Academic Journal of Science and Technology
ISSN: 2771-3032 | Vol. 14, No. 3, 2025

Monitoring of Meteorological Drought in the Indochinese Peninsula Based on Satellite Data

Haiyang Wang

College of Surveying, Henan Polytechnic University, Jiaozuo, Henan 454003, China

Abstract: This study utilizes precipitation data from the Global Precipitation Measurement (GPM) mission to calculate the Standardized Precipitation Index (SPI) at 1-month, 3-month, 6-month, and 12-month time scales. It systematically compares and analyzes the performance and spatiotemporal evolution characteristics of SPI at different time scales in the Indochina Peninsula. The results indicate that SPI at various time scales can reflect both short-term variations and long-term trends of drought events in the region. Short-term SPI (1-month and 3-month) are more sensitive to precipitation anomalies, while long-term SPI (12-month) better reveal the cumulative effects and persistence of regional droughts. Through comparative analysis, this study uncovers the spatiotemporal differentiation patterns of drought events in the Indochina Peninsula, providing a scientific basis for drought monitoring and risk management in the Southeast Asian monsoon region.

Keywords: Standardized Precipitation Index; Indochina Peninsula; Drought Monitoring.

1. Introduction

Drought, as one of the major natural disasters[1], directly impacts agricultural production, leading to reduced crop yields or even total crop failure. Studying drought helps in formulating response measures, optimizing water resource allocation, and ensuring food security. Against the backdrop of global warming, droughts have become more frequent, evolving from occasional natural disasters to global, systemic, and threatening phenomena. The IPCC Sixth Assessment Reportindicates[2] that drought frequency has gradually increased over the past half-century, posing significant challenges to traditional monitoring systems. Traditional meteorological station monitoring is limited by spatial sampling and data continuity, making it difficult to effectively cover large-scale regions. The breakthrough development of remote sensing technology has provided revolutionary solutions in this field. It enables real-time monitoring of large-scale drought conditions, offering high spatiotemporal resolution data for comprehensive assessment of drought severity and changes. Remote sensing is cost-effective, suitable for long-term monitoring, and particularly advantageous for remote areas.

From a disciplinary perspective, droughts can be categorized into four types: meteorological drought, agricultural drought, hydrological drought, and ecological drought[3]. Meteorological drought assesses drought severity through precipitation deficits; agricultural drought evaluates crop drought conditions using soil moisture data; hydrological drought assesses water resource shortages through hydrological data; and ecological drought evaluates the impact of drought on ecosystems using vegetation cover, biomass, and other data. There is a significant propagation effect among drought types. In terms of temporal sequence, meteorological drought usually serves as the initial driving factor. Therefore, identifying meteorological drought is of great significance.

This study uses GPM (Global Precipitation Measurement) rainfall data to calculate the Standardized Precipitation Index (SPI) [4], a meteorological drought index, to explore the frequency, intensity, and persistence characteristics of droughts in the Indochina Peninsula at different time scales.

2. Data and Methods

2.1. Study Area

The Indochina Peninsula features diverse and complex terrain and is prone to droughts due to monsoon influences. The region spans tropical and subtropical zones, encompassing Cambodia, Laos, Myanmar, Thailand, and Vietnam. It is characterized by a well-developed water system, primarily consisting of the Tonle Sap Lake, Irrawaddy River, Chao Phraya River, and Mekong River basins. The topography includes mountains, plateaus, and plains, with extensive forest and agricultural land distribution[5]. This unique geographical configuration provides important spatial heterogeneity for drought monitoring research. As a typical tropical monsoon region, the area exhibits significant seasonal and interannual precipitation variability: winters are dry with little rainfall, making seasonal droughts common, while summer precipitation heavily depends on monsoon strength, with monsoon anomalies often leading to insufficient rainfall. Droughts have significant impacts on agriculture, water resources, and ecosystems in the Indochina Peninsula. Agriculture, as the primary economic activity in the region, is affected by drought-induced precipitation shortages and irrigation water scarcity, leading to reduced crop yields and threats to food security. Systematic analysis of drought characteristics and driving factors in this region can provide a scientific basis for water resource management, agricultural planning, and climate change adaptation strategies, thereby effectively mitigating the negative impacts of drought on socio-economic and ecological environments.

2.2. Data

IMERG is a next-generation multi-satellite precipitation dataset introduced by the Global Precipitation Measurement mission. IMERG precipitation data provide three types of products: Early, Late, and Final, generated based on different data retrieval algorithms. The IMERGV07 version integrates information from GPM and TRMM (Tropical Rainfall Measuring Mission) Multi-satellite Precipitation Analysis

(TMPA) sensors. Through inter-calibration, merging, interpolation, and fusion techniques, it produces consistent precipitation estimates from June 2000 to the present. IMERG data is widely used in global-scale studies and is particularly suitable for regions lacking reliable ground observations or with sparse ground observation networks. In this study, the IMERGV07 Final product is used, with a spatial resolution of 0.1°×0.1°. Weekly and monthly precipitation data were calculated from the daily dataset.

3. Standard Precipitation Index

The SPI is used to demonstrate the probability of precipitation occurrence over a certain period and is one of the widely applied indicators for assessing meteorological drought. It offers advantages such as simple calculation, minimal data input, effective computational results, and applicability across different temporal and spatial scales. By fitting the precipitation data over a specific period using the Gamma distribution function and performing normal standardization based on the cumulative probability of precipitation, the value of the SPI index corresponds to the quantile of the normal distribution. The density function of this distribution is expressed as follows:

$$h(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \tag{1}$$

In actual precipitation samples, there may be instances where the precipitation value is zero. Therefore, it is necessary to modify the distribution function of precipitation. By transforming the integral formula and based on the standard normal distribution, the calculation process is as follows:

$$Q(x) = q + (1-q)g(x) \tag{2}$$

$$P(t) = \int_{-\infty}^{t} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \tag{3}$$

$$SPI = t = \mathrm{P}^{-1}[Q(x)] \tag{4}$$

According to the U.S. Drought Monitoring System, the SPI is classified into five categories.

Table 3-1 SPI Classification of Drought Levels

Drought level	SPI range
Mild drought	-0.5 ~ -0.7
Moderate drought	-0.8 ~ -1.2
Severe Drought	-1.3 ~ -1.5
Extreme drought	-1.6 ~ -1.9
Rare drought	≤-2

4. Results and Analysis

By plotting the SPI at different time scales, the spatiotemporal evolution characteristics of drought events in the Indochina Peninsula can be visually revealed. Short-term SPI(e.g., SPI-1 and SPI-3) can quickly reflect short-term precipitation anomalies, showing high variability, making them suitable for monitoring seasonal droughts. Medium-term SPI (e.g., SPI-6) can reflect the duration and spatial distribution of droughts but tend to be conservative in indicating drought intensity. Long-term SPI (e.g., SPI-12) can reveal the long-term cumulative effects and severity of droughts, displaying smoother trends. By analyzing multi-time-scale SPI line charts, it is evident that drought events in the Indochina Peninsula exhibit distinct seasonal and interannual variability. Short-term SPI are suitable for monitoring immediate droughts, while long-term SPI are more appropriate for assessing long-term drought trends.

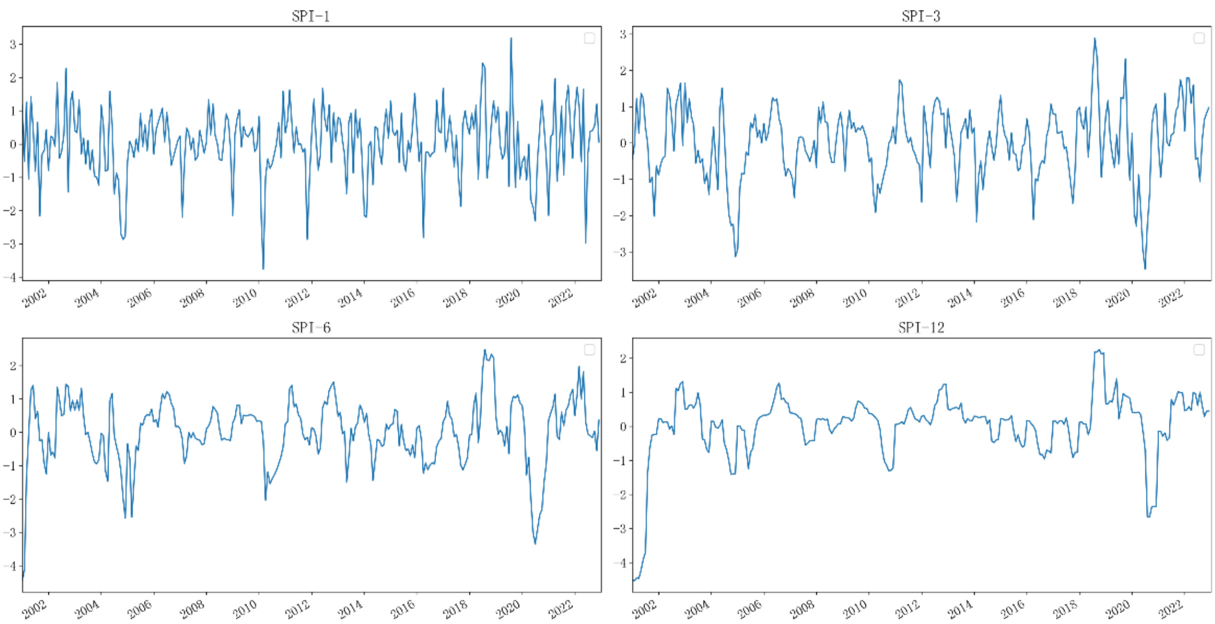

Figure 4-1 Line comparison chart of SPI at different time scales

El Niño[6], as one of the most significant interannual signals in the global climate system, has a substantial impact on regional precipitation patterns and drought occurrence. During El Niño events, abnormal sea surface temperature increases in the central and eastern equatorial Pacific lead to a reorganization of global atmospheric circulation, causing precipitation anomalies in specific regions and exacerbating drought events compared to normal years. For example, in 2016, due to the El Niño phenomenon, the Indochina Peninsula experienced severe and widespread drought conditions. Taking the 2016 large-scale drought event as an example, the performance of SPI at different time scales in drought monitoring is compared.

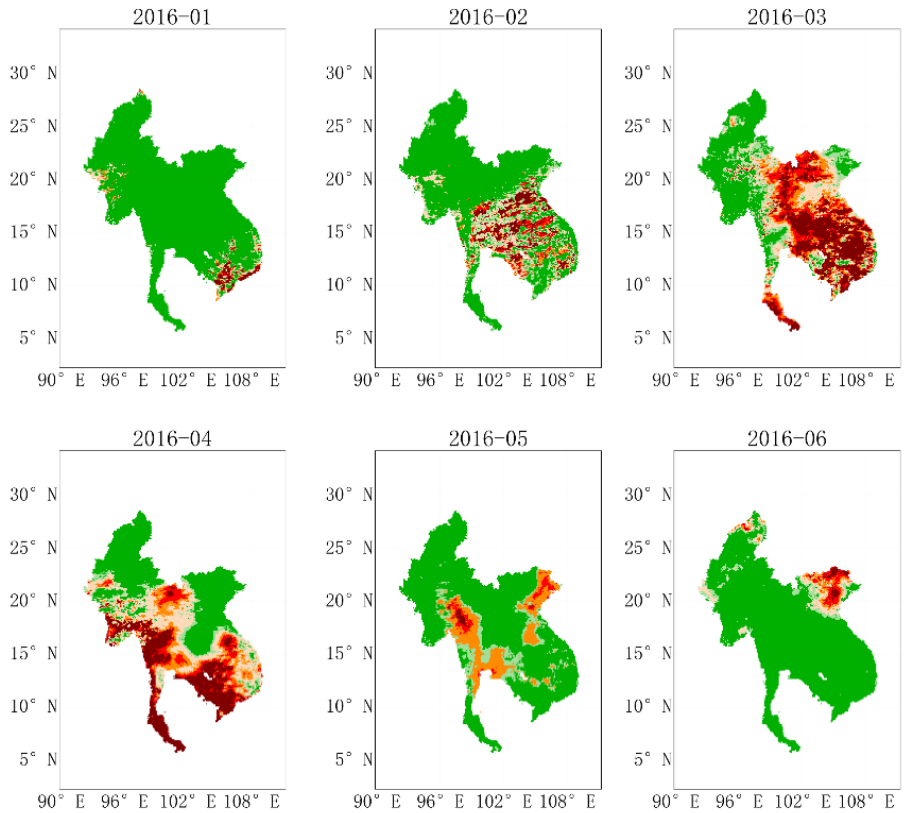

Figure 4-2. 2016 Drought Distribution Map SPI-1

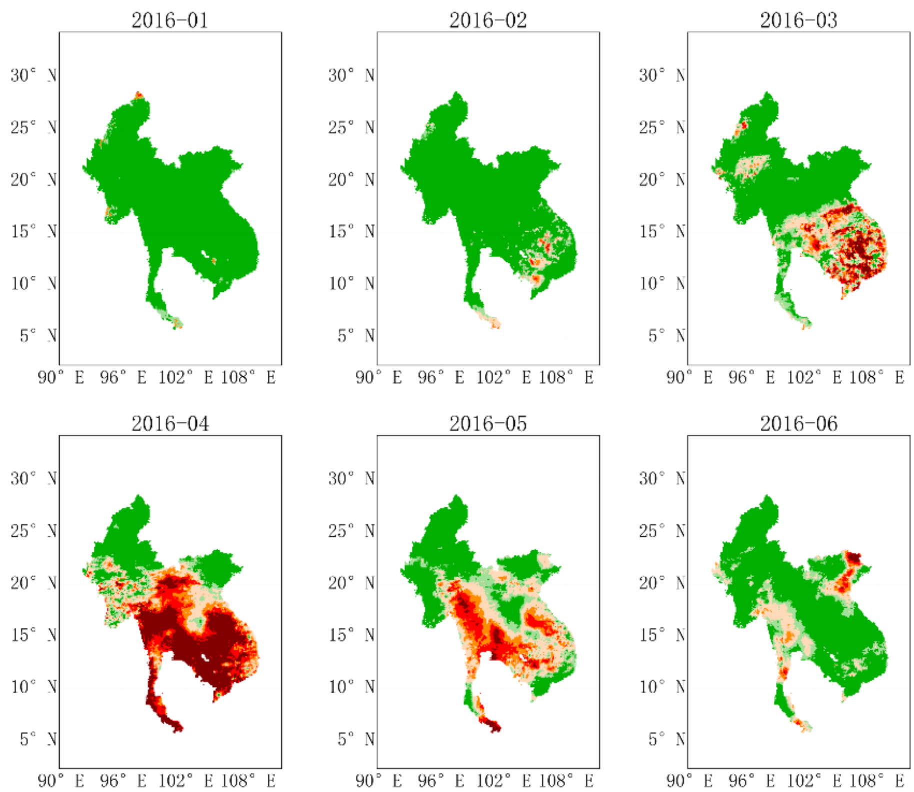

Figure 4-3. 2016 Drought Distribution Map SPI-3

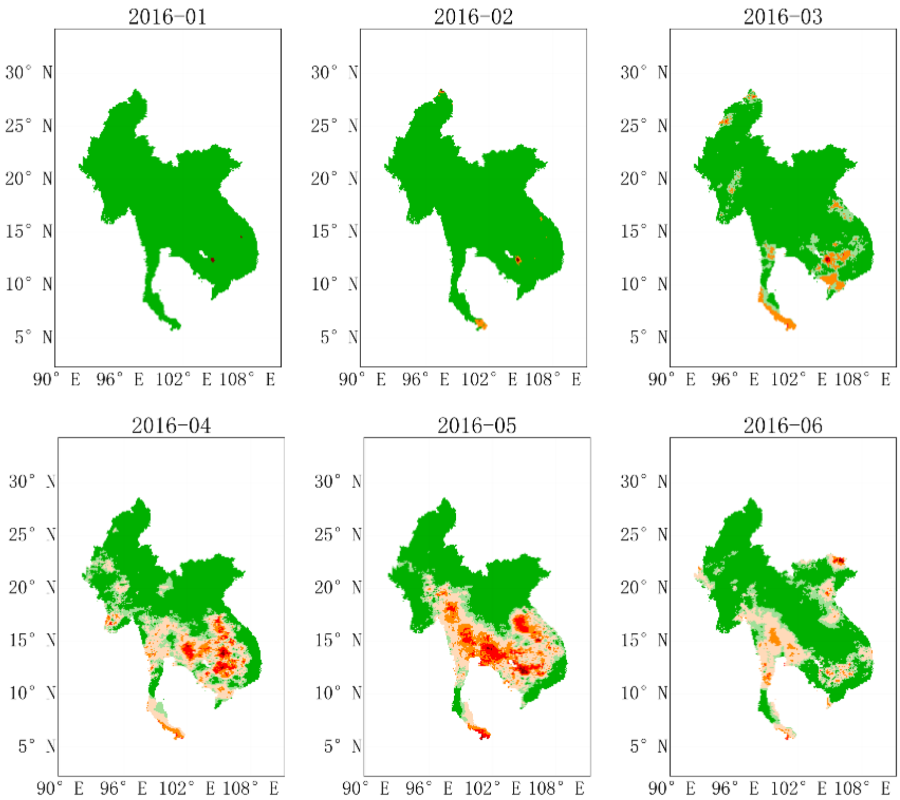

Figure 4-4. 2016 Drought Distribution Map SPI-6

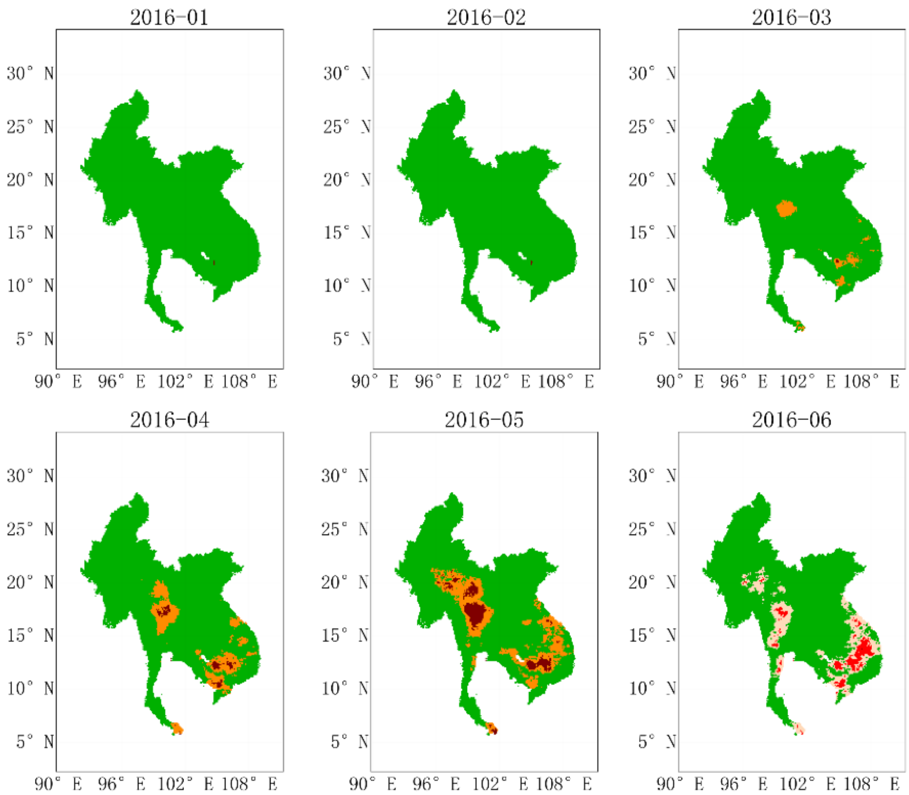

Figure 4-5. 2016 Drought Distribution Map SPI-12

Spatial comparative analysis of SPI distribution maps reveals significant differences in the monitoring capabilities of SPI at different time scales for drought events in the Indochina Peninsula. SPI-1, SPI-3, and SPI-6 can all capture large-scale drought events, indicating that short- to medium-term SPI are sensitive to precipitation anomalies and can reflect the immediacy and spatial distribution of droughts. However, while SPI-6 detects large-scale droughts, it often indicates mild drought conditions, failing to fully reflect the severity of droughts. In contrast, SPI-12 shows only small-scale drought areas, which do not align with the actual extent of drought events, highlighting the limitations of long-term

SPI in capturing short-term drought events.

Although SPI-12 generally indicates smaller drought areas, the severe drought regions it identifies (e.g., central and southeastern Indochina Peninsula) show high spatial consistency with those identified by SPI-1 and SPI-3. This suggests that while SPI-12 has limitations in responding to short-term drought events, it remains valuable for reflecting the long-term cumulative effects and spatial distribution of severe droughts. On the other hand, SPI-1 and SPI-3 are more sensitive to immediate drought changes and spatial distribution but lack the ability to capture long-term cumulative effects. Therefore, a comprehensive analysis combining SPI at multiple time scales can more thoroughly reveal the spatiotemporal evolution of drought events: short-term SPI (e.g., SPI-1 and SPI-3) are suitable for monitoring the immediacy and spatial distribution of droughts, while long-term SPI (e.g., SPI-12) are better at reflecting the long-term cumulative effects and severity of droughts. This multi-scale analytical approach provides a more scientific and comprehensive perspective for drought monitoring and assessment.

5. Conclusions

This study, through the analysis of the Standardized Precipitation Index (SPI) at different time scales, draws the following conclusions: Short-term SPI are more sensitive to precipitation anomalies, enabling rapid detection of immediate drought changes and spatial distribution characteristics, making them suitable for monitoring seasonal droughts and short-term precipitation anomalies. Long-term SPI, on the other hand, can reveal the long-term cumulative effects and severity of droughts, making them suitable for assessing long-term drought trends and water resource management. Despite these achievements, this study has some limitations that need to be addressed in future research: (1) In terms of data sources, high-resolution remote sensing data and climate models could be integrated to more accurately characterize the spatial distribution of drought events; (2) Methodologically, advanced techniques such as machine learning and deep learning could be introduced to improve the accuracy and timeliness of extreme drought event predictions. These improvements will contribute to building a more robust drought monitoring and early warning system, providing a scientific basis for regional drought risk management.

References

[1] A. S. Kiem et al. Natural hazards in Australia: droughts 2016,(37-54.

[2] R. Suresh, A. Shanmugam, S. Viswabharathy, J. B. Antony, S. Samuthirapandi, and S. Manonmani, "Climate Change Impact on Rice Production and Breeding for Climate Resilient Rice," in Climate-Smart Rice Breeding: Springer, 2024, pp. 1-24.

[3] Z. Hao and V. P. J. J. o. H. Singh. Drought characterization from a multivariate perspective: A review 2015,(668-678.

[4] T. B. McKee, N. J. Doesken, and J. Kleist, "The relationship of drought frequency and duration to time scales," in Proceedings of the 8th Conference on Applied Climatology, 1993, vol. 17, no. 22, pp. 179-183: California.

[5] Y. Li et al. Satellite-based assessment of meteorological and agricultural drought in Mainland Southeast Asia 2022,(6180-6189.

[6] A. Timmermann et al. El Niño–southern oscillation complexity 2018,(7715): 535-545.