Mapping Earth Systems for Local Sustainability Using Google Earth Engine, GLOBE Soil, and SMAP Data.

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Abstract
This study explores the integration of satellite data, field measurements, and IoT sensors to create detailed soil moisture maps for agricultural and environmental applications. Using SMAP satellite data from NASA, field data collected by students through the GLOBE program, and IoT sensor data, the study demonstrates how these resources can be combined to produce reliable, accessible maps. The study focuses on Trang Province, Thailand, where field measurements were taken at two sites: a rubber plantation and a coastal sand beach. The research investigates two key questions: (1) How can SMAP, GLOBE, and IoT data be combined to create useful soil moisture maps for local farmers and communities? (2) How well do these maps match field-collected moisture data? Results show that satellite data from SMAP, when compared with field measurements, provide accurate estimates of soil moisture, with values of 35.0 ± 2.65% in the rubber plantation and 5.0 ± 0% on the beach. The study successfully developed an interactive soil moisture map with 35 layers accessible through Google Earth Engine (GEE), offering temporal and spatial data on soil moisture dynamics from 2016 to 2021. This tool empowers local stakeholders by providing actionable data for sustainable agriculture planning, water resource management, and climate change adaptation, while also contributing to the United Nations Sustainable Development Goals. The findings emphasize the value of combining remote sensing, citizen science, and technology for solving local sustainability challenges.

Research Questions

1. How can we use SMAP satellite data, GLOBE student measurements, and Google Earth Engine to produce soil moisture maps for Trang Province that help farmers and local communities?
2. How well do our soil moisture maps match the soil moisture data collected by students and IoT sensors in Trang Province’s rubber plantations and coastal areas?

Introduction

The world is experiencing profound environmental changes, including global warming, natural disasters, and escalating resource crises. Water and food scarcity have led to widespread famine in many regions, posing severe threats to international stability if left unmanaged. One critical factor in this crisis is soil moisture, which plays a vital role in agriculture, water management, and climate regulation. Understanding soil moisture dynamics enables accurate predictions of droughts, floods, and agricultural yields, directly supporting the United Nations Sustainable Development Goals (SDGs), particularly those related to zero hunger, clean water, and climate action. Remote sensing technologies, such as NASA's Soil Moisture Active Passive (SMAP) satellite, provide essential global tools for monitoring soil moisture, advancing efforts to achieve these critical objectives.

The GLOBE (Global Learning and Observations to Benefit the Environment) project offers students worldwide the opportunity to participate in hands-on science by collecting real-world soil moisture data and comparing it with satellite observations. This initiative fosters a deeper understanding of Earth's natural processes while connecting local environmental measurements to global datasets. NASA's SMAP satellite, launched in 2015, measures soil moisture in near real-time, updating every three hours (Entekhabi et al., 2010). These high-resolution data support agricultural planning, water resource management, and disaster prediction efforts, particularly for droughts and floods (Colliander et al., 2017).

Google Earth Engine, a cloud-based platform for geospatial analysis, integrates SMAP data into its public database, enabling researchers to process large datasets efficiently without extensive computational resources (Gorelick et al., 2017). By combining SMAP data with GEE's analytical tools, soil moisture maps can be generated to monitor temporal changes, aiding decision-making in water management and agriculture, especially in areas prone to droughts or flooding (Mutanga & Kumar, 2019).

Trang Province, located in southern Thailand within Southeast Asia, is the focus of this study due to its diverse topography, which includes coastal plains, plateaus, and mountains. This region is ideal for examining soil moisture variations across different landscapes. Known for its agricultural production—such as rice, rubber, and oil palm—Trang's economy relies heavily on soil and water conditions (Phongpaichit & Baker, 2015). Additionally, its coastal areas feature mangrove forests that help prevent erosion, highlighting the interplay between natural and agricultural ecosystems (Kathiresan & Bingham, 2001). This diverse environment and varied soil types provide an excellent opportunity to study soil moisture in ecological and economic contexts.

This research focuses on integrating SMAP satellite data with Google Earth Engine (GEE) to create soil moisture maps at the community level. These maps serve as vital tools for future planning and management of local resources, particularly in agriculture and water management in regions covered by SMAP's data. SMAP employs an L-band radar and radiometer to measure soil moisture, penetrating clouds, and moderate vegetation with a resolution of up to 9 kilometers, making it highly accurate for local and global studies

(Entekhabi et al., 2014). Such capabilities support climate research, drought forecasting, and sustainable water management (McColl et al., 2017).

This study utilizes SMAP (Soil Moisture Active Passive) satellite data and Google Earth Engine (GEE) to create a soil moisture map of Trang Province, delivering valuable insights into soil and water conditions for stakeholders, including government agencies, farmers, and local communities. These insights facilitate agricultural planning, water resource management, and natural resource conservation, promoting local sustainability. The research combines multiple data sources: field data gathered manually by students using the Soil moisture SMAP block pattern protocol (GLOBE, 2018), real-time measurements collected via IoT-based sensors, and satellite-derived SMAP data processed through Google Earth Engine. Combining student-collected manual data and IoT sensor data enhances and verifies satellite observations, ensuring the soil moisture maps are accurate and reliable.

Materials and Methods

Study site

The study area lies within Trang Province, Thailand, in Southeast Asia, defined by geographic coordinates spanning 6.9493° N to 8.0984° N in latitude and 99.0547° E to 100.1424° E in longitude. This region features a diverse landscape of coastal plains, agricultural lands, and mountainous terrain, making it well-suited for examining soil moisture and environmental characteristics. The tropical monsoon climate of Trang Province, characterized by high rainfall and distinct wet and dry seasons (Peel et al., 2007), influences soil moisture variability, providing an ideal setting to investigate water dynamics and their impact on agriculture and natural resources. These boundaries focus the analysis on this distinct portion of Trang Province.

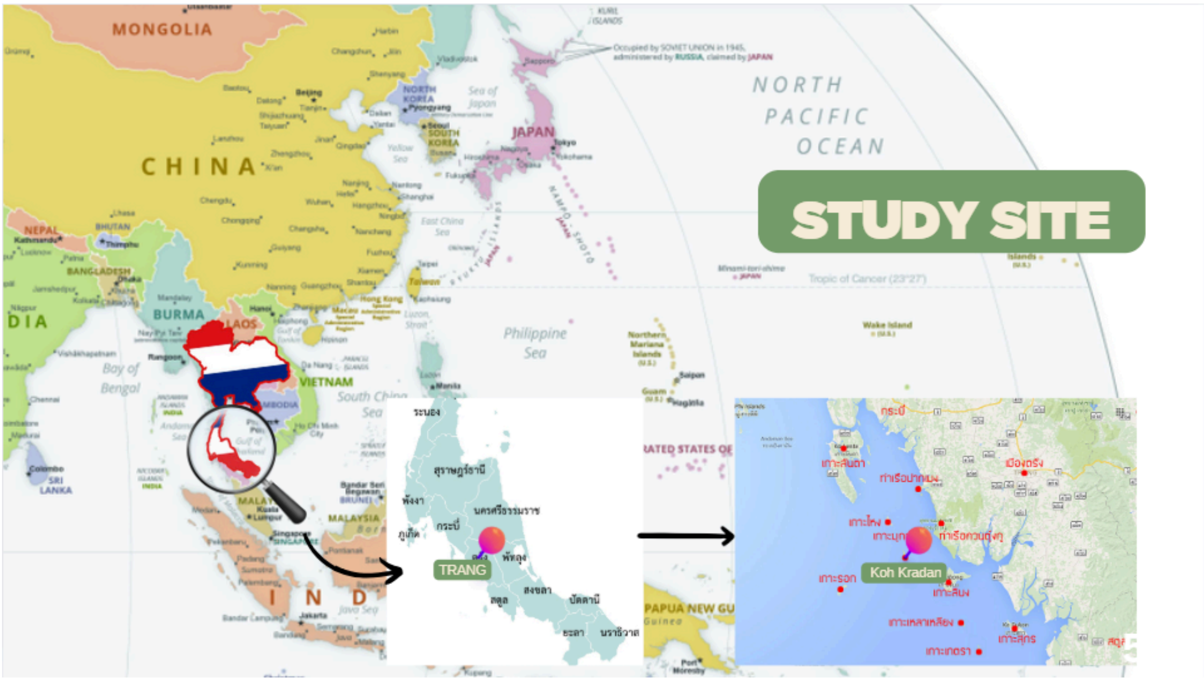

Figure 1. Study area in Trang Province, southeastern Thailand, Southeast Asia.

Two distinct sites are investigated within this designated area, each representing different land use patterns. The first site, located at 7.58375° N, 99.59084° E, is a rubber plantation, an agricultural land use type. Soil moisture content at this site is presumed regulated by irrigation practices or precipitation patterns associated with rubber cultivation. The second site, found at 7.30919° N, 99.25888° E on Koh Kradan Island along the coastline, is influenced by marine proximity. Soil moisture in this coastal zone is likely modified by tidal fluctuations or the prevalence of sandy substrates.

These sites exemplify distinct land use categories: agricultural plantations and coastal environments. The tropical monsoonal climate prevalent in Trang Province induces significant variability in soil moisture across these locations. Analyzing these sites facilitates a comprehensive understanding of the region's ecological and hydrological dynamics.

Data Collection and Analysis

Field Data Collection: We use the SMAP data collection protocol to collect the data. A 2-inch steel pipe is cut into sections 5 cm and sharpened to create a soil sampling cylinder. Strong equipment is required since some soils in Thailand are dense and clay-rich. According to the protocol, we use a wooden board as a base and drive the cylinder into the soil. Once the soil sample is collected, it is dried at 90°C before entering the data into the GLOBE Data Entry system. We measure data from 25 to 26 Feb 2025.

IoT-Based Data Collection: The wireless Vantage Vue, a research-grade weather station, provides all the features utilized in our study. Equipped with sensors, it collects soil moisture and rainfall data at depths of 10, 30, 60, and 90 cm. The collected data are automatically transmitted to the cloud and accessible on the website https://www.weatherlink.com/, where we can instantly generate graphs and download the data for analysis.

Data Sources: This study utilized SMAP (Soil Moisture Active Passive) satellite data from two primary platforms. The first source was the Google Earth Engine (GEE) Data Catalog (https://developers.google.com/earth-engine/datasets/catalog), which provided spatially continuous maps illustrating soil moisture distribution. The second source was AppEEARS (Application for Extracting and Exploring Analysis Ready Samples) (https://appeears.earthdatacloud.nasa.gov/), which facilitated the extraction of time-series soil moisture data, enabling an analysis of temporal variations. Two key SMAP datasets were selected: a) the NASA-USDA Enhanced SMAP Global Soil Moisture Dataset and b) the SPL4SMGP.007 SMAP L4 Global 3-Hourly 9-km Surface and Root Zone Soil MoistureDataset. These datasets provided high-resolution, three-hourly updated records of soil moisture at different depths, with surface moisture measured at 0-5 cm and root-zone moisture extending from 0-100 cm. This study used SMAP data to create maps that will be useful for the local community, which is the main objective of this research.

Data Analysis Approach: This study applied two complementary methods for soil moisture analysis. The first method, Remote Sensing Data Retrieval, involved processing SMAP data using Google Earth Engine for spatial analysis and AppEEARS for time-series analysis. The second method, Field Measurements, incorporated direct soil moisture sampling at study sites using the GLOBE Soil Moisture Data Protocol, which follows standardized manual sampling techniques. Additionally, real-time soil moisture monitoring was conducted through IoT-based sensors using the Davis Air and Soil Weather Station. Field data were used to confirm and support the accuracy of the maps generated from SMAP data. By integrating satellite-derived data with ground-based measurements, this study aimed to validate SMAP observations, enhance soil moisture accuracy assessments, and provide a comprehensive understanding of soil moisture variability across different land use settings.

Results

Surface soil moisture data were collected from two study sites, a rubber tree plantation, and a sand beach, using field measurements following the GLOBE Protocol and SMAP satellite data. The analysis includes annual averages for 2024, February 2024 averages, long-term averages from 2020 to 2024, and February averages over the same period (see Table 1).

For the rubber tree plantation, field measurements recorded a mean surface soil moisture of 35.0 ± 2.65% (90% confidence interval: 30.5–39.0%). SMAP data for 2024 indicated an annual mean of 41.2 ± 7.29% (CI: 41.5–41.8%), while the February 2024 average was 40.5 ± 1.61% (CI: 40.0–41.0%). The long-term SMAP dataset from 2020 to 2024 showed a mean of 41.5 ± 6.46% (CI: 41.3–41.8%), with the February 2020–2024 average at 39.9 ± 4.43% (CI: 39.3–40.5%) (see Fig 1, Fig 2).

For the sand beach, field measurements recorded a mean surface soil moisture of 5.0 ± 0% (CI: 5–5%). SMAP data for 2024 showed an annual mean of 42.2 ± 6.70% (CI: 41.6–42.7%), while the February 2024 average was 40.1 ± 1.68% (CI: 39.6–40.6%). The long-term SMAP dataset from 2020 to 2024 recorded a mean of 40.4 ± 6.76% (CI: 40.1–40.6%), with the February 2020–2024 average at 37.6 ± 5.60% (CI: 36.9–38.4%) (see Table 1).

Table 1: Surface Soil Moisture Statistics of Two Study Sites – Comparison of Field Data and SMAP Satellite Data (Mean ± SD, with 90% confidence interval)

	GLOBE protocol field Surface Soil Moisture (n=3)	SMAP data 2024 (n=366)	SMAP data February 2024 (n=29)	SMAP data 2020-2024 (n=1827)	SMAP data February 2020-2024 (n=142)

Rubber tree plantation	35.0 ± 2.65 (30.5 - 39.0)	41.2 ±7.29 (41.5-41.8)	40.5±1.61 (40.0-41.0)	41.5±6.46 (41.3-41.8)	39.9±4.43 (39.3-40.5)
Sand beach	5± 0 (5-5)	42.2±6.70 (41.6- 42.7)	40.1±1.68 (39.6-40.6)	40.4±6.76 (40.1-40.6)	37.6±-5.60 (36.9-38.4)

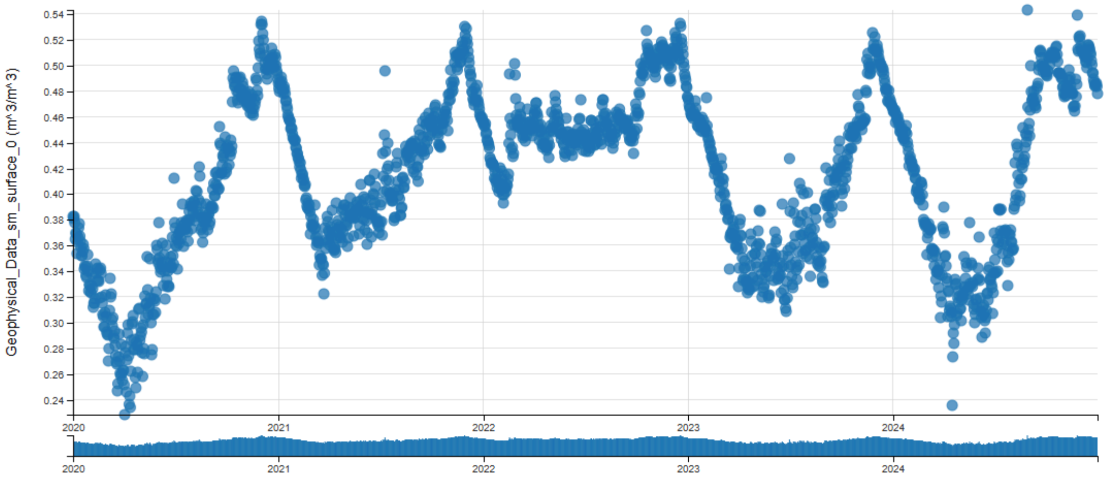

Figure 2. Surface soil moisture data for Study Site 1 from 2020 to 2025, based on field measurements and SMAP satellite data obtained from the AppEEARS platform.

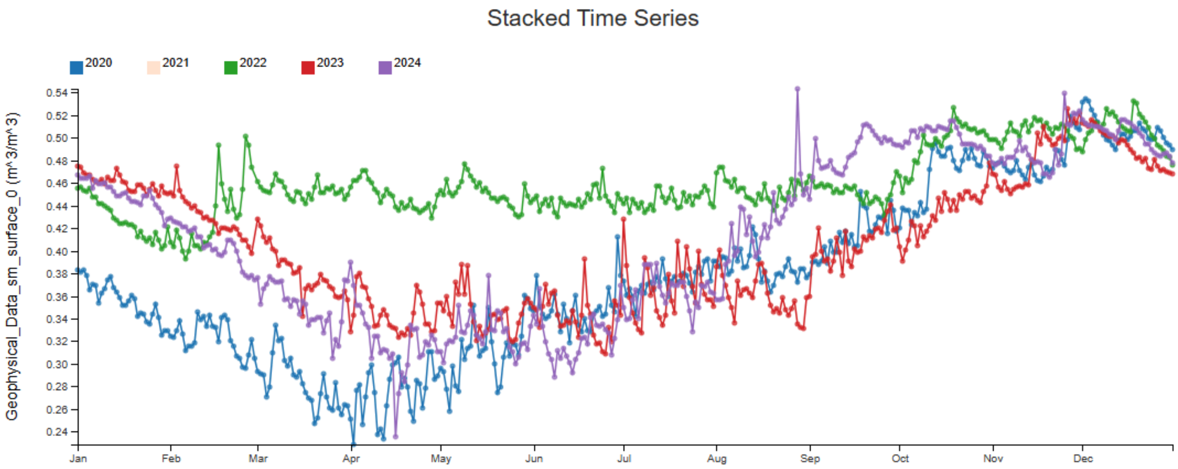

Figure 3. The time series of surface soil moisture at Study Site 1, derived from SMAP satellite data and field measurements, shows seasonal and annual trends.

The IoT sensor data indicates that during the collection period, rainfall caused fluctuations in soil moisture at the surface, while moisture levels in the root layer remained unchanged by the amount of rainfall, as shown in Figure 4. The maximum recorded rainfall was 6.8 mm in 15 minutes.

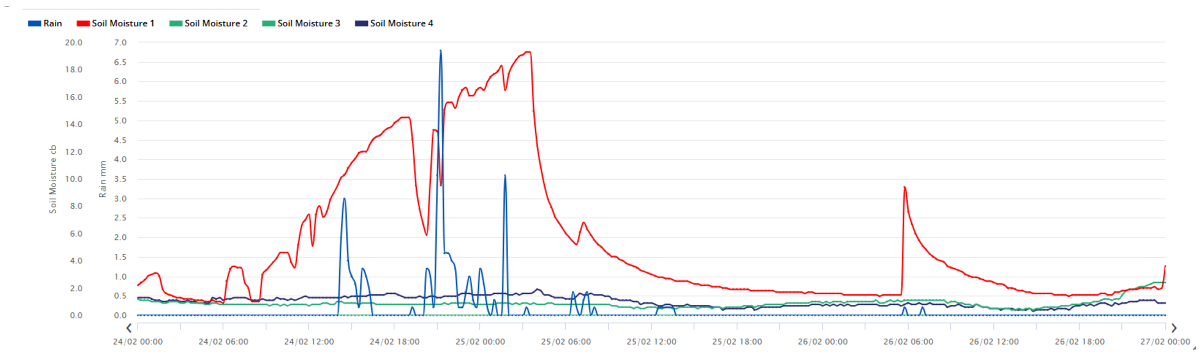

Figure 4. WeatherLink Cloud generated a graph using data from an IoT sensor, illustrating soil moisture levels and rainfall data.

The results of generating SMAP data for Trang Province indicate that it is feasible to create a soil moisture map covering the entire province using JavaScript (Figure 5). The map, with a spatial resolution of 10 km per pixel, represents soil moisture distribution with a color scale that can be customized based on the study's design. A total of 35 map layers were produced, including a single layer representing the average soil moisture for the entire province over the period from 2016 to 2021, six layers depicting the annual average soil moisture for each year within this period, four layers illustrating the average soil moisture for each quarter over the six-year duration, and 24 layers representing the quarterly averages for each individual year. This dataset provides a comprehensive spatial and temporal analysis of soil moisture dynamics across Trang Province.Using Google Earth Engine (GEE) and the code we developed, we were able to transform the map into a user-friendly version through the Google Earth Engine App. This allows users to access and view the map directly in a web browser, without the need for any additional software installations (Figure 6).

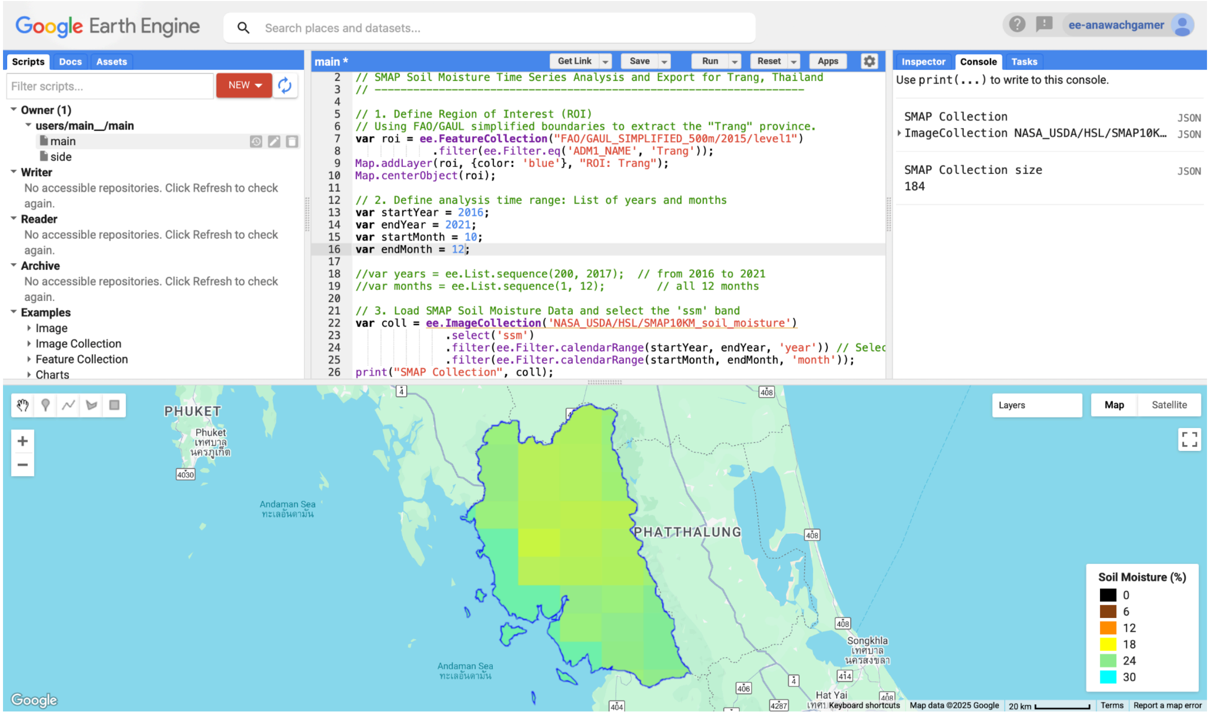

Figure 5. Soil moisture distribution map of Trang Province, generated using SMAP satellite data and Google Earth Engine (GEE), with coding capabilities offering opportunities to recreate similar maps for different regions in the future.

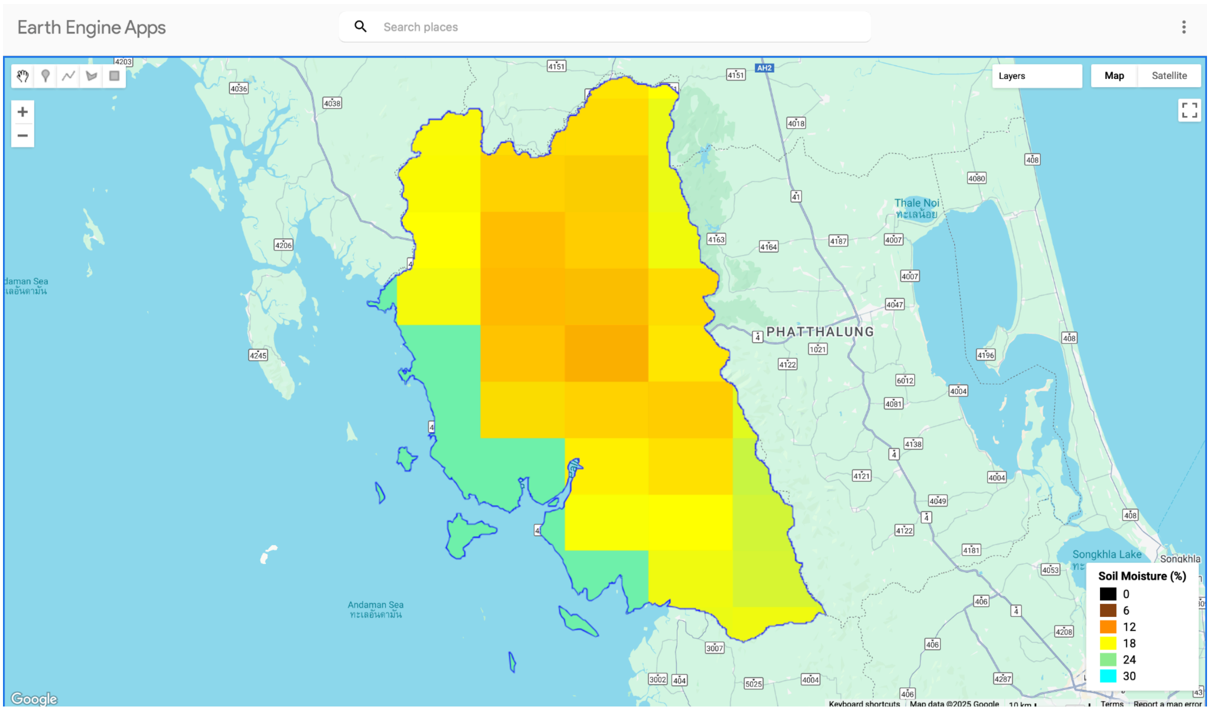

Figure 6. Interactive map within the Google Earth Engine (GEE) application, enabling farmers and organizations to visualize and analyze real-time data, including soil moisture levels, land cover, and flood events, to support informed decision-making for environmental management, agricultural planning, and sustainable practices.

Discussion

Although the field data shows some variation from the average values (Table 1), the measured data still fall within a reasonable range when examined in the graphs (Figures 2 and 3), confirming the reliability of the values from the SMAP data and the maps we created.The comparison between soil moisture data derived from the GLOBE Protocol and SMAP satellite measurements reveals notable discrepancies, primarily attributable to the coarse 9 km pixel resolution of the SMAP data (Entekhabi et al., 2010). This large pixel size integrates soil moisture values over expansive areas, potentially obscuring localized variations and compromising accuracy in regions with heterogeneous land cover. For instance, our study identified significant differences between measurements at Koh Kradan and the rubber plantation. These disparities may arise from the coastal area's diverse soil composition, including sandy soils and clay-rich mangrove forests (Soil Survey Staff, 2014). Field measurements in sandy soils yielded substantially lower values than SMAP averages, indicating that coastal zones with mixed soil types may be unsuitable for developing soil moisture algorithms, particularly for calibrating future satellite datasets (Chan et al., 2016).

Analysis of Figure 2 reveals pronounced seasonal patterns in soil moisture, accompanied by irregular fluctuations. This seasonality underscores the potential of SMAP data as a valuable resource for climate change studies, facilitating the tracking of soil moisture trends and their responses to shifting weather patterns over time (Kerr et al., 2016).

Google Earth Engine (GEE) proved more practical than the AppEEARS platform for map generation (Gorelick et al., 2017). GEE offers key benefits, including scalability, clear and interpretable visualizations, and straightforward graph generation capabilities comparable to AppEEARS. However, challenges include the learning curve required to master the platform and memory management issues during image processing. Without adequate programming expertise, these limitations can lead to system inefficiencies or freezes (Mutanga & Kumar, 2019).

In this study, we were unable to create a map using data from SPL4SMGP.007 SMAP due to its high level of detail, with data collected every 3 hours. When attempting to create a broad, long-term statistical map, the data's granularity exceeds the capabilities of Google Earth Engine. As a result, we had to rely on the NASA-USDA SMAP data, which is no longer being updated, limiting us to creating maps for past periods only. To address this issue, a more complex program would be required to overcome memory limitations and effectively process the detailed data.

Our approach utilized simple, cost-effective coding tools to develop a scalable soil moisture map adaptable to other regions. The replicability of these findings highlights the synergy between earth science and engineering in addressing community challenges sustainably, providing a framework for future environmental monitoring and management initiatives (Jackson et al., 2019).

Conclusion

This study demonstrates the potential of utilizing satellite data and existing scientific resources without requiring large financial investments. It highlights the advantages of using new technology for environmental monitoring and decision-making. However, the study also stresses the continued importance of fieldwork for developing accurate data. By combining satellite data with field data collection, we can achieve reliable results that are beneficial to local communities and stakeholders. Even with advanced technology, it is essential to have individuals who deeply understand science to fully leverage these tools. Furthermore, fostering youth development through programs like GLOBE is crucial, as it equips them with both scientific and technological knowledge that will be invaluable for future advancements.

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Claim for "I am a Data Scientist" Badge

Our project highlights our data science skills by combining GLOBE soil data, SMAP satellite data, and Google Earth Engine (GEE) to create detailed maps for Trang Province. We meticulously collected and cleaned student-reported data (raw data available in the Appendix), applied linear regression and time series analysis, and visualized soil moisture trends using GEE graphs and tables. Our statistical analysis, presented in Table 1, identified patterns that aligned with published SMAP data, despite challenges such as discrepancies in sandy soil, which we addressed through field validation. This project contributes to local sustainability efforts and paves the way for future IoT integrations, making us proud to earn the "I am a Data Scientist" badge.

Claim for "I AM A PROBLEM SOLVER" Badge

We use innovative technologies that are both practical and easily replicable, helping to address global challenges. Our approach demonstrates how these solutions can be adapted and implemented to solve real-world problems effectively, earning us the "I AM A PROBLEM SOLVER" badge.

Claim for "I AM AN ENGINEER" Badge

We developed an advanced system to monitor soil moisture in Trang Province. By designing and programming a solution using JavaScript in Google Earth Engine, our custom JavaScript code processed complex datasets and created a 35-layer mapping tool. We adapted sampling methods for dense soils to ensure precision and accuracy. This combination of technical design, programming, and systems thinking has provided valuable insights for agriculture and water management, showcasing our engineering skills and earning us the "I AM AN ENGINEER" badge.

Google Earth Engine Code

```
var roi = ee.FeatureCollection("FAO/GAUL_SIMPLIFIED_500m/2015/level1")
          .filter(ee.Filter.eq('ADM1_NAME', 'Trang'));
Map.addLayer(roi, {color: 'blue'}, "ROI: Trang");
Map.centerObject(roi);

// 2. Define analysis time range: List of years and months
var startYear = 2016;
var endYear = 2021;
var startMonth = 1;
var endMonth = 3;

//var years = ee.List.sequence(2009, 2017);  // from 2016 to 2021
//var months = ee.List.sequence(1, 12);       // all 12 months

// 3. Load SMAP Soil Moisture Data and select the 'ssm' band
var coll = ee.ImageCollection('NASA_USDA/HSL/SMAP10KM_soil_moisture')
            .select('ssm')
            .filter(ee.Filter.calendarRange(startYear, endYear, 'year')) // Select only the years
            .filter(ee.Filter.calendarRange(startMonth, endMonth, 'month'));
print("SMAP Collection", coll);
print("SMAP Collection size", coll.size());

// 4. Set visualization parameters for soil moisture
var soilVis = {
  min: 0.0,
  max: 30.0,
  palette: ['000000', '8B4513', 'FF8C00', 'FFFF00', '90EE90', '00FFFF'],
};

// 5. Display the overall mean soil moisture layer (clipped to ROI)
var soilMoistureMean = coll.mean().clip(roi);
Map.addLayer(soilMoistureMean, soilVis, 'Soil Moisture Mean');

// 6. Add legend to the map
var legend = ui.Panel({
  style: {
    position: 'bottom-right',
    padding: '8px 15px'
  }
});

var legendTitle = ui.Label({
  value: 'Soil Moisture (%)',
  style: {
    fontWeight: 'bold',
    fontSize: '14px',
    margin: '0 0 4px 0',
    padding: '0'
```

```
  }
});

var legendColors = ['000000', '8B4513', 'FF8C00', 'FFFF00', '90EE90', '00FFFF'];
var legendLabels = ['0', '6', '12', '18', '24', '30'];

var legendPanel = ui.Panel({
  layout: ui.Panel.Layout.flow('vertical')
});

for (var i = 0; i < legendColors.length; i++) {
  var colorBox = ui.Label({
    style: {
      backgroundColor: '#' + legendColors[i],
      padding: '8px',
      margin: '2px',
      width: '20px'
    }
  });
  var label = ui.Label({
    value: legendLabels[i],
    style: { margin: '2px 0 2px 6px' }
  });
  var row = ui.Panel({
    widgets: [colorBox, label],
    layout: ui.Panel.Layout.Flow('horizontal')
  });
  legendPanel.add(row);
}

legend.add(legendTitle);
legend.add(legendPanel);
Map.add(legend);

/* 7. Add month and year properties to each image in the collection
var smap = coll.map(function(img) {
  var d = ee.Date(img.get('system:time_start'));
  var m = d.get('month');
  var y = d.get('year');
  return img.set({'month': m, 'year': y});
});
print("SMAP with date properties", smap);

// 8. Generate a monthly average ImageCollection for each year
var byYearMonth = ee.ImageCollection.fromImages(
  years.map(function(y) {
    return months.map(function(m) {
      var monthlyImage = smap.filterMetadata('year', 'equals', y)
                    .filterMetadata('month', 'equals', m)
```

```
                            .select('ssm')
                            .mean()
                            .set('year', y)
                            .set('month', m)
                            .set('date', ee.Date.fromYMD(y, m, 1));
      return monthlyImage;
    });
  }).flatten()
);
print("Monthly SMAP ImageCollection", byYearMonth.first());

// 9. Perform zonal statistics (mean) for the ROI for each monthly image
var smapSummary = byYearMonth.map(function(img) {
  var features = roi.map(function(f) {
    return f.set({
      'date': img.get('date'),
      'month': img.get('month'),
      'year': img.get('year')
    });
  });
  // Use the projection of the first image in byYearMonth
  var proj = ee.Image(byYearMonth.first()).projection();
  return img.reduceRegions({
    collection: features,
    reducer: ee.Reducer.mean(),
    scale: 1000,
    crs: proj
  });
}).flatten();
print("Zonal Statistics Summary", smapSummary.limit(10));

// 10. Export the resulting table to Google Drive as a CSV file.
var selectors = ['year', 'month', 'ADM1_NAME', 'mean'];
Export.table.toDrive({
  collection: smapSummary,
  description: 'SMAP_Timeseries_Trang',
  folder: 'earth_engine_data',
  fileNamePrefix: 'SMAP_Timeseries_Trang',
  fileFormat: 'CSV',
  selectors: selectors
});*/
```