Climate-Adaptive Soil Moisture Assessment in Sugarcane Farms Surrounding Krasaew Dam Using SMAP Satellite Observations.

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Abstract

Accurate soil moisture monitoring is essential for protecting crops from drought and flooding, especially as Thailand's climate becomes more unpredictable. In this study, we assessed soil moisture on sugarcane and rice farms surrounding Krasaew Dam, Suphan Buri, by collecting in situ measurements and analyzing satellite data from NASA's Soil Moisture Active Passive (SMAP) mission. We aimed to 1) compare soil moisture measured in the field using the GLOBE method with satellite data from NASA's SMAP, 2) find out how soil moisture is different between sugarcane fields on higher ground and rice paddies in low areas, and 3) use simple statistics and graphs to find new patterns in the satellite data that can help farmers. Our results showed that field-measured surface soil moisture averaged 0.190 ± 0.009 m^3/m^3 in sugarcane fields and 0.477 ± 0.008 m^3/m^3 in rice fields. Corresponding SMAP satellite data indicated lower mean values due to wider spatial averaging: surface soil moisture was 0.149 ± 0.073 m^3/m^3 for sugarcane and 0.183 ± 0.086 m^3/m^3 for rice, while root zone moisture was 0.168 ± 0.048 m^3/m^3 and 0.214 ± 0.047 m^3/m^3 for sugarcane and rice, respectively. Statistical tests confirmed that rice fields remained much wetter than sugarcane fields in both field and satellite data. These findings show a strong positive correspondence between field and SMAP satellite soil moisture measurements. SMAP data also captured clear seasonal patterns, revealing dry periods from March to April and wetter soils from September to October. This project demonstrates that SMAP is a reliable, climate-adaptive tool for monitoring soil moisture in Thailand, helping farmers and decision-makers respond to environmental changes. Through our work, we developed expertise in research, statistical analysis, and satellite data, earning recognition as student researchers, satellite data users, data scientists, and earth system scientists.

Research Question and Hypothesis

1. Do soil moisture values obtained from GLOBE field measurements correspond to soil moisture data derived from the SMAP satellite in agricultural areas surrounding Krasaew Dam, Suphan Buri Province? Hypothesis: Soil moisture measured on the ground using the GLOBE protocol will show a positive correspondence with soil moisture estimates from the SMAP satellite.
2. Is there a difference in soil moisture between sugarcane fields on high ground and rice paddies in lower areas, based on both field data and satellite data? Hypothesis: Rice paddies in low-lying areas will have higher soil moisture than sugarcane fields on high ground, as indicated by field measurements and SMAP satellite data.
3. Can SMAP satellite data be used to detect past periods of soil moisture stress that affected crops around Krasaew Dam? Hypothesis: Historical SMAP satellite data can help identify episodes of soil moisture stress affecting local agriculture, supporting climate-adaptive management to enhance future crop resilience.

Introduction and Review of Literature

Thailand faces significant challenges from both drought and flooding almost every year, resulting in substantial losses for farmers and the economy (World Bank, 2025). In the future, experts predict that more areas will be affected and that risks will intensify due to a changing climate and weather patterns (Ali & Thakkar, 2023). The country needs better solutions for monitoring and managing soil moisture to protect crops, support farmers, and help government agencies develop innovative plans (World Bank, 2025).

One technology that helps is satellite remote sensing of soil moisture. NASA's Soil Moisture Active Passive (SMAP) satellite provides free, high-quality soil moisture data for anywhere in Thailand (Jotisankasa et al., 2023). Tools such as AppEEARS enable students, researchers, and farmers to access this data easily, and Google Earth Engine facilitates map creation and online analysis(Gorelick et al., 2017).

The value of accurate soil moisture information is clear: it helps predict droughts, monitor floods, and support more informed agricultural and water planning (Ahmed et al., 2023). Major reviews and validation studies indicate that SMAP soil moisture data closely match in situ measurements across many locations (Gruber, 2020; Colliander et al., 2021). For example, SMAP products are carefully validated using established procedures that combine in situ (ground) measurements, data from other satellites, and rain gauges to ensure the satellite readings are reliable (Wrona et al., 2017; Colliander et al., 2021; Do et al., 2024). SMAP data are accurate for both surface and root-zone moisture and have been adopted as a standard for climate, agriculture, and environmental studies (Colliander et al., 2021).

Studies worldwide show that SMAP soil moisture performs well, even in challenging environments. In China and on the Tibetan Plateau, SMAP captured soil moisture changes more accurately than other satellites, despite some regional errors (Chen et al., 2017). In Europe, SMAP was found to be more reliable than SMOS and to have accuracy comparable to that of ASCAT and Sentinel-1 (El Hajj et al., 2018). Other research has confirmed that SMAP's radiometer captures important changes in sea surface salinity and soil moisture, providing valuable data for weather, climate, and disaster risk (Tang et al., 2017; Zhao et al., 2018; Ambadan et al., 2022).

To improve the spatial resolution of SMAP data, scientists have employed random forest downscaling and data fusion to produce soil moisture maps at finer scales, thereby supporting local planners (Zhao et al., 2018). Even in areas with forests or mixed crops, SMAP products perform well when validated against "in situ" data (Colliander et al., 2021; Ambadan et al., 2022; Cheruiyot et al., 2024). SMAP soil moisture has also been shown to be beneficial for monitoring floods, droughts, and rapid changes in farm fields (Rahman et al., 2019).

Recent studies demonstrate creative approaches to validating satellite data, using not only ground sensors but also rainfall estimates and advanced algorithms such as SM2RAIN, which converts soil moisture changes into rainfall estimates to validate satellite accuracy when field sensors are unavailable (Do et al., 2024).

In this project, we studied soil moisture around Krasaew Dam in Central Thailand. We selected two sites—a sugarcane field on higher ground and a rice paddy in a low area—to compare their soil moisture patterns. Field measurements were conducted in accordance with the GLOBE SMAP protocol, and SMAP satellite data were downloaded via AppEEARS. By comparing these two methods, this study aims to demonstrate that SMAP satellite data are a reliable and climate-adaptive tool for monitoring soil moisture in sugarcane farming regions and to support improved water and crop management decisions in Thailand.

Research Methods and Materials

Study site

In this study, field data were collected at two locations in Suphaburi Province. The first site is a higher-elevation area used for sugarcane cultivation (Sugarcane cultivation area: 14.85620°N, 99.81973°E) and was selected as a representative site for drought studies. The second site is a lowland rice field (Rice cultivation area: 14.75367°N, 100.07359°E), selected for comparison with an area typically characterized by higher soil moisture. Both locations were deliberately selected to be more than 16 km apart to ensure that the field data from each site correspond to different pixels in the SMAP satellite data, which has a pixel size of approximately 11 km **(Figure 1)**.

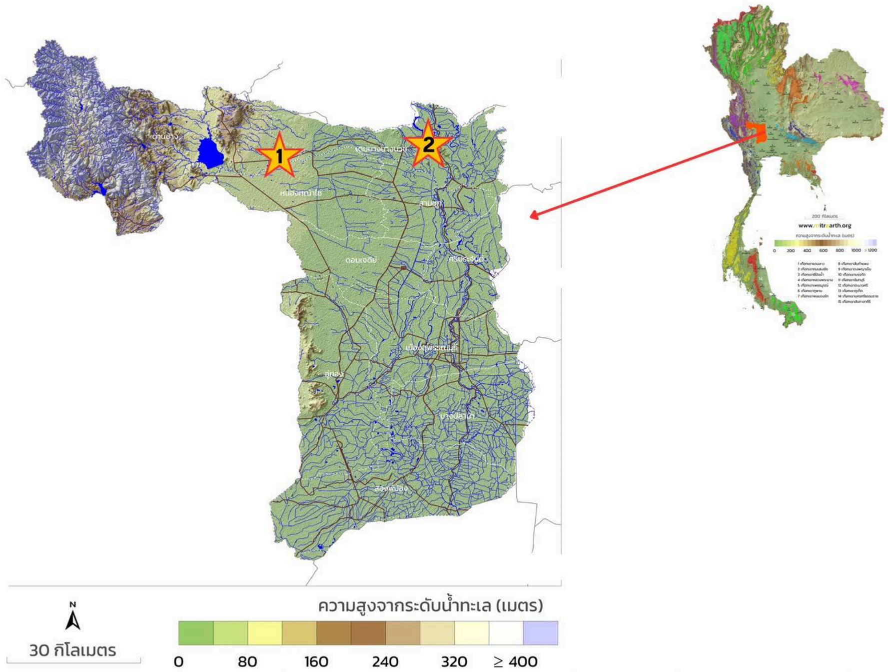

Figure 1. Map of study sites in Suphanburi Province, Thailand. Site 1 marks the sugarcane cultivation area, and Site 2 marks the rice cultivation area.

Data collection

Field soil samples in this study were collected using the GLOBE SMAP Soil Moisture Protocol. A small 4-ounce steel can was used for each sample. The can was gently pressed into the ground with a wooden block and hammer until the soil filled it. At each sampling spot, three separate samples were collected to ensure consistent, reliable data. All the samples were then dried in an oven at 90°C for 24 hours, or until fully dry.

Once dry, the samples were weighed, and soil moisture was calculated using two methods: gravimetric (by weight) and volumetric (by volume), in accordance with GLOBE's standard procedures. All data were uploaded to the GLOBE website via the classic soil data entry page (Pedosphere section). The website was used instead of the GLOBE mobile app because only the website supports reporting both gravimetric and volumetric soil moisture.

For the satellite data, this study used the SPL4SMGP.008 SMAP Level 4 Global dataset. This data provides high-accuracy measurements of soil moisture in the surface and root zones around the world every 3 hours, with each data "pixel" representing an area 9 kilometers across. The SMAP data were downloaded from NASA's AppEEARS website. For each location in the study, the SMAP dataset provided multiple parameters. However, five were selected for closer examination: surface soil moisture, root-zone soil moisture, surface temperature, soil temperature in the first layer, and precipitation. The study spanned nine years, from early 2016 to late 2025.

Data analysis

The data analysis in this study included three main statistical approaches. First, a t-test was used to compare field-measured soil moisture between the sugarcane and rice cultivation areas, allowing us to determine whether there were significant differences in average soil moisture between the two land uses. Next, we calculated descriptive statistics for the SMAP satellite soil moisture data, which summarized the range, variability, and typical values for each data band over the nine-year study period. This step provided a better understanding of overall changes in soil moisture and temperature patterns, as well as any anomalous readings at both locations. Analysis of variance (ANOVA) was also used to compare SMAP-derived soil moisture values between the two sites and across months. This enabled detection of both seasonal and spatial patterns, as well as significant differences due to location or time of year.

In addition, we used box-and-whisker plots to display the monthly distribution of surface soil moisture over each year. These plots enabled us to visually explore patterns, identify drought periods, and demonstrate that SMAP data reliably capture seasonal changes and soil moisture variability.

Results

Descriptive statistics for field-measured soil surface moisture (n = 3 for each group), reported as both weight per weight and volume per volume, are as follows. In sugarcane cultivation areas, mean soil surface moisture (weight per weight) was 0.121 ± 0.00998, and surface moisture (volume per volume) was 0.190 ± 0.00902. The standard errors were 0.00576 and 0.00521, respectively. The 95% confidence intervals were 0.0966-0.146 for soil surface moisture (weight per weight) and 0.168-0.213 for surface moisture (volume per volume). Median values were 0.121 and 0.195, with minimums of 0.112 and 0.180, and maximums of 0.132 and 0.195 for weight per weight and volume per volume, respectively.

In rice cultivation areas, mean soil surface moisture (weight per weight) was 0.578 ± 0.049,9, and surface moisture (volume per volume) was 0.477 ± 0.00781. The standard errors were 0.0288 and 0.00451, respectively. The 95% confidence intervals were 0.454–0.702 for soil surface moisture (weight per weight) and 0.457–0.496 for surface moisture (volume per volume). Median values were 0.600 and 0.477, minimum values were 0.521 and 0.469, and maximum values were 0.614 and 0.484 for the respective measures.

An independent-samples t-test was conducted to examine differences in surface soil moisture (volume per volume) between sugarcane- and rice-cultivation areas. The mean surface soil moisture for sugarcane (M = 0.19, SD = 0.01) was significantly lower than for rice (M = 0.48, SD = 0.01), $t(4) = 41.60$, $p < .001$.

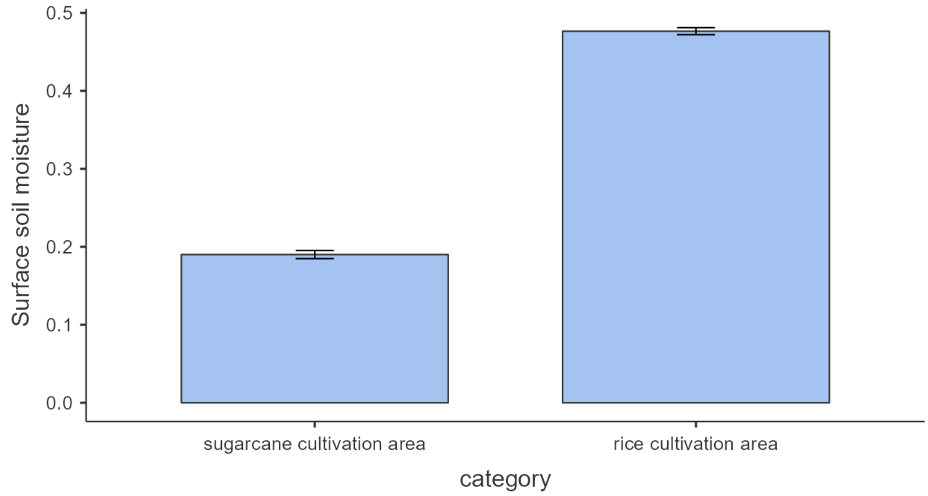

Figure 2. Bar chart comparing surface soil moisture between sugarcane and rice cultivation areas. Each bar represents the mean, with error bars indicating the standard deviation based on data collected using the GLOBE soil moisture protocol.

Descriptive statistics for soil moisture and temperature from SMAP satellite data retrieved via AppEEARS, based on 28,736 samples per cultivation area, are as follows. In sugarcane cultivation areas, the mean surface soil moisture (sm_surface) was 0.149 ± 0.0731, and root zone soil moisture (sm_rootzone) was 0.168 ± 0.0480. The mean topsoil temperature was 301 ± 3.84 K (27.85 ± 3.84 °C), and the mean surface air temperature was 302 ± 5.73 K (28.85 ± 5.73 °C). In rice cultivation areas, the mean surface soil moisture was 0.183 ± 0.0863, and root zone soil moisture was 0.214 ± 0.0471. The mean topsoil temperature was 302 ± 4.14 K (28.85 ± 4.14 °C), and the mean surface air temperature was 302 ± 6.41 K (28.85 ± 6.41 °C).

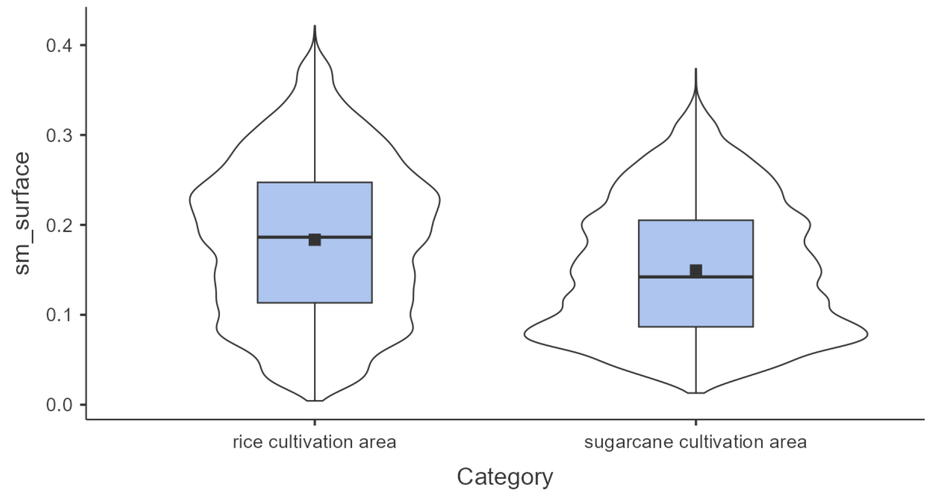

Figure 3. Violin and box-whisker plots of SMAP satellite data showing the distribution of surface soil moisture in sugarcane and rice cultivation areas.

The 95% confidence intervals for sugarcane were: sm_surface, 0.148–0.150; sm_rootzone, 0.167–0.168; top soil temperature, 301–302 K (27.85–28.85 °C); surface air temperature, 302–302 K (28.85–28.85 °C). For rice: sm_surface, 0.182–0.184; sm_rootzone, 0.214–0.215; top soil temperature, 302–302 K (28.85–28.85 °C); surface air temperature, 302–303 K (28.85–29.85 °C).

Minimum and maximum values in sugarcane areas were: sm_surface, 0.0130–0.374; sm_rootzone, 0.0821–0.329; top soil temperature, 288–317 K (14.85–43.85 °C); surface air temperature, 283–325 K (9.85–51.85 °C). For rice: sm_surface, 0.00436–0.422; sm_rootzone, 0.142–0.361; top soil temperature, 289–319 K (15.85–45.85 °C); surface air temperature, 284–329 K (10.85–55.85 °C).

An independent-samples t-test was conducted to compare surface soil moisture (sm_surface) between sugarcane- and rice-cultivation areas using SMAP satellite data. The mean surface soil moisture for sugarcane was 0.149 (SD = 0.0731, n = 28,736), while for rice it was 0.183 (SD = 0.0863, n = 28,736). This difference was statistically significant, $t(57{,}470) = 51.3$, $p < .001$, Cohen's $d = 0.43$. Levene's test was significant ($p < .05$), indicating that the assumption of equal variances was violated; therefore, results are reported using "equal variances not assumed."

Table 1. Surface and root zone soil moisture in sugarcane and rice fields, as measured in the field and estimated from SMAP satellite data.

Values are means ± standard deviations.

Land cover	Field Surface Soil Moisture (m^3/m^3)	SMAP Surface Soil Moisture (m^3/m^3)	SMAP Root Zone Soil Moisture (m^3/m^3)
Sugarcane	0.190 ± 0.009	0.149 ± 0.0731	0.168 ± 0.0480
Rice	0.477 ± 0.00781	0.183 ± 0.0863	0.214 ± 0.0471

An analysis of variance (ANOVA) was conducted to examine the effects of land cover category (sugarcane vs. rice), month, and their interaction on surface soil moisture (sm_surface) derived from SMAP satellite data. The results showed that both category and month had significant effects on surface soil moisture. The category effect was strong, with a sum of squares of 16.85 and an F-value of 6146.1 ($p < .001$), indicating that soil moisture differed significantly between sugarcane and rice areas. Likewise, the month effect was highly significant (sum of squares = 207.57, $F = 6884.9$, $p < .001$), reflecting seasonal changes in soil moisture across the year. There was also a significant interaction effect between category and month (sum of squares = 2.58, $F = 85.4$, $p < .001$), indicating that soil moisture patterns across months differed by crop type (sugarcane vs. rice). Levene's test indicated unequal variances across groups ($p < 0.001$), warranting caution in interpretation; however, given the large sample size, the results are robust, so ANOVA is appropriate. Post hoc tests using Bonferroni correction showed that the rice cultivation area had significantly higher surface soil moisture than the sugarcane area, with a mean difference of 0.0343 ($p < .001$). Multiple pairwise comparisons across months revealed significant differences in soil moisture between nearly all months ($p < .001$), highlighting strong seasonal variation. For example, the early months had higher moisture than the mid-year months, which showed lower values, consistent with dry or drought periods. In summary, both land-use type and season strongly influence soil moisture levels, and SMAP satellite data capture these differences well.

The monthly box-whisker plots of SMAP soil moisture revealed clear seasonal patterns across the years. The data indicated a cyclic variation associated with Thailand's climatic seasons. The driest periods typically occurred during March–April, corresponding to the dry season, while the highest soil moisture values were observed in September–October, reflecting the peak of the wet season **(see Figures 4 and 5)**.

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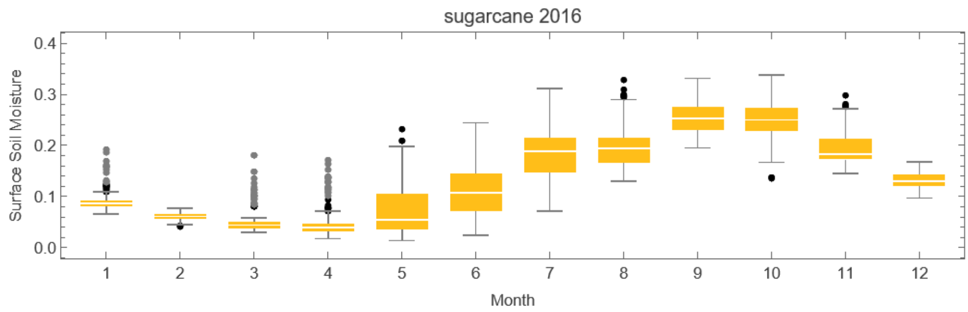
(a)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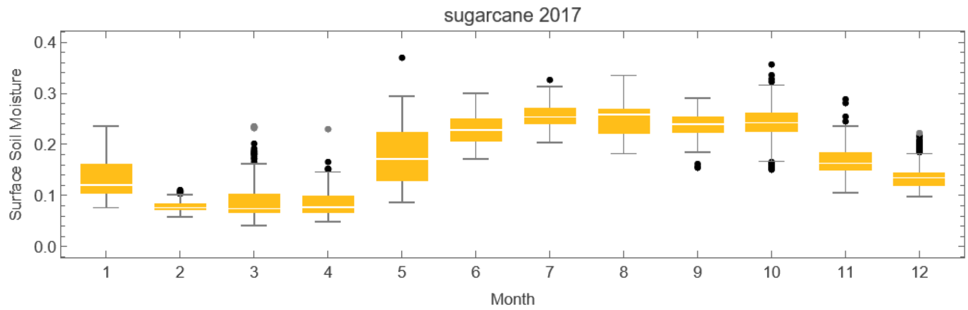
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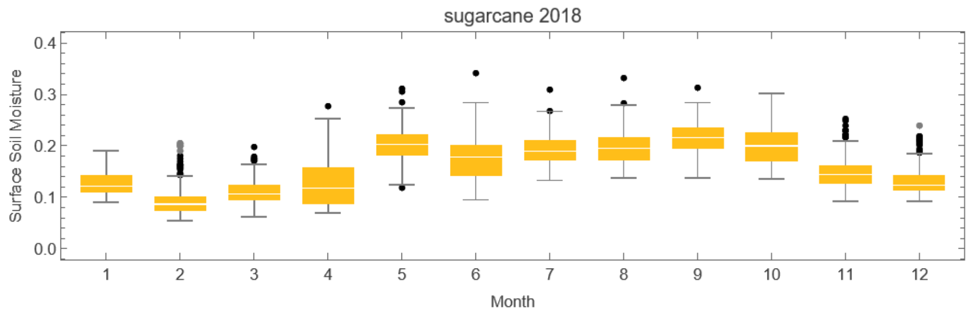
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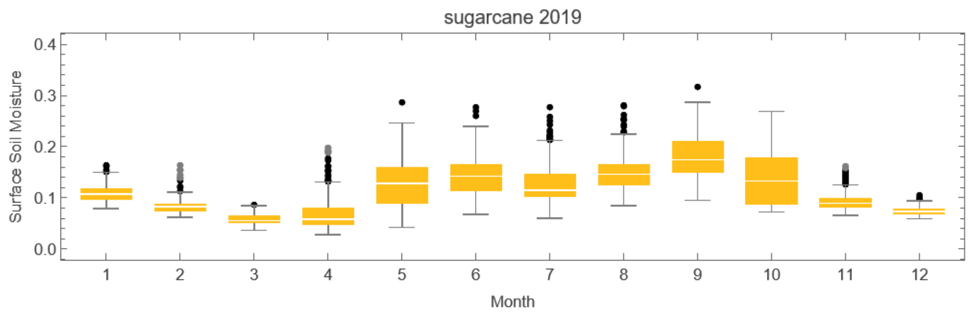
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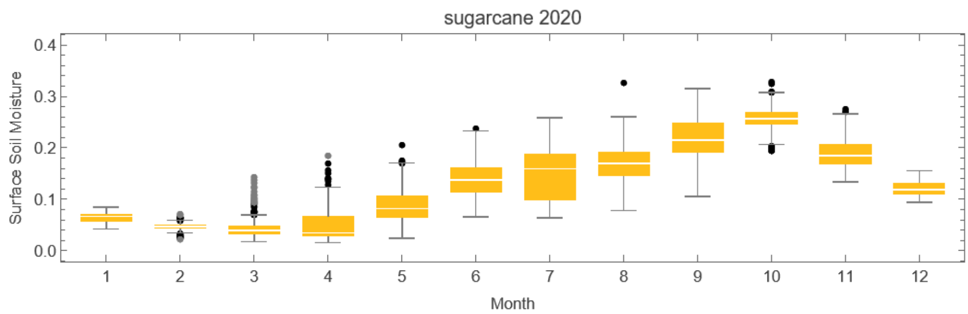
sugarcane 2020
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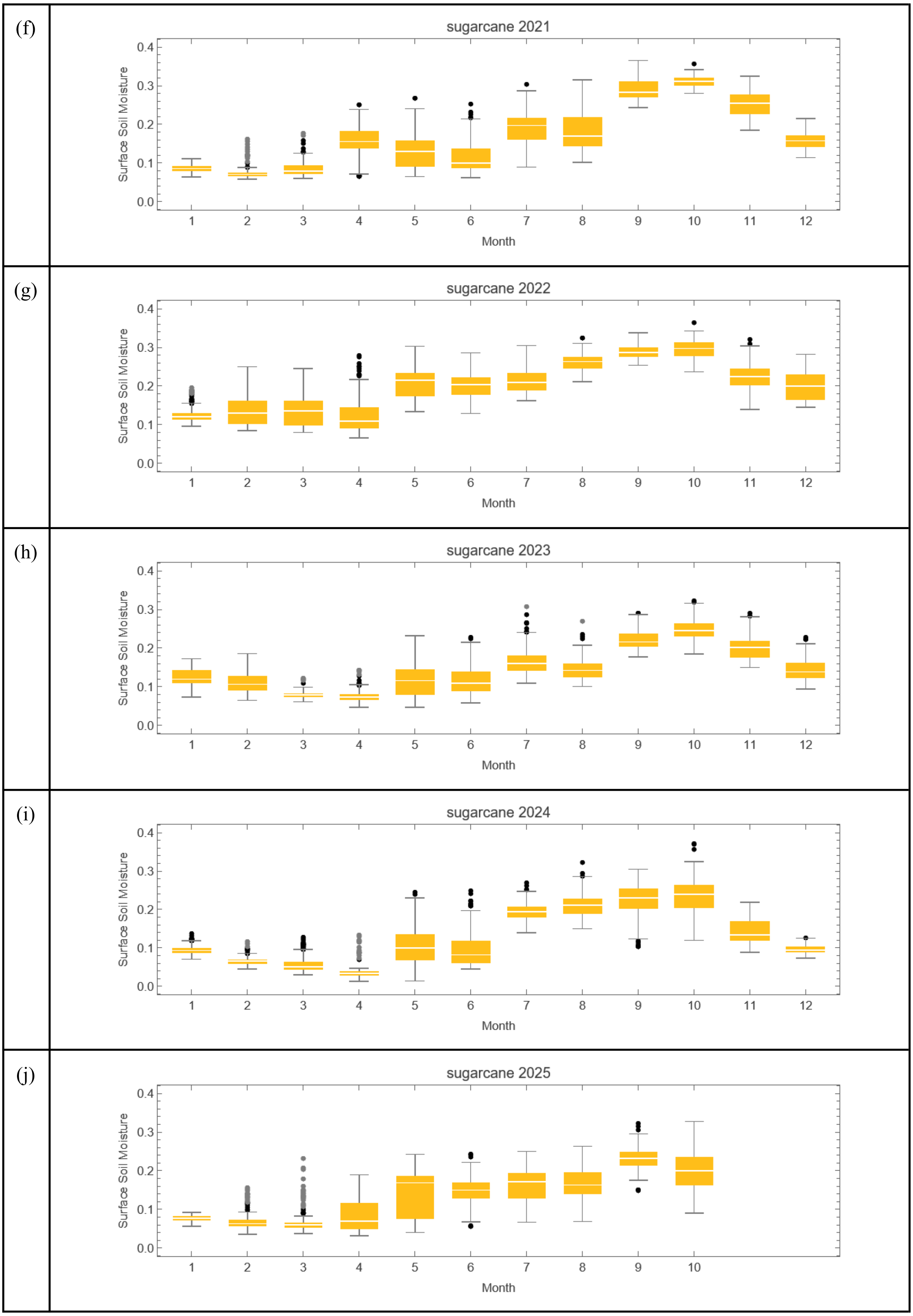
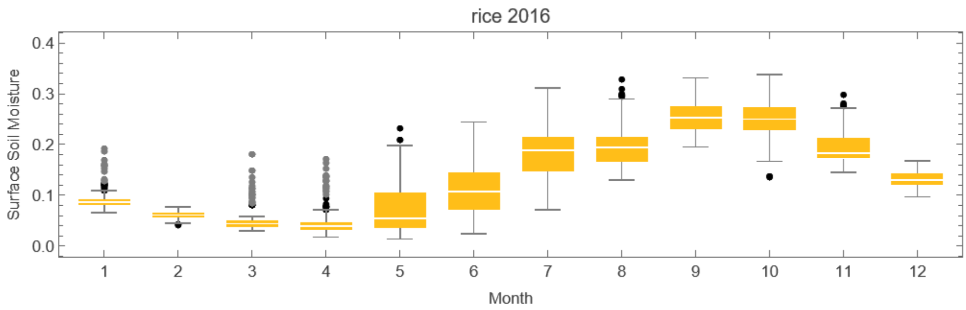


Figure 4. Monthly boxplot of SMAP satellite-derived surface soil moisture for 2016–2025 in sugarcane cultivation areas surrounding Krasaew Dam. Each box displays the distribution of surface soil moisture

values for each month across the study years, highlighting seasonal, annual, and interannual variability in soil moisture conditions.

(a)


rice 2016
Surface Soil Moisture
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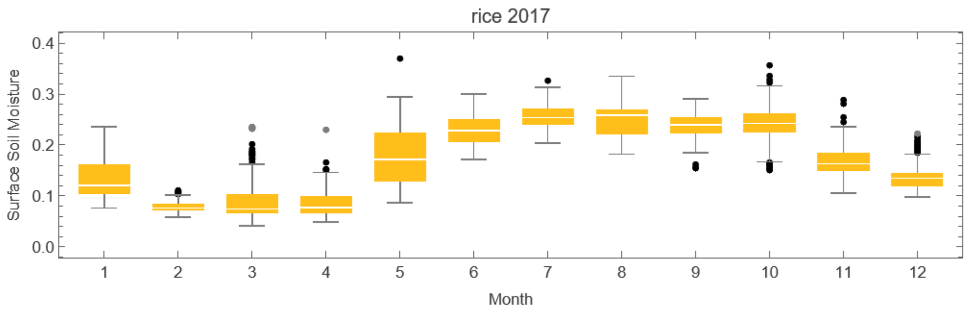
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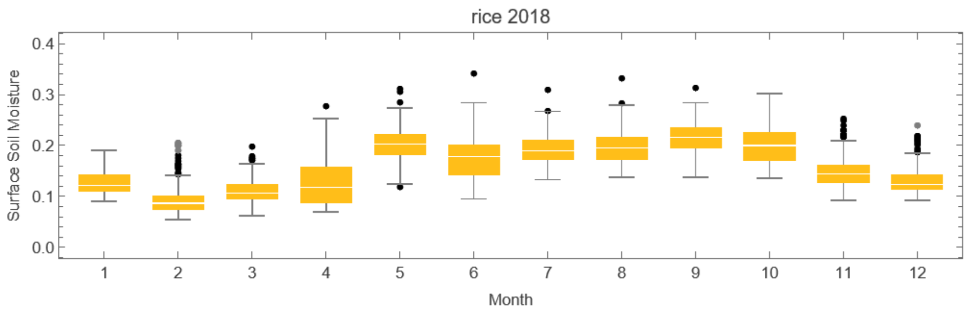
rice 2018
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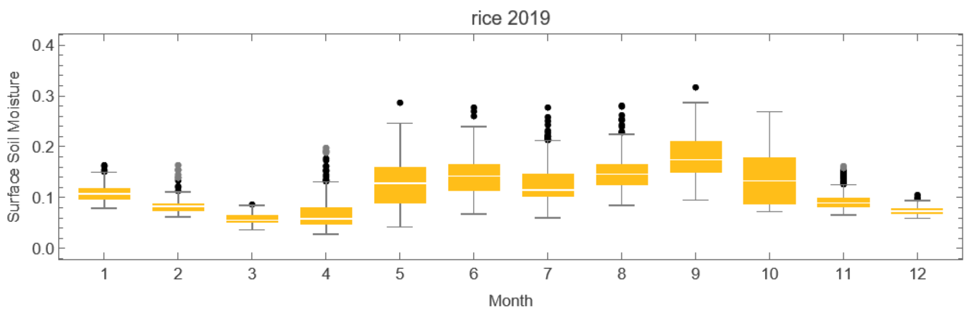
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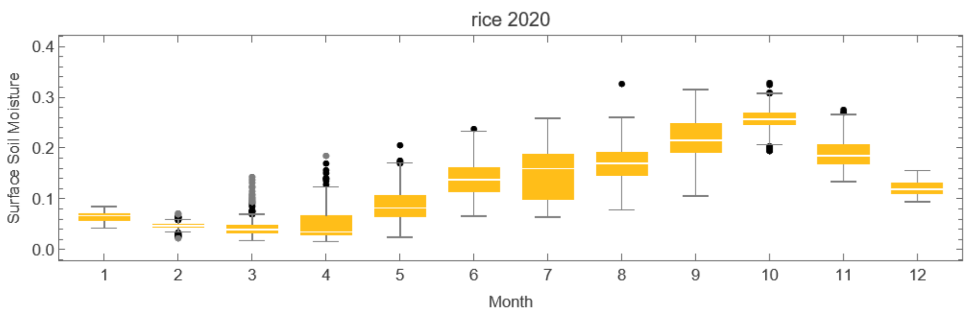
rice 2020
Surface Soil Moisture
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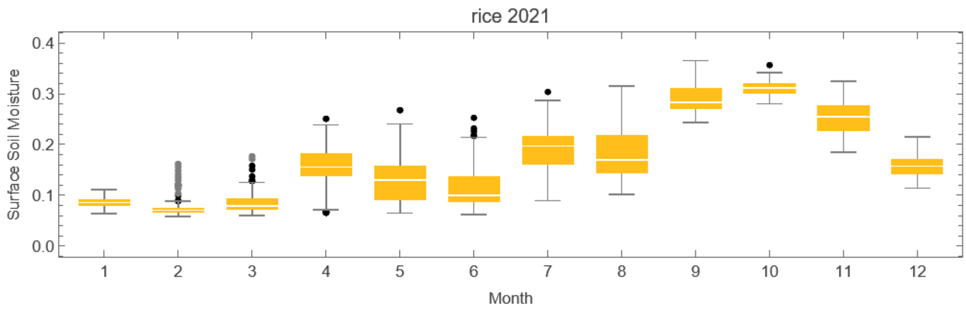

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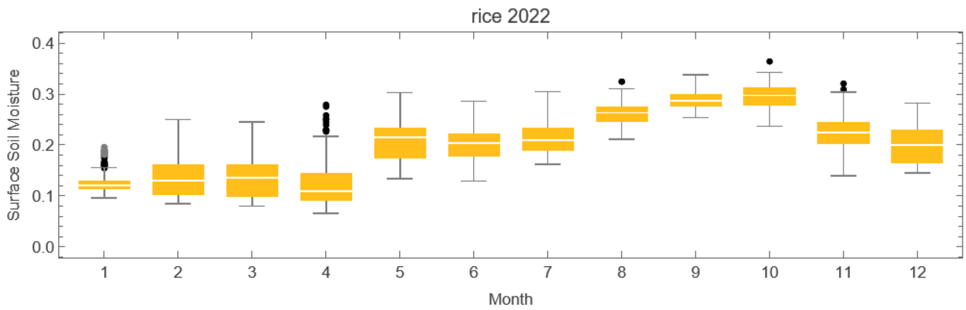

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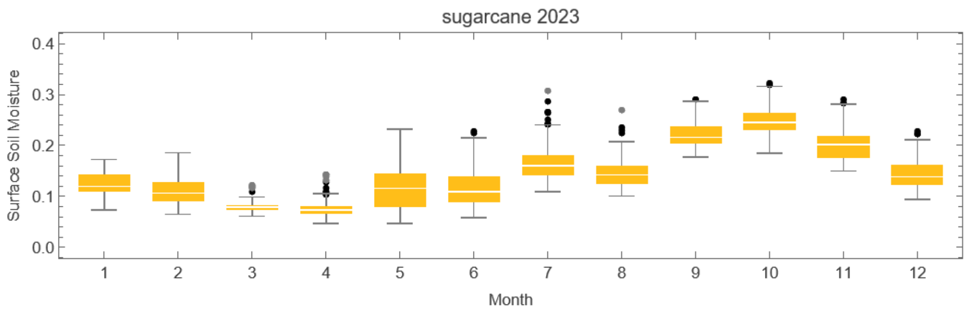

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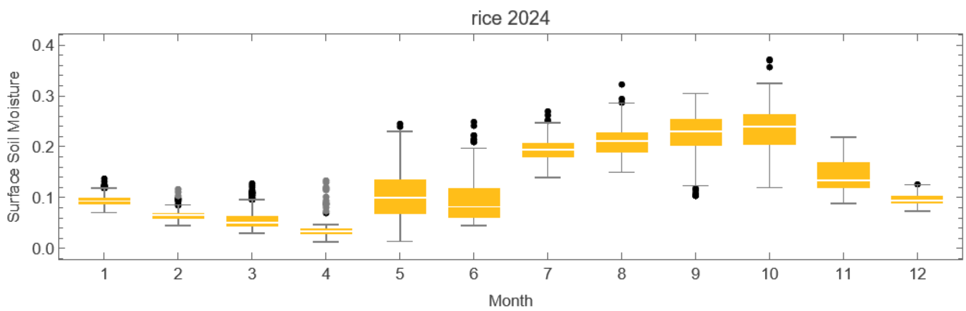

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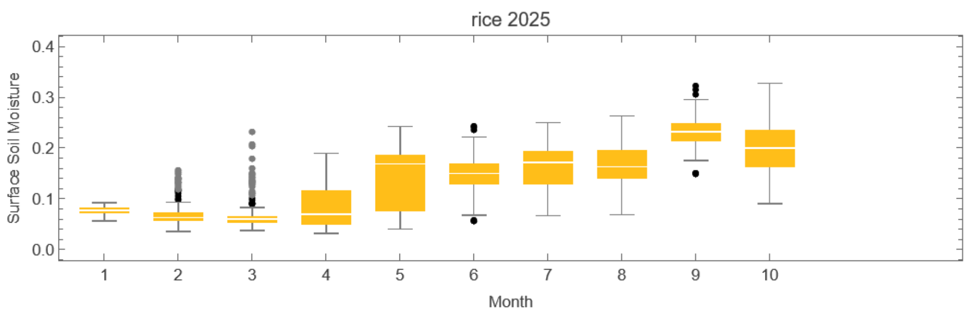

Figure 5. Monthly boxplot of SMAP satellite-derived surface soil moisture for 2016–2025 in rice cultivation areas surrounding Krasaew Dam.

Discussion

This study shows that soil moisture measurements obtained with both gravimetric and volumetric field techniques closely align with SMAP satellite data, supporting the accuracy of both methods for observing soil water in agricultural landscapes. When comparing the two main crop types, rice paddies consistently had higher surface soil moisture than sugarcane fields, regardless of whether the data were obtained from field-based sampling or from SMAP remote sensing. These differences were consistent with expectations because rice is grown in wetter, low-lying fields, whereas sugarcane prefers drier, upland conditions. Statistical tests, such as t-tests, confirmed that differences between field sites were significant in both datasets, indicating that SMAP satellite data can reliably capture soil moisture variations across both crops and landscapes.

Looking at the results in Table 1, field data from rice sites showed higher soil moisture than SMAP satellite data; for instance, rice field samples were about 0.477 m^3/m^3, while SMAP indicated 0.183 m^3/m^3 at the surface and 0.214 m^3/m^3 in the root zone. This happens because SMAP soil moisture values are averages over a large 9 km pixel that can include a mix of rice paddies, dryland crops, buildings, and other land features. At the same time, field measurements reflect conditions at a specific time and place. Sugarcane fields followed the same pattern: field measurements (about 0.190 m^3/m^3) were higher than the SMAP surface value (0.149 m^3/m^3), but both data sources showed that sugarcane is much drier than rice. Even though the specific numbers may differ, both datasets consistently show the same trend: rice areas are wetter than sugarcane areas.

The main reasons for differences between SMAP and field measurements are differences in data collection methods and locations. Field data represent a single point in time and space and provide precise information on local soil conditions. At the same time, SMAP averages moisture across a pixel over a wider region and multiple passes, thereby smoothing out small-scale differences. Additionally, while the field method directly captures the unique wetness of rice paddies, SMAP combines data from multiple land uses within a single pixel, thereby reducing the soil moisture value displayed for that pixel, particularly in landscapes with mixed land cover. Despite these challenges, the strong agreement in patterns between the two approaches demonstrates the value of integrating satellite and field measurements to improve farm water management and regional agricultural planning.

In this study, monthly boxplots of SMAP satellite data on surface soil moisture for 2016–2025 in rice-growing areas near Krasaew Dam exhibit apparent seasonal variation. These boxplots illustrate how soil moisture varies by month, highlighting wet and dry periods **(see Figures 4 and 5)**. Specifically, they reveal a marked dry season from January to April in 2024, during which soil moisture drops sharply **(see Figures 4(i) and 5(i)).** Interestingly, some months during that dry period exhibit outliers with unusually high soil moisture, which may be due to additional water supplied by Krasaew Dam **(see Figures 4(i) and 5(i)).** To confirm this, future studies should use related data, such as dam water releases or rainfall, alongside SMAP soil moisture records. Combining these data sources will improve the interpretation of soil moisture changes and more accurately assess drought risk in the area.

Conclusion

This research shows that SMAP satellite data can help us watch soil moisture in farms around Krasaew Dam. The satellite data closely matches what we measured by hand in the field. We found that rice fields in the low areas always have wetter soil than sugarcane fields on high ground. SMAP data also helps us observe changes in soil moisture over many years, including during wet seasons. Our results show that SMAP is a valuable tool for farmers and planners in Thailand better to manage crops and water in a changing climate.

I would like to claim IVSS badges

1. I AM A STUDENT RESEARCHER

We would like to claim the "I AM A STUDENT RESEARCHER" badge because, in this project, we worked together to collect field data using the GLOBE protocol. We also formulated a scientific hypothesis, tested our ideas, and compared the results using field measurements and satellite data. Our teamwork and investigation show that we have practiced important science skills as high school student researchers.

2. I WORK WITH SATELLITE DATA

We would like to claim the "I WORK WITH SATELLITE DATA" badge because our research involved using SMAP satellite data from NASA to study soil moisture. We practiced technology skills by processing satellite data for our research sites, which strengthened our science abilities and helped us connect classroom lessons to real-world data and analysis.

3. I AM A DATA SCIENTIST

We would like to claim the "I AM A DATA SCIENTIST" badge because, during this project, we learned how to collect, organize, and analyze data from both our fieldwork and from satellites. We used descriptive statistics, t-tests, and ANOVA to identify patterns and differences in our data. By working with diverse datasets and applying scientific methods to conclude, we gained experience as high school data scientist**s.**

4. I AM AN EARTH SYSTEM SCIENTIST

We would like to claim the "I AM AN EARTH SYSTEM SCIENTIST" badge because, throughout this project, we studied how soil moisture changes due to different land uses and elevations in our area. Using environmental data—such as field measurements and SMAP satellite data—we learned how water, soil, and temperature interact within the Earth system. This project helped us better understand how natural processes are interconnected and why they matter to people and agriculture.

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