Consistency Analysis of Common Remote Sensing Drought Monitoring Indices in Kazakhstan (Postprint)

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Abstract

Utilizing Soil Moisture Active Passive (SMAP) satellite soil moisture data, this study compared the consistency of three common remote sensing drought indices [Anomaly Vegetation Index (AVI), Vegetation Health Index (VHI), and Vegetation Supply Water Index (VSWI)] from global operational systems for agricultural drought monitoring in Kazakhstan at the same spatial scale. Pearson correlation coefficient (r) and Kendall rank correlation coefficient (τ) were employed to examine the correlations between drought indices and soil moisture, as well as their agreement in drought level classification, thereby evaluating the applicability of remote sensing for drought monitoring during the mid-to-late crop growing season in Kazakhstan. The results indicated that the consistency among different drought indices was low in this region. Vegetation-based remote sensing drought indices exhibited low correlation with soil moisture, whereas composite indices integrating vegetation and land surface temperature demonstrated significant positive correlation. In comparisons across different soil layers, the VSWI index showed strong correlation with soil moisture in the crop root zone (0–100 cm) (r>0.6), indicating its good responsiveness to soil moisture conditions during the mid-to-late plant growing season.

Full Text

Consistency and Comparison among Remote Sensing Drought Indices and SMAP Soil Moisture in Kazakhstan

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Abstract

In order to evaluate the applicability of remote sensing drought indices for agricultural drought monitoring in the arid zone of Central Asia, several typical indices (i.e., AVI, VHI, and VSWI) from current global drought monitoring systems were assessed using active and passive microwave soil moisture data (SMAP). Data from late June, the middle and late period in the plant growing season, were utilized for this experiment. According to datasets for existing land use and land cover, more than 2650 samples fully covered by vegetation were chosen. Correlations between remote sensing drought indices and soil moisture were examined using the Pearson correlation coefficient (r) and Kendall rank correlation coefficient (τ). Results show that AVI and soil moisture are not significantly correlated. However, VHI and VSWI are significantly positively correlated with soil moisture at two layers, including the surface layer (0-10 cm) and the root zone layer (0-100 cm). By comparison, VSWI exhibits a strong correlation with soil moisture at root zone level (r > 0.6), which also shows a good response to drought conditions in the middle and late stages of the growing season in Kazakhstan. For determining drought grade, VHI shows a weak positive correlation with soil moisture.

Keywords: remote sensing drought index; SMAP; soil moisture; validity test; Kazakhstan

1. Introduction

Drought monitoring in arid regions relies heavily on remote sensing vegetation indices that capture plant response to water stress. Widely used indices include the Vegetation Condition Index (VCI), Vegetation Health Index (VHI), and Vegetation Supply Water Index (VSWI), which are operational in global drought monitoring systems such as CropWatch and NOAA' s platform [17]. These indices integrate vegetation status and land surface temperature to assess agricultural drought conditions [3-6].

Previous studies have demonstrated that combining vegetation indices with thermal measurements improves drought detection accuracy [7, 10-12]. The SMAP (Soil Moisture Active Passive) mission provides microwave-derived soil moisture data that serve as robust reference data for validating remote sensing drought indices [21]. This study focuses on Kazakhstan in Central Asia, where agricultural production is highly vulnerable to water stress.

2. Materials and Methods

2.1 Data Sources

Three remote sensing drought indices were selected: the Angular Vegetation Index (AVI) [22], Vegetation Supply Water Index (VSWI) [23], and Vegetation Health Index (VHI) [24]. These indices were derived from MODIS data (2009-2017) at 1 km spatial resolution [7].

SMAP soil moisture products provided reference data for both surface (0-10 cm) and root zone (0-100 cm) layers. The study period focused on late June through the middle and late growing season when drought impacts are most pronounced.

Based on land use/land cover classification datasets, 2,650 sample points fully covered by vegetation were systematically selected across Kazakhstan to ensure representative statistical analysis.

2.2 Statistical Analysis

Correlation analysis employed two complementary approaches: (1) Pearson' s correlation coefficient (r) to quantify linear relationships between each drought index and SMAP soil moisture, and (2) Kendall' s rank correlation coefficient (τ) to assess monotonic relationships. Significance was tested at the 95% confidence level ($P < 0.05$), with analyses stratified by soil depth to evaluate index performance across different layers.

3. Results

3.1 Correlation Matrix Analysis

Table 2 presents the correlation matrix between remote sensing drought indices and SMAP soil moisture across different soil layers.

Table 2. Correlation matrix among different remote sensing drought indices and SMAP soil moisture (SM) by soil layer (Pearson' s r)

Index	SM (0-10 cm)	SM (0-100 cm)
AVI	0.03 ns	–
VHI	Significant	Significant
VSWI	Significant	$r > 0.6$

Note: ns indicates not significant ($P > 0.05$). SM denotes SMAP soil moisture.

AVI demonstrated no significant correlation with soil moisture at either depth. In contrast, both VHI and VSWI showed significant positive correlations with soil moisture in both surface and root zone layers. VSWI exhibited particularly strong correlation with root zone soil moisture ($r > 0.6$), indicating robust sensitivity to drought conditions during the middle and late growing season in Kazakhstan. VHI, while significantly correlated, displayed weaker relationships compared to VSWI.

4. Discussion

The superior performance of VSWI likely derives from its integration of vegetation condition and temperature anomalies, providing a more direct indicator of water stress [27]. The weak correlation of AVI suggests that angular vegetation information alone is insufficient for reliable drought monitoring in this region.

These findings align with previous research demonstrating that combined vegetation-temperature indices outperform vegetation-only indices for drought detection [28-31]. The strong correlation between VSWI and root zone moisture is particularly valuable for agricultural applications, as root zone moisture directly influences crop productivity.

SMAP soil moisture data provide reliable validation references, though differences in spatial resolution and measurement depth should be considered when interpreting correlations [21]. Future research should explore temporal dynamics and develop operational thresholds for drought classification.

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Note: Figure translations are in progress. See original paper for figures.