, and hydrological droughts. Although the correction of meteorological, agricultural, and hydrological drought indices calculated based on satellite and ground data may differ academically, as a way to minimize the deviation from the results monitored in the field, the optimization technique was applied to the extent that the calculation results of the raw data (drought index) did not change.

Drought specificity and accuracy before and after weight correction for meteorological, agricultural, and hydrological drought indices calculated using satellite data were analyzed (Figures 3 and 4). In the case of the meteorological drought index (SPI) calculated based on satellite data, drought specificity and overall accuracy significantly improved after correcting the weight through drought forecast data analysis. The drought specificity in the meteorological field improved significantly from 0.25 to 0.88 after index correction (Figure 3), and the overall accuracy was slightly enhanced from 0.47 to 0.55 after index correction (Figure 4). However, in the case of VHI, there was no change in drought specificity and overall accuracy before and after weight correction. There was little change in the correction of the drought index through the application of weights to vegetation or soil moisture data. Regarding the hydrological drought index (WBDI), although the drought specificity improved from 0.13 to 0.50 after weight correction, the overall accuracy did not significantly change. Therefore, although there was relatively little forecast and warning information, it showed the possibility of improving drought specificity and accuracy by correcting the drought index via weight application.

3.2. Results of Correlation Analysis with an Integrated Drought Index

In the development of the integrated drought index, values of the integrated drought index were calculated by applying the meteorological drought index SPI, agricultural drought index SRSI, and hydrological drought indices SRSI and SDI, calculated based on ground data, to the dimension reduction model through linear and nonlinear models. For 167 administrative district-based basins, an integrated drought index was developed by applying a Bayesian PCA (BPCA)-based combination model that explains the variation of 66.8% on average (67.3% after index correction) for the four drought indices (SPI, SRI, SRSI, and SDI). The integrated drought index showed a relatively high correlation with SRI (median value: 0.87), a correlation of 0.79 with the meteorological drought index SPI, and a correlation of 0.75 with the hydrological drought indices SRI and SDI (Figures 5 and 6). In this study, the BPCA method was applied to the basin when all three drought indices
were provided for 167 municipalities, and the LSCORE method, showing a relatively high correlation, was applied to basins when only two drought indices were provided.

Figure 3. Specificity distribution of the ground data-based drought index (before and after weight correction).

Figure 4. Accuracy distribution of the ground data-based drought index.

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Figure 5. Comparison of the correlation analysis results by the drought index for each method.

3.3. Comparison of Drought Index Calculation Results Based on Satellite Data and Ground Data

For the forecast and warning operation period from 2017 to 2019, a meteorological drought index (SPI), VHI, and hydrological drought index (WBDI) calculated from satellite data were spatially illustrated, compared, and analyzed with the drought index for each type of drought calculated from ground data (Figure 7). In the case of meteorological drought indices, since the same SPI was applied, the spatiotemporal drought patterns of the drought index calculated using ground and satellite data appeared to be similar. However, the agricultural and hydrological drought indexes exhibited significantly different spatiotemporal changes, such as the depth and time of drought. In the case of satellites-based indices, VHI, an agricultural drought index, was calculated by applying vegetation-related indices, whereas WBDI, a hydrological drought index, was calculated and applied through the basin-wise water balance. Hence, there is a significant difference between these and the drought indices calculated based on ground data. In the case of satellite data, there is a
time delay in providing data, and it is difficult to calculate indices that can replace actual drought forecast operating data.

![Comparison of drought index calculation results based on satellite data and ground data](image1)

**Figure 6.** Results of correlation analysis for the application of the integrated drought index.

![Comparison of drought index calculation results based on satellite data and ground data](image2)

**Figure 7.** Comparison of drought index calculation results based on satellite data and ground data in 2017.

Although monitoring drought using satellite data offers many advantages (e.g., monitoring ungagged basins, utilizing various hydrological factors, etc.), there are several drawbacks as well, such as the difficulty of real-time monitoring, the need for extensive data processing to derive desired hydrological factors, and large deviations from ground observation data. To this end, a plan for integrating drought forecast and warning based on a drought index using ground data was proposed in this study.

### 3.4. Evaluation of the Applicability of the Integrated Drought Map

Using the 2019 drought forecast and warning operation information, drought monitoring information by field was illustrated, and the applicability of the integrated drought map calculated based on the drought index was evaluated (Figure 8). In 2019, the cumulative
precipitation from January to July was 569.5 mm, corresponding to 75.8% and 78.4% of the cumulative precipitation in a normal year and the previous year, respectively. A total of 15 cities and counties were subjected to limited water supply, and the number of victims of transport water supply was estimated to be 9789. Based on the operation information of the drought forecasts and warnings, a caution level was announced, mainly in the central region, from June to September, which gradually eased after October. According to the spatial illustration results of SPI, a meteorological drought index based on ground data, the attention level was issued in May, and an alert level was issued in the central region in August. Similar to the forecast and warning operation information, the drought stage gradually eased after October.

![Figure 8. Evaluation and analysis of the OneMap drought index drought based on ground data (2019 drought forecast and warning operation information).](image)

In the case of the operation of agricultural drought forecasts and warnings, caution-level was issued in some areas in July and August, but most cities, municipalities, and districts did not exhibit any particular changes. In the case of the SDI drought index based on ground data calculated from agricultural reservoir information, the alert and severity stages occurred mainly in the central region in July and August.

The information on the operation of hydrological drought forecasts and warnings showed that attention and caution levels were issued in the southwestern part of the Han River and the Chungcheong-do area beginning in August. However, in the case of ground data-based hydrological drought indices SDI and SRI, attention-level warnings were issued in the central region beginning in May, and severe warnings occurred in July and August.

As drought intensifies due to climate change and the frequent disruption of the supply of agricultural, living, and industrial water, the government of South Korea is advancing various measures to strengthen the response to drought. Accordingly, since 2016, ministries such as the Ministry of Public Administration and Security, the Ministry of Agriculture, Food and Rural Affairs, the Ministry of Environment, and the Meteorological Administration have formed a joint task force to examine the government’s drought response procedures, announce drought forecasts and warnings, and prepare comprehensive drought response measures. In 2019, the Ministry of Public Administration and Security decided to reflect drought information in national statistics with Statistics Korea and various related ministries and has been publishing collections of statistics since 2020. Furthermore, the National Disaster Management Research Institute of the Ministry...
of Public Administration and Security is planning measures to establish an integrated national drought information forecast and warning platform, to improve the accuracy of water supply evaluation, enabling efficient drought information management. However, since it is difficult to intuitively understand drought situations because various maps are provided based on the division of business fields under the authority of each ministry, technology is needed to integrate the available information and comprehensively assess drought situations.

In this study, we used multivariate statistical modeling using BPCA to develop a OneMap drought index that unifies existing measures of drought conditions, including meteorological, agricultural, and hydrological drought indices. This study also recommends implementing step-by-step drought management action plans using the OneMap drought index to generate drought forecasts and warnings, thus promoting concerted and effective responses from local governments and authorities. The action plan for integrated drought management should be configured with connectivity by drought degree (attention, caution, alert, or severity), by field (local government, agriculture, or living), and by the ministry involved. The action plan for integrated drought management should also be configured to coordinate drought response in three areas (local government, agriculture, and living), and it should be a link between the drought countermeasures of the Ministry of the Interior and Safety and those of local governments, such that the drought countermeasures of local governments can be linked step-by-step to drought management policies issued by central ministries and water supply agencies.

4. Conclusions

As climate change exacerbates extreme events such as drought, there is a growing need for an integrated drought index combining meteorological, agricultural, and hydrological drought indices. To this end, in this study, a OneMap drought index based on a multivariate statistical model was developed. After evaluating the accuracy of the corrected OneMap drought index based on the self-organizing migrating algorithm optimization technique, it was found that the applicability of the OneMap drought index and its ability to regenerate drought were excellent for ground and satellite data.

Despite several efforts to cope with drought as a crisis type, some political and practical difficulties remain with regards to drought management. In particular, although a joint task force (TF) representing related ministries was organized to respond jointly to crises and develop a cooperative system, the concerned ministries and individual agencies are still judging the crisis stage based on their own standards and implementing separate measures. Since multiple ministries and agencies are involved, the subjectivity of local governments that should play a primary role in disaster management and dependence on the central government is often mentioned as an underlying issue. Therefore, the Ministry of Public Administration and Security, which operates a joint TF with related ministries, should issue an integrated forecast and warning for administrative districts and operate a well-organized response process, such as preliminary preparation and emergency measures, in line with these integrated forecasts and warnings, coordinating and directing related ministries and local governments. However, since it is difficult to intuitively understand a drought situation because various maps are provided depending on the division of ministry-specific business fields, a new framework is required to integrate the information available and assess the situation comprehensively.

The OneMap drought index developed in this study can provide reasonable and scientific drought information for use in forecasts and warnings. Although the actual drought forecast and warning operation information and the drought monitoring information calculated using the drought index exhibited similar spatial and temporal changes, there was a significant difference in the degree of drought stage determined. To tackle these issues, weight correction of forecast and warning information and spatial accuracy for the long-term drought monitoring assessment should be improved. Furthermore, for the utilization of integrated drought forecasting and warning technology, the integrated
drought stage should be based on the integrated drought forecast and warning issuance of the Ministry of Public Administration and Security, except when the forecast and warning stage is determined at the “Situation Judgment Meeting (Crisis Evaluation Meeting)”, in accordance with the drought disaster crisis management standard manual. If tangible damage can be minimized by immediately operating existing emergency water supply measures and water supply stabilization measures, it may be possible to apply a “caution” level of adjustment mechanism and public communication method. When joint measures of related ministries are implemented, it is important to systematically establish step-by-step measures of related organizations (local governments, each ministry) for “concerted action”. It is also necessary to calibrate the step-by-step drought response systems of other institutions to suit the action plan for each stage of integrated drought.

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