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Module: Advanced Remote Sensing Innovations (ARSI)

Module component: Remote Sensing Change Detection Principles

Abstract

This study focuses on the analysis of Soil Surface Moisture (SSM) in Phnom Penh and its suburbs using Sentinel-1 C Band Synthetic Aperture Radar (SAR) data. SSM is a critical component influencing soil, plant growth, and ecosystem dynamics, with implications for agriculture and environmental health. Cambodia, heavily reliant on subsistence agriculture, faces severe impacts from various droughts, prompting the need for comprehensive early warning systems. The study employs high-resolution optical multispectral and SAR data to calculate SSM, utilizing the TU Wien Change Detection Approach. Google Earth Engine facilitates data processing, removing built-up and water cover using Sentinel-2 optical data. Results indicate significant changes in SSM over five years, highlighting the impact of urbanization on soil moisture. The study contributes valuable insights for environmental researchers and policymakers, emphasizing the role of remote sensing in monitoring and addressing environmental challenges.

Introduction

Soil surface moisture (SSM) content is a crucial component of the Earth's water cycle and plays a vital role in various environmental processes. It directly influences the physical, chemical, and biological characteristics of the soil, affecting plant growth, agricultural productivity, and ecosystem dynamics. The soil surface moisture content is influenced by factors such as precipitation, evaporation, transpiration, temperature, and soil composition. It fluctuates dynamically based on weather conditions, seasonal variations, and land use practices. Adequate soil surface moisture is essential for supporting plant growth and sustaining ecosystems, while variations in moisture levels can impact agricultural activities, water availability, and the overall health of terrestrial environments. Measuring soil surface moisture is crucial for assessing drought conditions, managing water resources, and implementing effective agricultural practices. Remote sensing technologies, such as satellite-based sensors and ground-based instruments, are commonly used to monitor and map soil moisture levels over large areas.

In Cambodia, various communities dependent on subsistence agriculture, particularly paddy cultivation, face severe impacts from various types of droughts. The country has witnessed the loss of paddy crops and insufficient water supply, exacerbated by the intersection of drought vulnerability and the ongoing effects of climate change. To enhance resilience, the researchers has emphasized comprehensive drought early warning systems that utilizing indicators such as rainfall-SPI, soil surface moisture and water, groundwater levels, and NDVI to effectively identify and monitor drought onset.[1]

This study focuses on analysing the SSM for the Cambodian capital Phnom Penh and its suburb areas. The study area has been highly affected by urbanisation in recent years resulting in reducing water bodies, open land, and vegetation areas. We want to check how the soil moisture level has changed in these years. The outcome of the study is expected to aid the environmental researchers to understand the surface moisture, underground water dynamics, and drought vulnerability. At the same time, it will help the policy makers to make timely decisions to tackle various environmental hazards.

The study utilizes high resolution Optical Multispectral and C- Band SAR Electromagnetic satellite data to calculate the soil surface moisture and its change. For calculating the soil moisture, it utilizes the TU Wien Change Detection Approach which was first proposed in [2] to understand the relationship among vegetation cover, surface moisture and scatter meter data, and further applied for SSM derivation in [3] In this study we utilized Sentinel 1 C Band Synthetic Aperture Radar (SAR) data to calculate the SSM. Since SSM can not be derived from optical satellite data, and most of the electromagnetic satellites are either not open source or of very low spatial resolution, we used Sentinel 1 satellite data. For the processing of data, google earth engine has been used which contains a large archive of various planetary data including Sentinel-1 SAR Ground Range Detected (GRD) dataset. This dataset comprises S1 GRD scenes, processed (Thermal noise removal, Radiometric calibration, Terrain correction) using the Sentinel-1 Toolbox to produce a calibrated, ortho-corrected product. The collection is refreshed daily, with new assets incorporated within two days of their availability. [4]

Material and Methods

Data

The study uses Sentinel 1 C Band SAR data from sentinel 1 for SSM estimation. C-band radar is highly affected by the physical landcover such as water and built-up areas. For removing the waterbodies and built-up areas Sentinel 2 SR Harmonized dataset was used. The area boundary has been collected from ongoing research project in Eberswalde University for Sustainable Development.

Methodology

The study aimed to analyse the SSM change between the 5-year time period from 2019 and 2023. The respective sentinel 1 images have been fetched from the archive. The image from 2019 date to 2019-03-01 and the one from 2023 dates to 2023-03-06.

The study area has a diverse landcover including permanent water body, agricultural land, and densely located built up areas. The SAR data is highly responsive to these variations of landcover. But the aim of the study was to measure the moisture content on surface. Therefore, water bodies and built-up areas must be removed from the processing. To remove the built-up and water covers, Normalized Water Index (NDWI)[5] and Normalized Built-up Index (NDBI)[6] derived from cloud masked Sentinel 2 multispectral optical satellite data from 2019-03-12 and 2023-03-06 using equation 1 and 2 respectively. The reason for using Sentinel 2 is, it provides the optical data in 10–100-meter spatial resolution in almost the same temporal resolution as Sentinel 1.

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NDWI = (B03 - B08)/(B03 + B08) ... ... ... ... (equation 1)
NDBI = (B11 - B08)/(B11 + B08) ... ... ... ... (equation 2)
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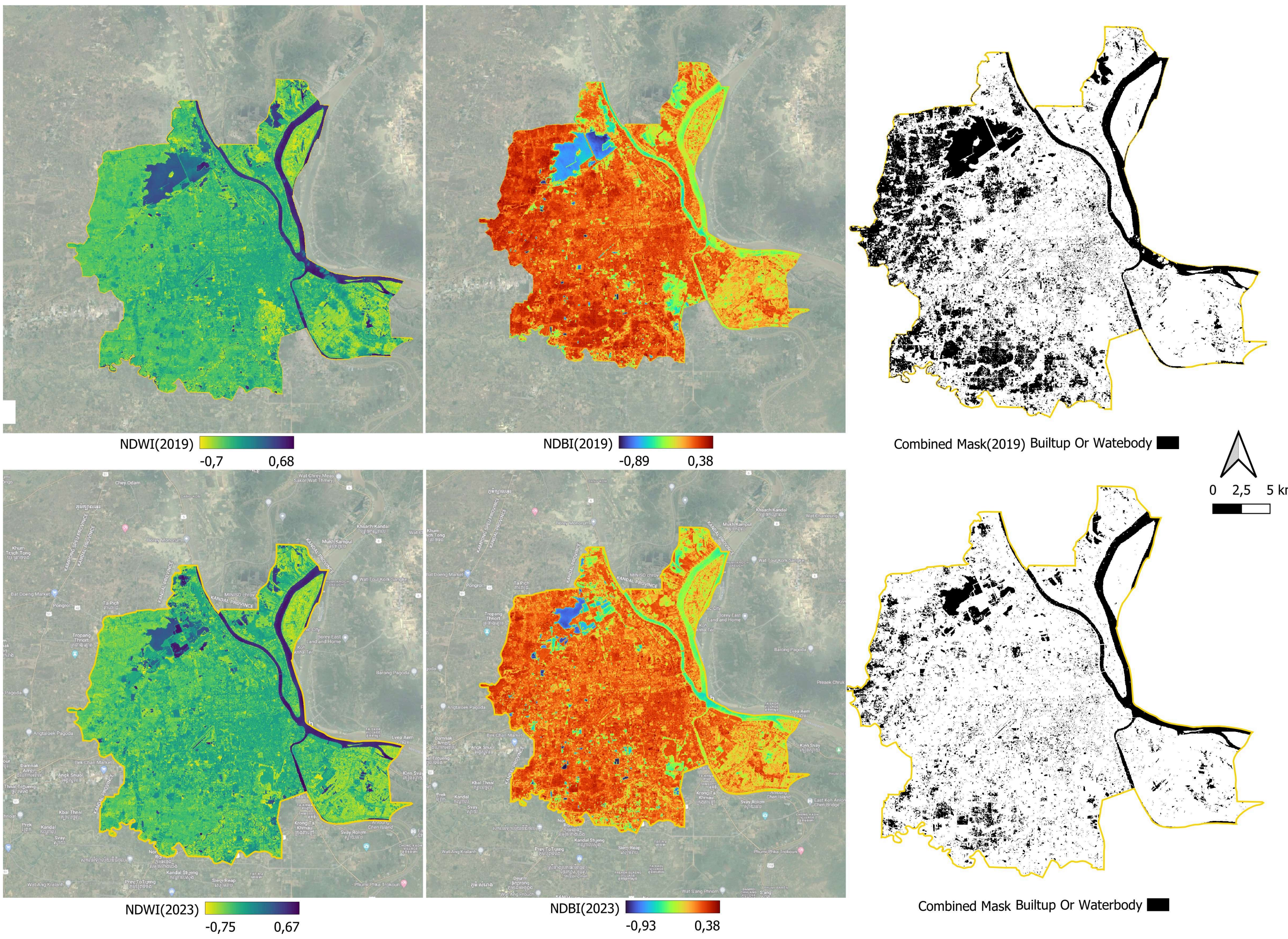
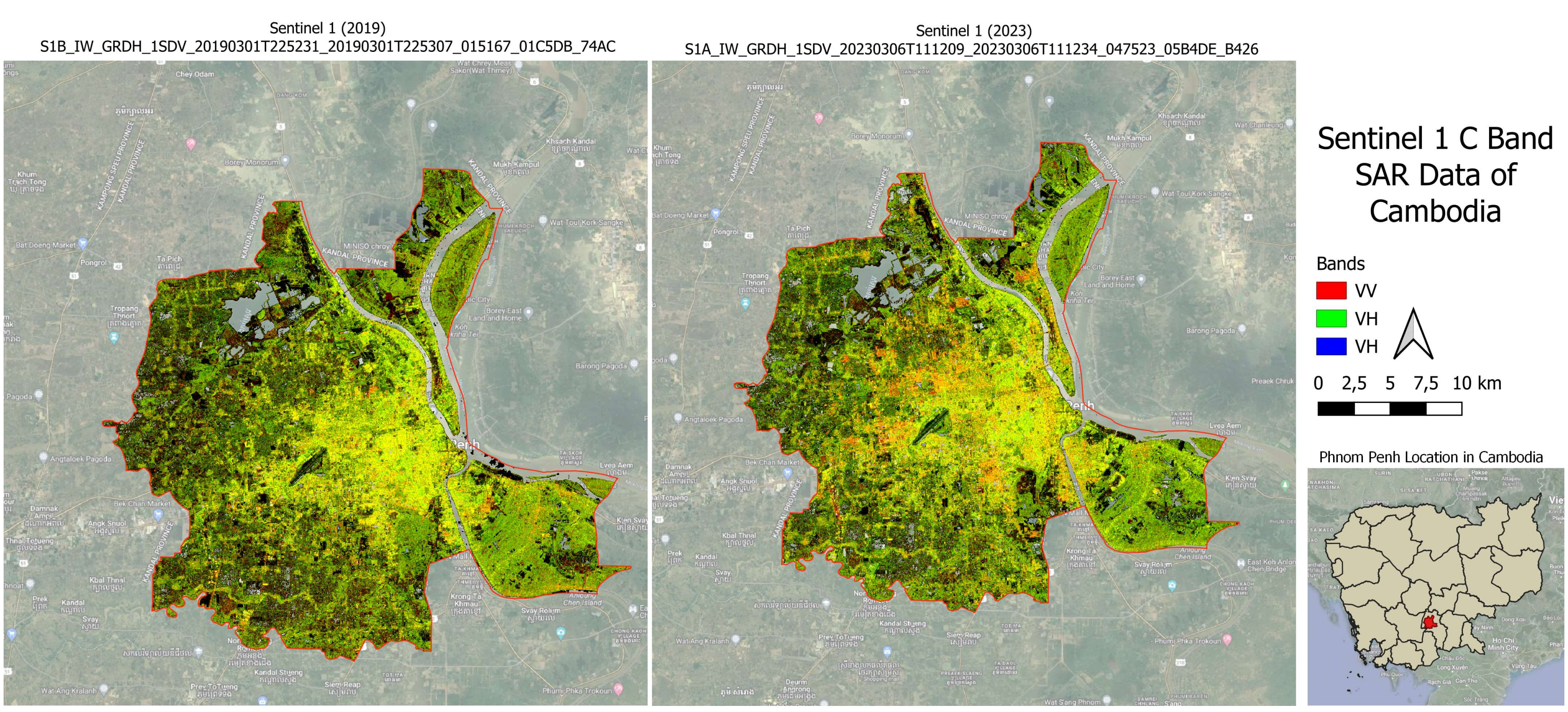


After deriving the NDWI and NDVI for the area, Water and Built-up masks were generated using the thresholds 0.1 and 0.15 respectively for waterbodies and build-ups. It was assumed that pixels greater than these thresholds are covered by respective landcovers. After thresholding, a combined mask was generated by removing these land classes which holds only those pixels where there is no built-up and waterbody. After that, the mentioned land classes have been masked out of the Sentinel 1 images too using the masks produced from Sentinel 2 images.



After removing the land classes, the sensitivity for each pixel has been calculated using the equation 3.

```
Sensitivity(S) = Wet Reference - Dry Reference ... ... ... ... (equation 3)

    Wet Reference = Historical maximum back scatter intensity of pixel from the year of reference
    Dry Reference = Historical minimum back scatter intensity of same pixel from the year of
reference
```

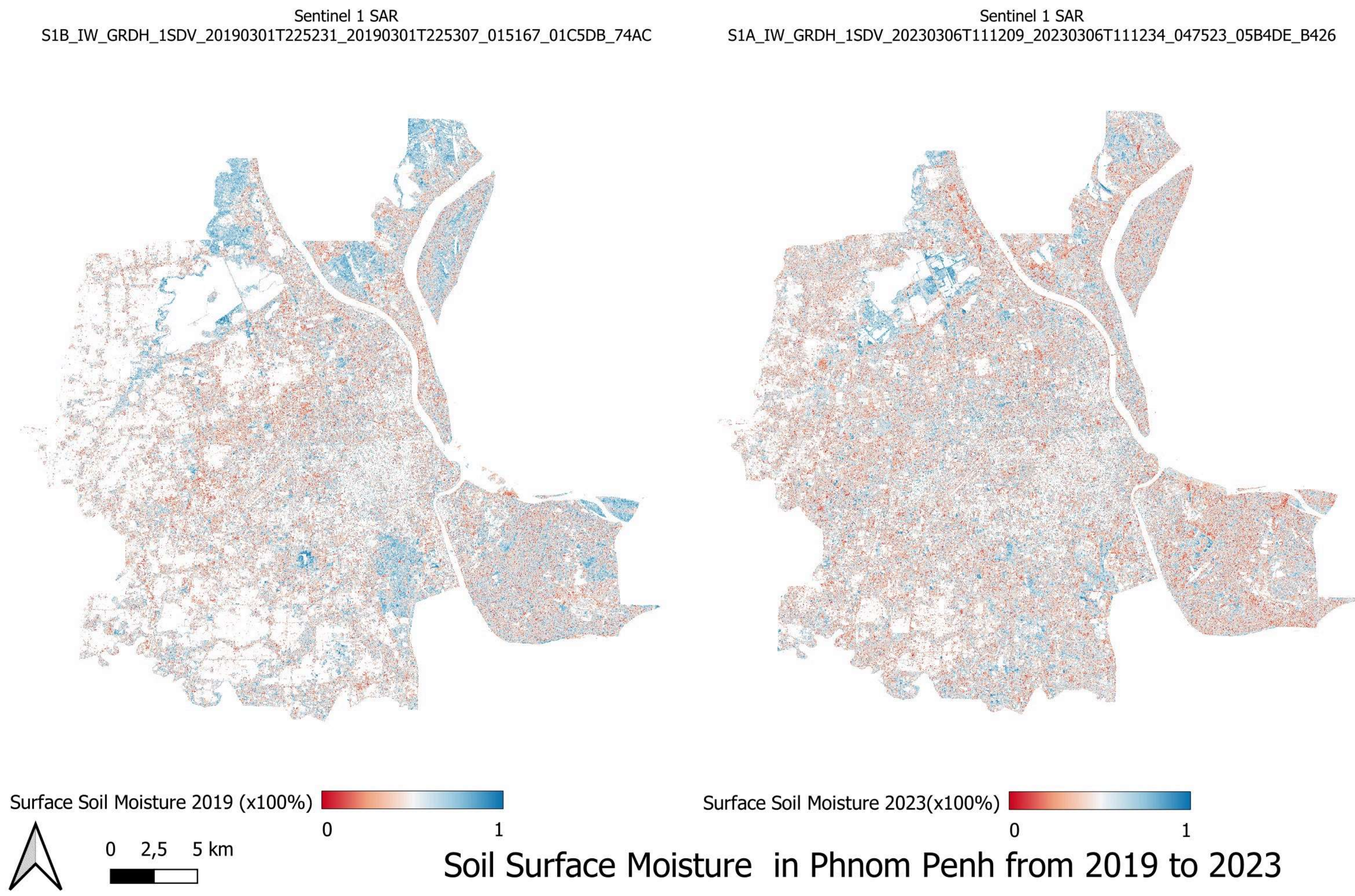
For retrieving the historical minimum and maximum back scatter, minimum and maximum composites were created. In this case, a 3-year gap has been considered. For the year 2019, historical images from 2016 to 2019 have been considered, and for 2023 the timeframe was from 2019 to 2023. The number of images considered for historical values is 295 and 316 for 2019 and 2023 respectively.

Finally, SSM was calculated from the pixel backscatter intensity of the year under consideration, dry reference, and sensitivity using the following equation 4.

```
    Surface Soil Moisture(SSM) = (Back scatter intensity of pixel - Dry reference of pixel) /
Sensitivity of pixel
```

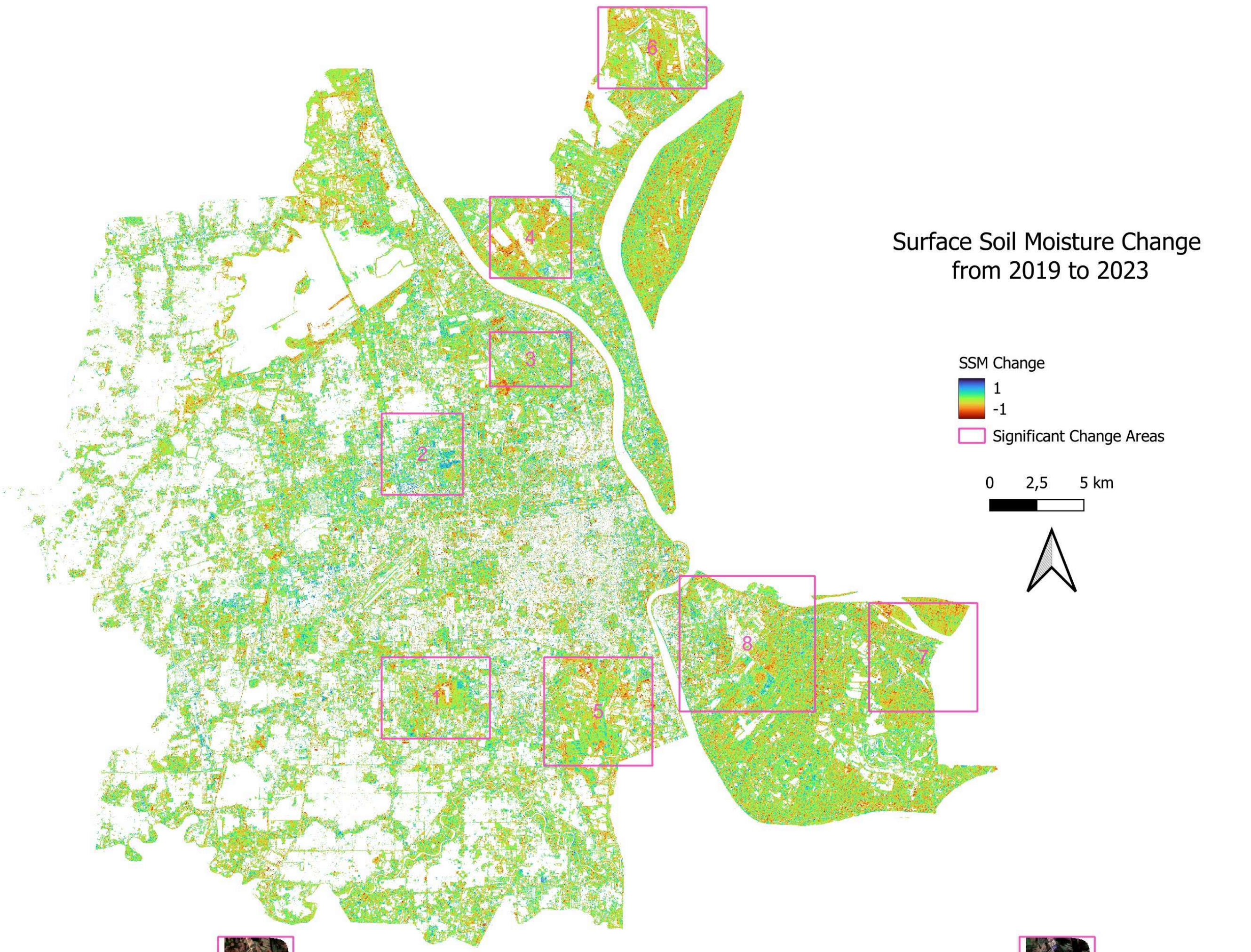
For all the data processing, Google Earth Engine Python API on Google Colab Platform. Both of these services are offered by Google for free.

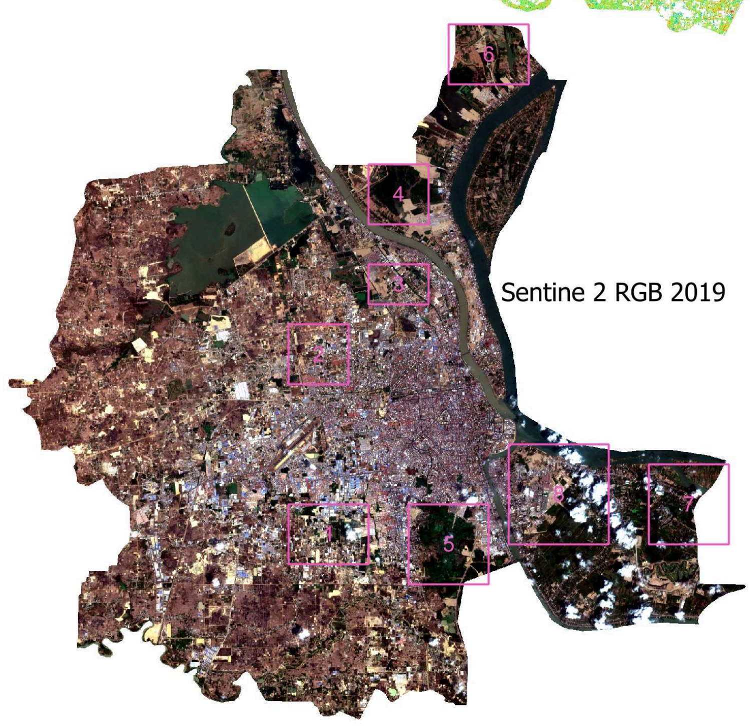
Results

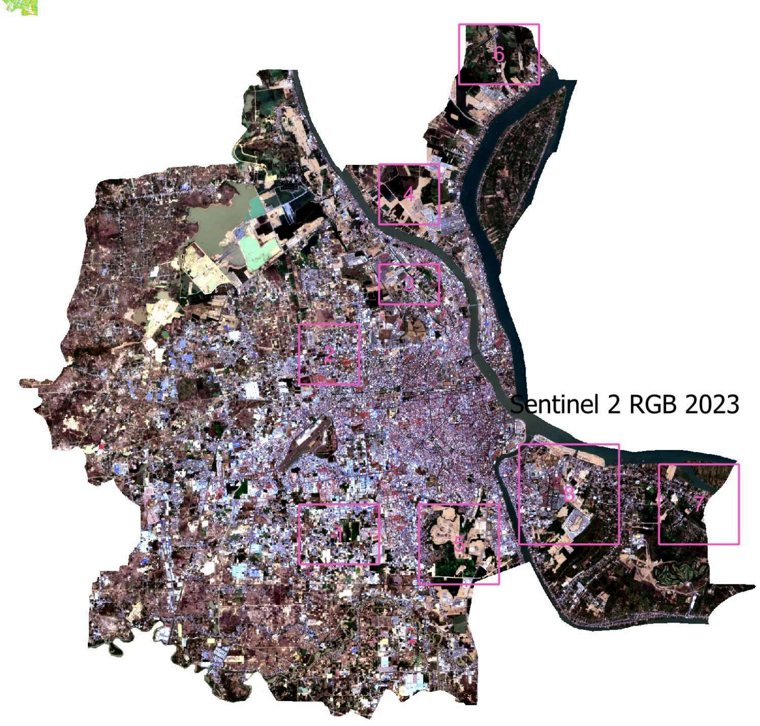


The figure above shows the SSM maps for the are for year 2019 and 2023. It is seen that SSM has changed considerably in these 5 years. The values in red colour ranging from 0.5 represents the area with low surface soil moisture as low as 50%. On the other hand, the areas with blue colour represents the possibility of higher surface soil moisture. The waterbodies and built-up areas have been removed and seen as while colour. The blue coloured areas have decreased in 5 years. The results also show that, the masked areas have also increased in this time.

The below figure highlights the significant change areas during the time.







It shows among the 8 blocks it is seen that, in 7 blocks typically the SSM has changed over the time. The sentinel 2 image shows the change in land cover too. In block 8, it was seen that, the SSM has decreased in the core central part of stadium. However, around the tracks the SSM has decreased.

Discussion

The area 1, was dominated by agricultural fields in 2019 which is a significant basin for soil moisture. But in 2015, the number of built buildings has increased in the block. Similar incident happened in block 3, 4 as well. Block 4 was barren land and swamp area in 2019, which was covered by a business unit in 2023. The most significant change has taken place in block 5, which was earlier completely dominated by agricultural field, but in 2023 it was filled for infrastructure development. In block 8 the new stadium has been built after 2019. In 2019, block 7 was covered by cloud, which can be seen in Sentinel 2 RGB image. However, Sentinel 1 can penetrate through the cloud. Hence, the change in water content could be identified. Among the very few segregated areas where SSM has increased, block 2 is representative of that. However, in this area too the landcover has changed. It could there were small water bodies scattered around the block resulting in the distortion of radar backscatters.

Since, it is seen that, in the representative block when the landcover has changed from vegetated to urbanisation the surface soil moisture has been decreasing. Therefore, it can be interpolated that, the continuous urbanisation has a negative correlation with the SSM. In block 8, the bounding (running tracks) areas has showed increase of SSM. From the RGB images it can be identified as a change due to some shadow giving or urban green infrastructure. Therefore, it can be said that, urban green infrastructures has a positive co-relation with the SSM.

Conclusion

In this study the Soil Surface Moisture (SSM) has been derived from Sentinel 1 C Band SAR radar data. Although the process does not give exact volume of the water, it provides with a ratio of water content considering the lowest back scatter as the driest sample. The outcomes showed relatable correlation with the land cover types of the area. Therefore, it can be said that, SSM from Sentinel 1 imagery could be a crucial tool to tackle challenges in Phnom Penh. Nevertheless, the to produce exact water content, further interdisciplinary research is needed combining both Remote Sensing and Soil Science focus.

References

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Appendix

1. Further supportive attachments can be found in the link https://nextcloud.hnee.de/s/TNiw25qme9zwmAx
2. Code can be run from https://colab.research.google.com/drive/1Dac1Vm4rbMBkvFIG4Qn7ySIJBp-I1-LG?usp=sharing