Development of a Framework for Mapping the Potential for Farmer-Led Irrigated Areas in Southeast Asia

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1. Introduction

The majority of global cropland (80%) is rainfed, with irrigated areas primarily established within major irrigation schemes and river valleys. A similar pattern is observed in Southeast Asia, where only 23% of the cropland areas are irrigated. This has traditionally not been an issue with greater abundance of water in the ASEAN region. However, with the advent of in increased population and economic growth, urbanization, and climate change, flood and droughts have become common, affecting over 60 million people in the region.

Large scale irrigation systems typically require high upfront costs for development and have been shown to have low performance in terms of crop yields. An alternative to large scale farming systems is farmer led initiatives. Farmer-led irrigation involves farmers individually or in small groups, investing and implementing irrigation practices to increase their income and crop productivity. Farmer-led irrigation offers several advantages over large-scale irrigation schemes. It has lower infrastructure costs, can be implemented in isolated areas, and is suitable for small cultivation plots. Additionally, it provides flexibility and customization, making it ideal for urban agriculture and providing the potential for increased agricultural productivity.

This study proposes the development of a framework for mapping farmer-led irrigated areas based on a multi-criteria analysis using free and open geospatial data. The initial study was carried out in Cambodia.

2. Methodology

The framework employs multiple drivers to generate various indicators of suitability for farmer-led irrigation. These indicators include biophysical suitability, water availability, and socioeconomic factors. To assess land suitability, we obtained relevant drivers from various sources. Each input driver was standardized to transform different measurement units into comparable suitability values. The input drivers were then reclassified on a scale from not suitable (0) to highly suitable (5), based on standardization ranges commonly used in Analytic Hierarchy Process (AHP) literature.

By integrating these diverse factors, the framework provides a comprehensive assessment of potential areas suitable for farmer-led irrigation. The input drivers represent criteria that define the degree of suitability for each area of interest. We categorized the drivers into five main categories: soil suitability, topography, surface water, groundwater, and socioeconomics.

2.1 Soil Suitability

To identify areas with optimal conditions for agricultural activity and irrigation, we used three soil characteristic layers: texture, available water content, and organic carbon. These layers were obtained with a spatial resolution of 250 meters from HiHydroSoil v2.0 (Simons, Koster, and Droogers 2020).

2.2 Topography

Topographic suitability for farmer-led irrigation was evaluated using slope and elevation layers derived from 30-meter resolution SRTM data. The analysis identified moderate slopes and low-lying areas as more favorable for irrigation, optimizing water retention and minimizing erosion risks.

2.3 Groundwater Availability

We inferred groundwater availability using groundwater recharge estimates obtained from the PCR-GlobWB model (Sutanudjaja et al., 2018). The PCR-GlobWB 2 model is an open-source hydrology and water resource model that is dynamically coupled with a global two-layer groundwater model. The estimates reflect the potential for annual groundwater recharge from 1959 to 2015, providing long-term average estimates of groundwater recharge (safe yield) for each location.

2.4 Surface Water Availability

To represent water availability, we utilized surface water sources such as rivers, lakes, reservoirs, and inland valley wetlands. Rivers and streams are significant sources of surface water for irrigation, particularly during the dry season. To identify rivers that could provide year-round water, we combined data on the global prevalence of non-perennial rivers and streams (Messager et al., 2021) with HydroSHEDS Data-HydroLAKES (Messager et al., 2016) and calculated proximity to these surface water features.

2.5 Socioeconomic Suitability

Socioeconomic indicators mapped the influences on irrigated agriculture. We used a population density map from Linard et al. (2012) to identify areas with a higher likelihood of purchasing and maintaining irrigation pumps, accessing vegetable seeds, and finding markets for their crops. A market access map was created from the 2015 Global Accessibility Map (Weiss et al., 2018) for populations of 50,000. The Global Roads Open Access Data Set (gROADS) provided a measure of travel costs along potential irrigation development routes.

Modern irrigation pumps are often equipped with wireless technology that allows control via mobile phones. The Internet of Things (IoT) plays a significant role in servicing these systems. Additionally, agricultural advisory services, mobile money payments, and voice-over-IP (VOIP) services can influence the uptake of vegetable production. We also included a layer showing the distance to cell phone towers to predict more market-oriented systems.

2.6 Final Suitability Map

The final suitability map is created by calculating a weighted average of the five suitability indicators, with weights defined by the AHP method. final suitability map classifies in to 5 classes.

2.7 Constraints

These constraint layers indicate areas where farmer-led irrigation cannot occur, mainly due to land use type and protected lands. We created a combined constraint map by multiplying these two constraint maps to identify regions to exclude. This constraint layer was then overlaid with the suitability results to extract the final locations for farmer-led irrigation suitability.

We utilized the ESRI yearly land cover map with a resolution of 10 meters, which includes nine general classes based on Sentinel-2A observations: trees, shrubland, grassland, farmland, flooded vegetation, rangeland, bare land, built-up areas, snow/ice, and water. All land cover classes, except for farmland, rangeland, and bare land, were treated as constraints, as we aimed to avoid expanding agricultural land into forests or exposing land to climate extremes (e.g., flooded vegetation, snow/ice).

Protected areas are crucial for conserving natural habitats, reducing biodiversity loss, and providing ecosystem services. Therefore, we excluded all protected areas, including national parks and wildlife conservation areas, from our analysis using the 2022 World Database on Protected Areas (WDPA) (UNEP-WCMC and IUCN, 2022).

2.8 Field Data Collection

The framework was tested in Cambodia and validated with ground truth data collected from the field. The dataset consists of 2,134 ground-sampled irrigated locations gathered across the country. A suitability map was compared with the locations identified in the ground survey.

3. Results and Discussion

The preliminary outcomes of the study are illustrated in Figure 1, which depicts the geographic distribution of farmer-led irrigation suitability areas across Cambodia. The suitability layers have been reclassified into five categories, as detailed in Table 1, which also presents the extent of suitable land identified within each category.

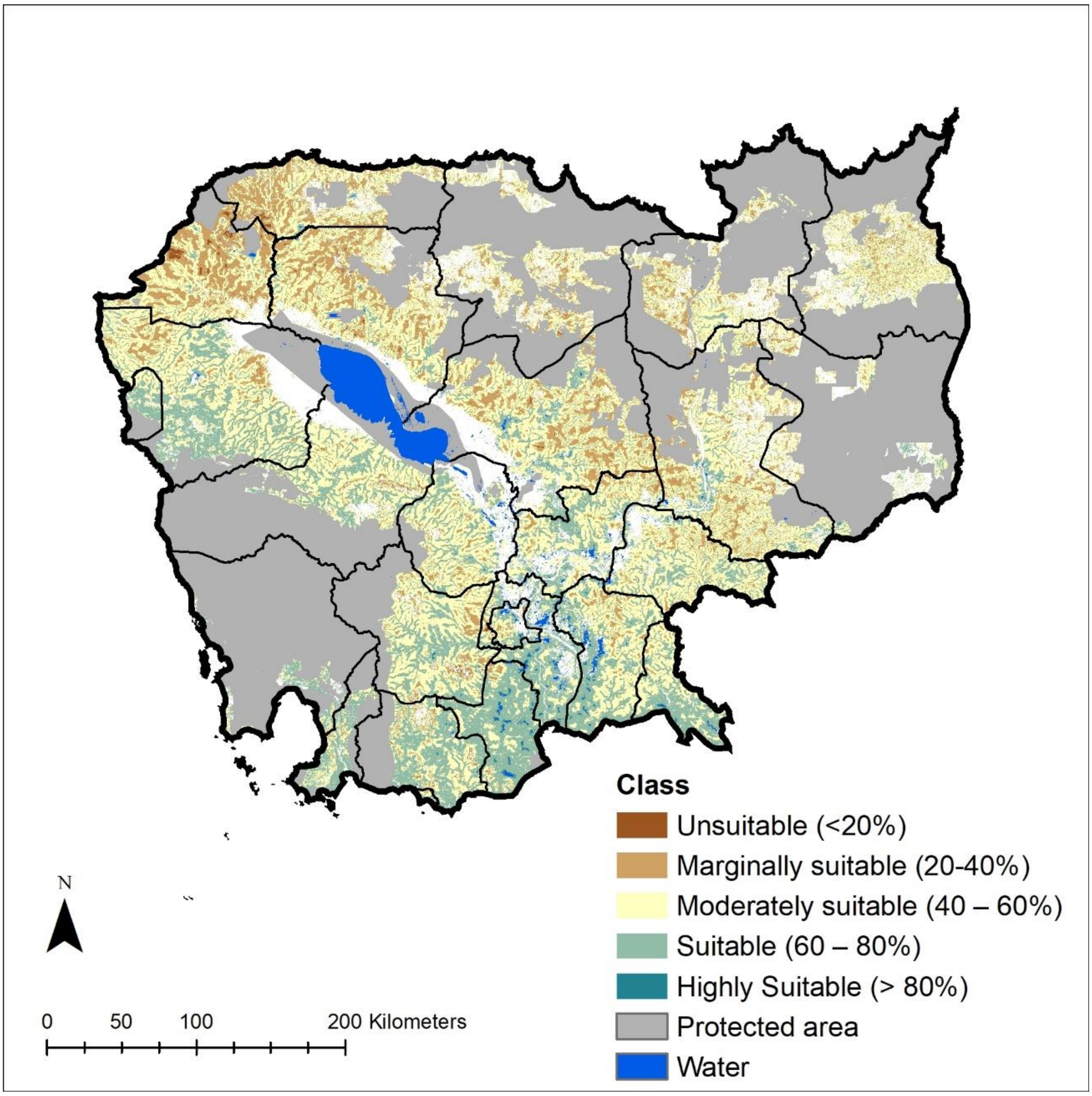

Figure 1: The final suitability map for farmer-led irrigation in Cambodia.

Table 1: Extent of each suitability class detected through multi-criteria analysis, including their corresponding classification ranges for assessing potential areas for farmer-led irrigation.

Suitability Class	Area (ha)
Unsuitable (<20%)	606,324
Marginally suitable (20-40%)	104,842
Moderately suitable (40 – 60%)	6,222,008
Suitable (60 – 80%)	2,414,599
Highly Suitable (> 80%)	27,429

Overall, the analysis revealed that approximately 27,429 hectares were classified as highly suitable for farmer-led irrigation, while 2.4 million hectares were deemed suitable, and 6.2 million hectares were identified as moderately suitable.

Table 2: Accuracy assessment

Suitability Class	Number of Samples	Percentage (%)
Unsuitable (<20%)	0	0%
Marginally suitable (20-40%)	7	0.3%
Moderately suitable (40 – 60%)	394	18%
Suitable (60 – 80%)	1,208	57%
Highly Suitable (> 80%)	65	3%
Constraint	460	22%
Total	2,134	

Table 2 presents the results of the accuracy assessment, showing the distribution of ground sample locations across each suitability class. Notably, the majority of sample locations align with the identified suitable areas. Specifically, 22% of the samples fell into constraint areas, with 76% of those correctly identified by the derived suitability map. Importantly, no samples were classified as unsuitable, and only 7 samples fell into the marginally suitable class. The remainder of the samples corresponded to moderately suitable or higher classes, highlighting the accuracy and reliability of the proposed framework.

4. Conclusion and Recommendation

This study proposed a framework for mapping potential areas for farmer-led irrigation in Southeast Asia using multi-criteria analysis and incorporating free and open geospatial data. The case study was conducted in Cambodia, revealing promising results. The accuracy assessment of the maps was determined to be 76%. Specifically, 27,400 hectares were classified as highly suitable, while 2.4 million hectares were identified as suitable for irrigation.This high level of accuracy underscores the framework's potential for expansion to other countries within the ASEAN region. By accurately identifying areas suitable for farmer-led irrigation, this framework can significantly contribute to the development of the farmer-led irrigation sector, promoting climate-resilient agricultural practices across ASEAN.

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