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Integrating GIS and Remote Sensing for Food Security Analysis in Paddy Cultivation: Evidence from Horana DSD, Sri Lanka

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Abstract – Food security is a pressing global concern, increasingly intensified by the COVID-19 pandemic and persistent economic instability. In Sri Lanka, rural regions are particularly vulnerable, necessitating targeted assessments of food availability and production. This study evaluates food security related to paddy cultivation in the Horana Divisional Secretariat Division (DSD) using Geographic Information Systems (GIS), remote sensing, and spatial interpolation techniques. The primary objective is to quantify rice production and assess its sufficiency against local food requirements, calculated based on caloric needs. Data were collected through stratified random sampling from five Grama Niladhari Divisions (GNDs): Uduwa North, Kahatapitiya, Meewanapalana East, Pannila, and Dambara. Spatial analysis, including Kriging interpolation, was employed to map rice availability and food deficits. Results show a total rice yield of 455,000 kg, compared to a requirement of 1,483,250 kg, revealing a substantial shortfall of 1,028,250 kg. Only Meewanapalana East achieves self-sufficiency, while the remaining GNDs are food insecure. ArcGIS Online was used to publish and visualize these disparities through web GIS, enabling accessible and dynamic data presentation. The findings highlight severe food insecurity and stress the need for strategic interventions, such as improved agricultural practices, better distribution systems, and policy reforms. By integrating GIS, remote sensing, and interpolation methods, this study offers an innovative, spatially-driven approach to food security assessment, addressing a gap in existing literature that often overlooks the balance between local production and caloric demand.

Keywords- Food Security, GIS, COVID-19, Remote Sensing, Spatial Analysis

Recommended APA Citation

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1. Introduction

Several social and economic problems have become more pressing as a result of the COVID-19 epidemic. Therefore, it can be claimed that during this period, food security has been the focus of global attention. Food security has become a global priority in recent years due to rising economic instability, climate change, and conflict. In 2022, an estimated 735 million people or 9.2% of the global population, were undernourished, up from 618 million in 2019 (FAO, 2023). This increase threatens health, productivity, and economic stability, especially in vulnerable regions. The World Food Programme (2023) reports that over 345 million people now face acute food insecurity. These challenges highlight the urgent need for coordinated global action to protect livelihoods and achieve Zero Hunger (SDG 2). According to FAO estimates, the global under-nutrition rate might increase from 83 million to 132 million people as a result of the COVID-19 pandemic. According to the 2013 Global Food Security Index (GFSI), Sri Lanka ranked 60th internationally with a score of 48.6, making it one of the most food-secure countries in South Asia at the time. However, more recent data from the 2022 GFSI based on pre-pandemic indicators ranked Sri Lanka 79th out of 113 countries. This decline reflects growing concerns around food availability, affordability, quality, and safety. Despite its relatively strong historical ranking in the region, Sri Lanka has long struggled with underlying food insecurity, particularly child hunger. In 2009, 88% of households were reported to have adequate food. By contrast, more recent estimates suggest that fewer than 10% of households currently have sufficient food access (Sanderatne & De Alwis, 2014). This shift highlights the country's worsening food security situation over the past decade.

According to the 2016 Demographic and Health Survey, 17.3% of Sri Lankan children under five were stunted, 15.1% were wasted, and 20.5% were underweight (Department of Census and Statistics, 2016). The COVID-19 pandemic further worsened food insecurity through lockdowns and supply chain disruptions, despite efforts to maintain food distribution. These shocks highlighted the fragility of Sri Lanka's food systems during crises. Sri Lanka's rich agricultural heritage, particularly in rice cultivation, makes it central to food security efforts (Hewapathirana & Nuskiya, 2024). Since 2021, the country has faced a severe food crisis, worsened by rising input costs and food inflation. In 2019, agriculture contributed 7% to GDP (Nuskiya, 2019), yet food price inflation has placed Sri Lanka among the top ten countries globally, with paddy cultivation remaining the backbone of the national food supply.

Sri Lanka's public debt rapidly became unsustainable due to prolonged fiscal deficits, a sweeping tax cut introduced in 2019, and the economic impacts of the COVID-19 pandemic (World Bank, 2022). By early 2022, the country was facing a full-scale balance-of-payments and debt crisis, exacerbated by sharp declines in foreign exchange earnings and global price shocks in food and energy (ADB, 2022). Surveys indicated that approximately 11% of households had lost all income, while 62% reported a reduction in income, severely limiting access to adequate and nutritious food (WFP, 2022). Compounding the crisis, a sudden nationwide ban on chemical fertiliser imports in April 2021, implemented without adequate planning, farmer training, or organic alternatives, resulted in a dramatic drop in agricultural productivity. Although the ban was lifted in November 2021, the damage was already done: the 2021/22 Maha season saw a 40–50% decline in paddy output (FAO, 2022). With increased production costs, only 24% (128,652 ha) of the usual 524,778 hectares were cultivated during the subsequent Yala season, as many farmers opted not to cultivate due to input cost inflation, particularly for paddy (Central Bank of Sri Lanka, 2022). Consequently, food prices surged, and widespread shortages were anticipated.

In light of these challenges, this study seeks to address a critical knowledge and policy gap by assessing local food security in the context of paddy cultivation, specifically within the Horana Divisional Secretariat Division (DSD). Employing Geographic Information Systems

(GIS) and remote sensing techniques, this research spatially analyzes rice production and food needs across five selected Grama Niladhari Divisions (GNDs). The integration of GIS enables a data-driven evaluation of food availability and allows for the visualization of insecure areas through a Web GIS platform offering practical, actionable insights for planners and policymakers to target interventions more effectively. This approach not only contextualizes food insecurity at the sub-district level but also demonstrates how spatial technologies can support resilience and food system planning during times of crisis.

2. Materials and Methods

The methodology section describes the method of designing and data collection of Food Security Assessment for Paddy cultivation in Horana DSD. This presents the background of the Study area, research design, population and sampling, data collection methods, conceptual framework, and methods of data analysis of Horana Divisional Secretariat Division.

Study Area

Horana Divisional Secretariat is located in the Kalutara district in Western Province. It is a wet zonal divisional secretariat. Horana has a tropical climate. The Latitude of Horana is 6.718°. The Longitude of Horana is 80.06°. Horana Divisional Secretariat, which is situated in the northern part of the Kalutara district of Western province, is close to the Colombo District in the north, Ingiriya Divisional Secretariat in the east, Madurawala Secretariat in the south and Bandaragama Divisional Secretariat in the west (Figure 1). Horana DSD, which belongs to Udagahapaththu and Kumbuke Paththu. RaigamKorale is a place of historical background and aesthetics.

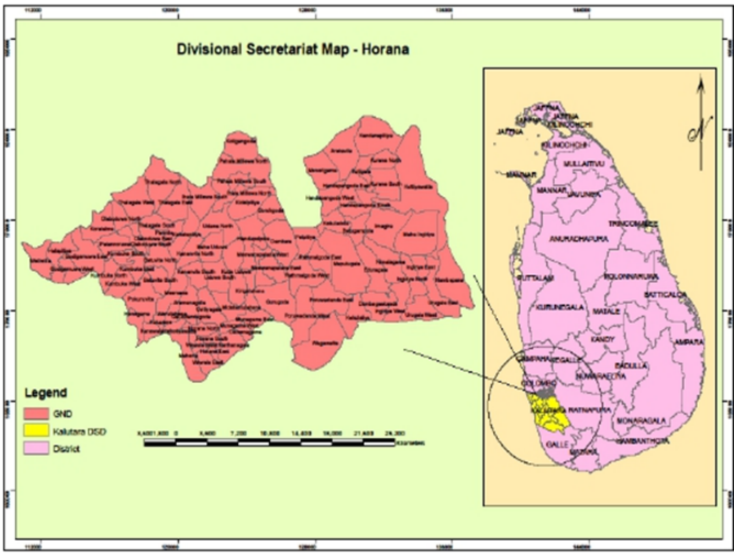

Figure 1. *Study Area of Horana Divisional Secretariat Division*

Method of Data Collection

This study uses both primary and secondary data sources to accomplish its goals. The information gathered for the study by the researcher is known as primary data. Primary data is typically highly accurate. The data collection approach used in this study is a questionnaire survey. The target groups are the households in the chosen GN that makeup the entire Horana DSD population. Three techniques can be used to get primary data regarding food accessibility for householders in Horana DSD: questionnaires, interviews, and observation.

Sample area selected

A field survey was conducted within the Horana Divisional Secretariat Division (DSD) to identify representative areas for assessing paddy-related food security. Five Grama Niladhari Divisions (GNDs): Uduwa North, Kahatapitiya, Meewanapalana, Pannila, and Dambara were selected using a stratified random sampling method. This approach ensured representation from both farming and non-farming households, based on shared demographic and agricultural characteristics. The stratification process was guided by local agricultural officers to enhance the reliability and relevance of sample selection.

Out of a total population of 2,249 households across the selected GNDs, a sample size of 99 households (approximately 5%) was drawn. While this proportion is commonly used in exploratory studies, the sample corresponds to a confidence level of approximately 90% with a margin of error of ±9%, assuming a 50% response distribution. This level of precision is acceptable for preliminary assessments where resources or access constraints limit larger sampling. The number of households sampled in each GND was calculated using proportional allocation based on the total households in each division:

Table 1

Results on the sample population via the Stratified Sampling method

GN Division	No. of Households	Formula	Samples
Uduwa North	586	(586/2249)*99	26
Kahatapitiya	481	(481/2249)*99	21
Meewanapalana	252	(252/2249)*99	11
Pannila	430	(430/2249)*99	19
Dambara	500	(500/2249)*99	22
Total	2249		99

Source: Field Survey and Author's Calculation

Satellite Imagery

This study acquired the crop and other land details availability through Satellite images using USGS Earth Explorer. The USGS Earth Explorer provides Satellite data like the Landsat series. This consists of several spectral bands. The USGS Earth Explorer gives some extra capabilities as downloading data over chronological timelines. The image quality is quite good because the cloud cover is very few (<5%) and only covers a small portion of the research area (Zahir et al., 2021). This study is based on data acquisition, images using 2018 and 2020 in the Landsat 8 series. Landsat 8 OLI was used for identifying the agricultural land, both paddy fields and other land, using multispectral classification methods. Landsat 8 OLI specifications are aligned with the research purpose. The OLI measures in the visible, near-infrared, and shortwave infrared portions (VNIR, NIR, and SWIR) of the spectrum. The TIRS measures land surface temperature in two thermal bands with a new technology that applies quantum physics to detect heat. Landsat 8 images have 15-meter panchromatic and 30-meter multi-spectral spatial resolutions along a 185 km (115 mi) swath.

Landsat 8 contains eleven spectral bands, including pan, Cirrus, and thermal (TIR) bands (Table 2). Landsat 8 mainly carries two sensors. The Operational Land Imager sensor and the Thermal Infrared Sensor. OLI captures data with improved radiometric precision over a 12-bit dynamic range, which improves the overall signal-to-noise ratio.

Table 2
Landsat 8 Specification

Sensor	Band Number	Wavelength µm	Resolution	Sensor
Operational Land Imager (OLI	1	0.433–0.453	30 m	Visible (Coastal aerosol)
	2	0.450–0.515	30 m	Visible (Blue)
	3	0.525–0.600	30 m	Visible (Green)
	4	0.630–0.680	30 m	Visible Red (Red)
	5	0.845–0.885	30 m	Near Infrared
	6	1.560–1.660	30 m	SWIR 1
	7	2.100–2.300	30 m	SWIR 2
Thermal Infra-red Sensor (TIRS)	8	0.500–0.680	15 m	Panchromatic
	9	1.360–1.390	30 m	Cirrus
	10	10.6-11.2	100 m	TIRS 1 (Thermal Infrared)
	11	11.5-12.5	100 m	TIRS 1 (Thermal Infrared)

Also, a second objective to reach the data depends on pilot survey data using the Questionnaire method for the food security assessment process and acquiring data over the agrarian centre to identify the rice production details in selected GN. So, this purpose is to follow both primary and secondary data in the study. The fourth objective of this study is to use ArcGIS online service to visualize a food security map.

Methods of Data Analysis

This study employed both qualitative and quantitative data analysis methods to assess food security concerning paddy cultivation across selected GNDs. Primary data were collected through field surveys, while secondary data included satellite imagery, statistical records, scholarly publications, and government datasets. The sample area was selected using the Stratified Random Sampling method to ensure a representative cross-section of both farming and non-farming households.

Quantitative methods were applied to analyze rice production, household food requirements, and spatial patterns using GIS and remote sensing tools. Satellite data were obtained from Landsat 8 imagery, and image processing was conducted using supervised classification and Normalized Difference Vegetation Index (NDVI) analysis to map vegetation health and potential crop productivity.

To ensure the accuracy of satellite classifications, a ground truthing process was carried out using GPS data collected from the field. These ground control points were used to validate classified outputs and assess classification accuracy. An accuracy assessment was performed using a confusion matrix, from which overall accuracy and the Kappa coefficient were calculated to evaluate the reliability of the remote sensing results.

Additionally, spatial analysis methods such as the Kriging interpolation technique were used to estimate food availability based on rice production data from Agrarian Service Centres.

These spatial estimates were visualized using ArcGIS Online, facilitating the development of an interactive Web GIS platform to communicate food security patterns across the study area.

Results & Discussion

Analysis of Paddy availability

This way select the Horana DSD area to be shown on the paddy availability map. Thus achieve the first objective, the Supervised Classification and NDVI methods follow for implementation (Ayoob et al., 2019). Therefore, Landsat 8 satellite Images in 2018 and 2021 are used for the mapping process to create Paddy availability maps. Firstly, Figure 2 uses Landsat 8 in 2018 and 2021 satellite images for identifying the agricultural lands and other lands using multispectral classification methods in the study area, respectively. The Landsat series is suitable for identifying vegetation types on Land surfaces. Hence, land use cover change comparison is important to identify via a map of vegetation and non-vegetation using spatial analysis, compared with the 2018 and 2012 land patterns. This method follows the image classification method of supervised classification. This row of satellites contains 11 bands. Thus, recognising land category through satellite image in both years initially needs to be converted to a single band using composite bands in the Raster processing tool.

Thereby, following the supervised classification method via the image classification tool. This method involves the use of training areas to represent surficial units to be classified. Initially, the study area was extracted by mask and assigned the pixel in land use using the draw polygon tool. Before the process begins divided into five classes: water bodies, Built-up, Agriculture, Forests, and barren land. After assigning pixels in the precise area by deciding classes for both years in separate Landsat 8 bands (Figure 2). In addition, generate the signature file to create the map in maximum likelihood classification. When generating a map, look at the surrounding individual pixels to remove them using the majority filter.

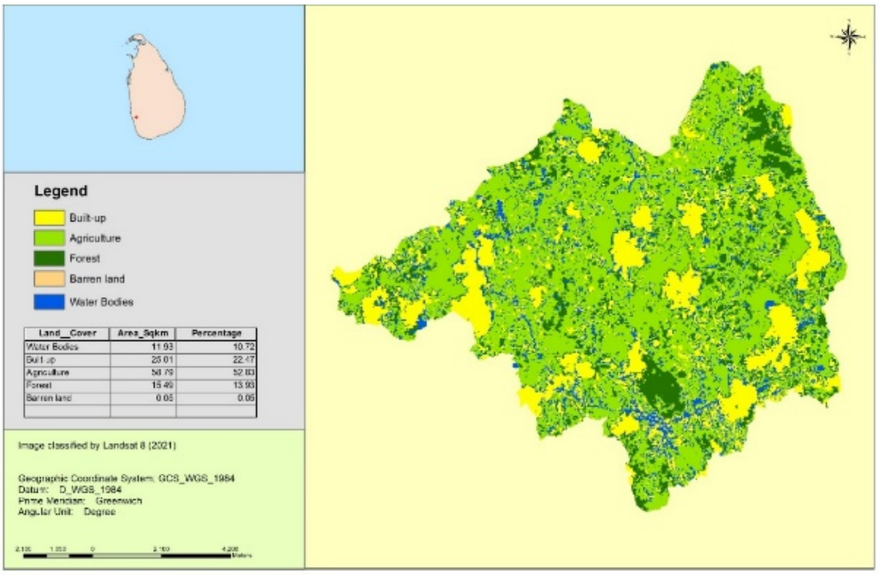

Figure 2. *Classified area of Horana DSD in 2018*

Figure 2 displays the outcomes of supervised classification on a categorised image from 2018. Across the 111.27 sq km, there was 10.89 sq km of built-up area, 5.29 sq km of forest, and 93.27 sq km of agricultural land. As a result, the results also indicated that the area had the bulk of the vegetation. This makes it possible to identify, for example, the distribution of agricultural lands within the built-up region.

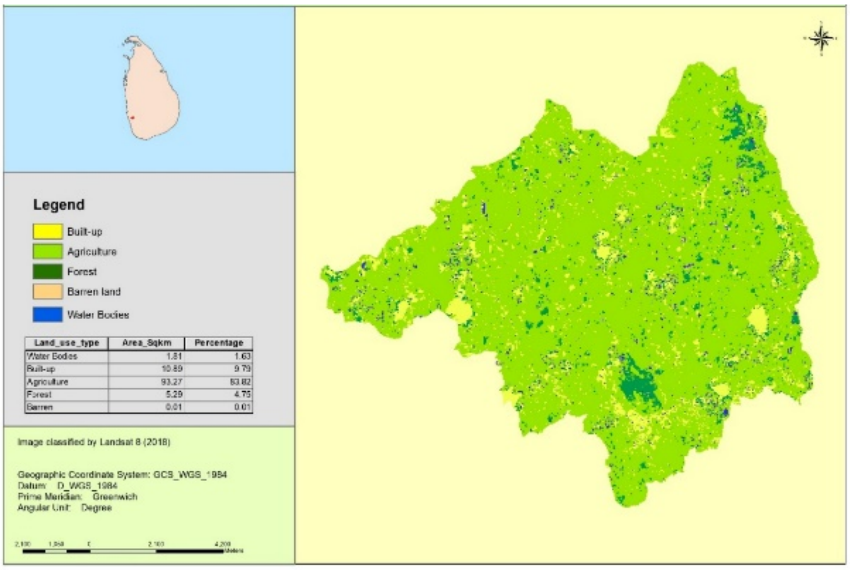

Figure 3. *Classified area of Horana DSD in 2021*

The outcomes of supervised classification on classed photos in 2021 are shown in Figure 3. Built-up area was 25.01 sq km, agricultural area was 58.79 sq km, forest was 15.49 square kilometres, barren terrain was 0.05 sq km, and water bodies were 11.93 sq km out of the 111.27 sq km. Importantly, changes in the land use mix between 2018 and 2021 can be found by comparing the land classes in those years. According to this, there was less agricultural land in 2021 than in 2018. The percentage of agricultural land was reduced by 30.99% in 2018. growth in built-up land in 2021. In 2018, 12.68% was converted to built-up land. Additionally, there was a 0.05% increase in Barren land in 2021. In 2018, the difference was 0.04. These figures for the two years demonstrate that there were more variations in land type conversion in 2021 than in 2018.

NDVI Analysis for Identified Paddy Lands

NDVI is used to identify vegetation or non-vegetation lands through pixels the range of land values depends on existing publications such as research experience. This research follows a range of greenish to identify paddy lands (Table 2).

Table 3

Greenness level classification of the plant

Class	NDVI value	Level greenish / land cover conditions
1	<-0.03	The land is not vegetated
2	-0.03 - 0.15	The greenery is very low
3	0.15 - 0.25	low greenish
4	0.26 - 0.35	The greenery was
5	0.36 - 0.61	high greenery

Source: Wahyunto et al. (2003)

The NDVI is highly useful in detecting the surface features of the visible areas of paddy lands. The vegetation index is useful for measuring vegetation greenness values (Bhandari et al., 2012). NDVI, which produces a plant greenness level 5 class for identifying vegetation. This can be useful for highlighting the live green paddy land and the abandoned paddy land. Probably, Landsat 8 images are used in the process of NDVI. The bands of 5 and 4 in NIR and Red bands in 30m. The corresponding NDVI formulation is:

$$NDVI = (\rho NIR - \rho Red) : (\rho NIR + \rho Red) \quad (1)$$

And by applying bands into the formula shown below:

In Landsat 8,

$$NDVI = (Band\,5 - Band\,4) / (Band\,5 + Band\,4) \quad (2)$$

The value of greenery levels is shown in Figure 4 as follows: high green at 26.19 sq km, very low green at 3.16 sq km, green at 55.29 sq km, and low greenish at 26.21 sq km. Depending on the water locations, there is extremely little vegetation. Low greenish areas were either shrublands or bare land. The greenery was thought to be abandoned paddy or other crops. High greenery is seen as a healthy level of vegetation. Similarly, swaths of verdant, living paddy fields are seen. Determine which paddy field has other crops that rely on a water source. The area's water level is 11.81 sq km. The margin paddy area in 2018 determines this.

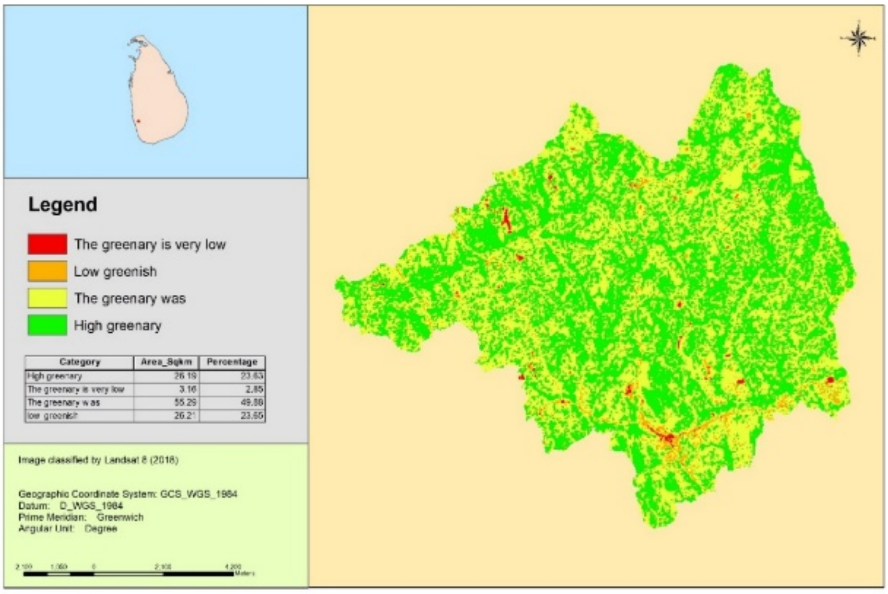

Figure 4. *Land class with greenery levels in 2018*

Greenery levels in 2021 were as follows: high green was 58.64 sq km, green was 24.53 sq km, low greenish was 19.45 sq km, and very low green was 8.6 sq km, as shown in Figure 4. Depending on the photograph, which shows water and some problems with cloud cover, there is very little flora. Low greenish was a settlement or a desolate area. In such observable regions of vibrant, green paddy fields, high greenery is regarded as the vegetation level.

Based on the findings from 2018 and 2021, this research most likely also demonstrates that the paddy area's NDVI minimum and maximum values are lower than the study site's NDVI in green level in 2018. Compared to 2018, the green level was higher in 2021. Accordingly, there will be more live paddy available in 2021 than in 2018. Band 4 is used to identify vegetated land, open land, and vegetation that is less able to reflect drought conditions. This is because the water will cover the lowest NDVI values, while the vegetative phase in rice fields has NDVI values lower than the forest cover. Additionally, Band 5 will reflect the higher spectral dry plant and is sensitive to the plant's water content. Paddy fields look to be significantly different from places with an abundance of paddy, as indicated by the green hue that the Landsat NDVI statistical value gives. The NDVI value ranges from low to high during the vegetative phase, whereas it would be extremely low during the water phase. Consequently, the vegetative NDVI is higher than the vegetative paddy NDVI. If the cover is left open, the negative NDVI vegetation cover will drop to its lowest NDVI. The availability of live paddy will be determined in 2021 based on these factors.

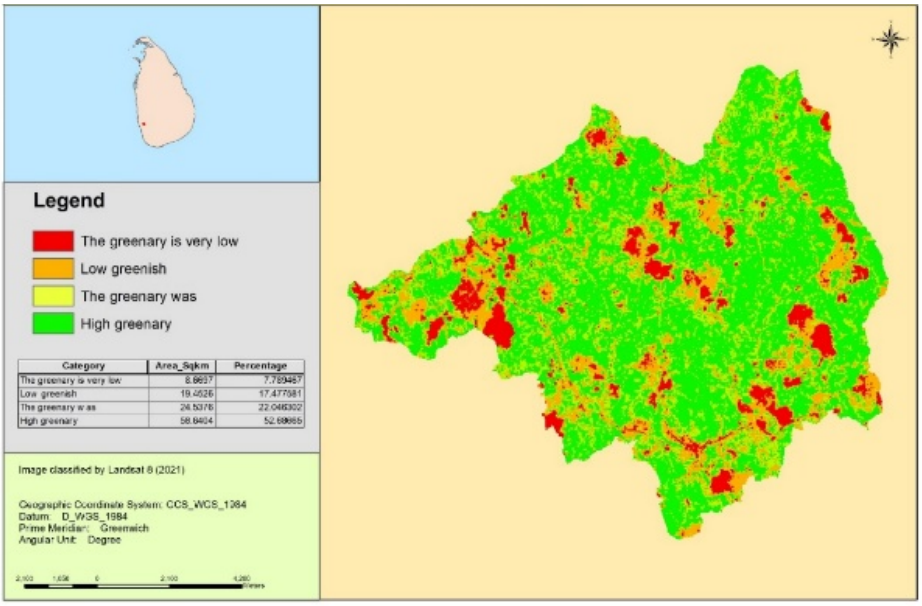

Figure 5. *Land class with greenery levels in 2021*

Analyse the Food Security

This section addresses the second objective of the study: to assess food security related to paddy cultivation in the selected Grama Niladhari Divisions (GNDs) within Horana DSD. The analysis combines primary survey data, field observations, and secondary data from agrarian records. The five GNDs selected: Uduwa North, Kahatapitiya, Meewanapalana East, Pannila, and Dambara were chosen using stratified random sampling based on the presence of active agricultural communities. To estimate food needs, the population's caloric requirements were calculated using the standard of 2,100 kilocalories per person per day, as recommended by the Central Statistics Agency (2021). The following formula was applied:

$$Food\ needs/year\ (kcal) = Population \times 2{,}100\ kcal/day \times 365\ days \quad (3)$$

These calorie needs were then converted into rice equivalents using an average annual per capita rice consumption of 107 kg, as reported by the Department of Agriculture (2021). The resulting food needs in kilograms (kg) for each GND are shown in Table 4**.**

Table 4.
Food needs in selected GNDs

GND	Population	Annual Food Needs (kcal)	Annual Food Needs (kg)
Uduwa North	2,012	1,542,198,000	342,040
Kahatapitiya	1,806	1,384,299,000	307,020
Meewanapalana E.	962	737,373,000	163,540
Pannila	1,950	1,494,675,000	331,500
Dambara	1,995	1,529,167,500	339,150
Total	**8,725**	**6,687,712,500**	**1,483,250**

Source: Author's calculations using Department of Agriculture data (2021)

To assess food security, actual rice production data (in kilograms) for each GND were obtained from the local Agrarian Services Center. The food security (FS) status was determined by comparing rice production with calculated food needs, using the following formula:

$$FS = Rice\ Production\ (kg) - Food\ Needs\ (kg) \qquad (4)$$

Table 5.
Food Security Status of Selected GNDs (2021)

GND	Population	Food Needs (kg)	Rice Production (kg)	Surplus/Deficit (kg)	Status
Uduwa North	2,012	342,040	25,800	–316,240	Insecure
Kahatapitiya	1,806	307,020	164,900	–142,120	Insecure
Meewanapalana E.	962	163,540	194,650	+31,110	**Secure**
Pannila	1,950	331,500	29,750	–301,750	Insecure
Dambara	1,995	339,150	39,900	–299,250	Insecure
Total	**8,725**	**1,483,250**	**455,000**	**–1,028,250**	**Insecure**

Source: Agrarian Services Center & Field Data, 2021

The food security analysis reveals a severe rice production deficit in four out of five GNDs. While the total annual food requirement for the study population is 1,483,250 kg, the actual rice production in 2021 was only 455,000 kg, resulting in a deficit of 1,028,250 kg. Only Meewanapalana East achieved a surplus of 31,110 kg, making it the only food-secure GND in the study. In contrast, Uduwa North, with a population of 2,012, showed the highest food gap (–316,240 kg), followed closely by Pannila and Dambara, with deficits exceeding 299,000 kg each.

These significant shortfalls indicate that local production is insufficient to meet even basic caloric needs, making these areas highly vulnerable to food insecurity. The situation is further exacerbated by rising food prices, reduced access to fertilizer, and increased cultivation costs, all of which were major factors in 2021. The findings emphasize the urgent need for targeted interventions, including productivity improvements, better resource allocation, and food distribution planning. The spatial distribution of secure and insecure GNDs is further visualized using interpolation methods in GIS (see Figure 6), allowing policymakers to prioritize interventions geographically.

Figure 6. *Map of Food Insecurity*

Publish a WebGIS map for food availability

As part of the fourth specific objective, a Web GIS platform was developed to visualize food availability and security status across the selected Grama Niladhari Divisions (GNDs) in Horana DSD. This interactive map was created using ArcGIS Online, incorporating food production, consumption needs, and spatial patterns derived from earlier analyses. The geospatial data were prepared in shapefile format and projected in the WGS 1984 coordinate system, in accordance with ArcGIS Online’s compatibility requirements (Löwe et al., 2022). Rather than serving as a purely technical output, the Web GIS map was designed with practical usability in mind, aiming to support local government officers, agrarian planners, and development stakeholders in identifying food-insecure areas. Through visualizing the rice production-to-need ratios, the map provides an intuitive, spatial decision-support tool that can inform targeted interventions such as input subsidies, cultivation planning, or food assistance distribution.

The map was initially presented to a group of local agricultural officers and administrative personnel from the Divisional Secretariat, who provided positive feedback on its clarity and usability. However, some participants suggested enhancements such as the inclusion of real-time crop monitoring and seasonal forecasting layers, which are being considered for future development. Currently, the Web GIS map is a static publication, reflecting data from the 2021/22 Maha season. Future iterations may incorporate dynamic updating mechanisms using live data feeds from agrarian centers and satellite-derived NDVI layers to support near-real-time monitoring of crop health and food security trends.

The publishing process of the online server. Before you publish layers to the portal need an ArcGIS online account. Then add the ArcGIS server in the sign-in. Then, to publish to an ArcGIS Enterprise portal, we must add the portal in the ArcGIS Administrator. ArcGIS Desktop connects to ArcGIS Online by default. The account you use to sign in must have privileges to publish hosted layers. General information that which layer name can be inserted in the summary description of your hosted web layer and tags. Select the capabilities setting using the tick on the KML option. Next, validate the data using the analysis tab. If errors don't occur next step is to publish the map. When displaying the dialogue box, copy data to the server by selecting the shape file layers on Food Security. Publish to create the hosted web layer item in your portal. When connected to the portal, it will see the web layer on the My Content tab of the Contents page. Then need to open the web map layer as Figure 13. The published food security layer can be visible via an open map viewer. Especially, the ArcGIS online portal facilitates changing background layers with customised changes in base maps, adjusting colour scheme and Symbology, and choosing an attribute to show, or keep the default as Show location only. And also facilitates changing the pop-up box that wants to shows details by clicking on the polygon layer.

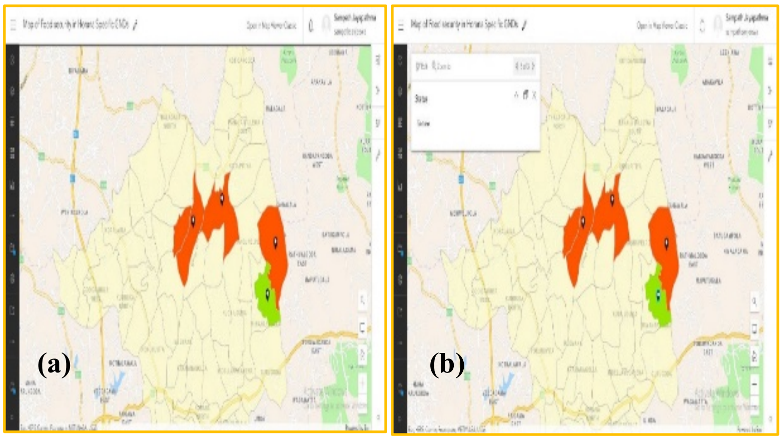

Figure 7. *(a) Map of Food availability in the Web map layer; (b) Secure Status of food security in the Web map layer*

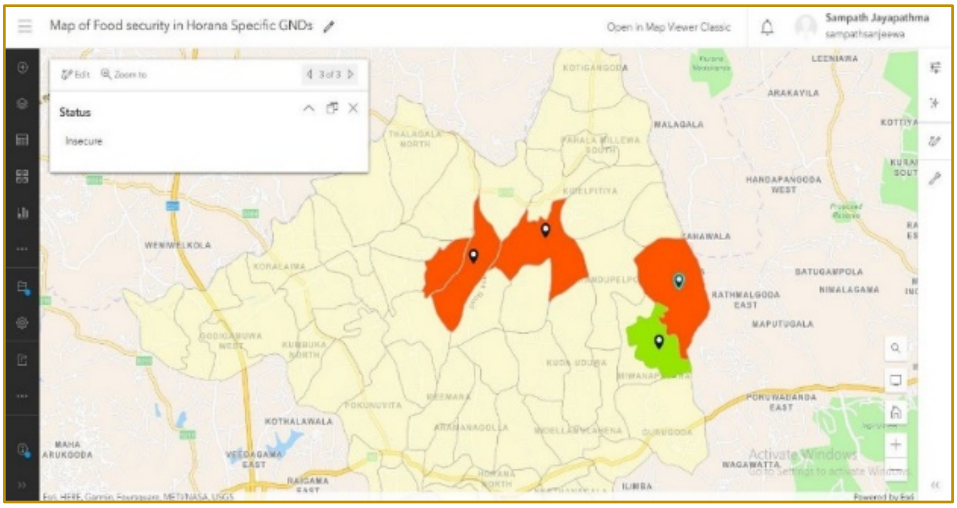

Figure 8. *Insecure Status of food security in the Web map layer*

Figures 7 and 8 show the status of food availability. The web map layer provides to display their details by the pop-up box by adding a point layer that needs a polygon to visualise. Colours can be changed by the user as well as symbology. This web map layer shows food secure and Insecure GNDs to identify food availability areas in Horana GNDs.

3. Conclusions and Recommendations

Food security remains a pressing issue in both developed and developing countries, including Sri Lanka, where inflation, climate variability, and insufficient agricultural production significantly contribute to food insecurity. This study focused on assessing food security in the Horana Divisional Secretariat Division (DSD) through the integration of Geographic Information Systems (GIS), remote sensing, and spatial analysis techniques. Results indicated a 30.99% reduction in agricultural land between 2018 and 2021, largely due to urban expansion and land degradation. Although the Normalized Difference Vegetation Index (NDVI) showed relatively higher green cover in 2021, suggesting healthier vegetation, this did not correspond to increased rice production. This apparent contradiction likely stems from factors such as fertilizer bans, rising production costs, and suboptimal farming practices, which affect crop yield despite vegetation presence. Therefore, NDVI alone is insufficient to assess agricultural productivity without corroborating field-level data and socio-economic considerations.

The study revealed that total rice production in the selected study area amounted to 455,000 kilograms, significantly below the estimated food requirement of approximately 1,483,250 kilograms, indicating a deficit of nearly 1,028,250 kilograms. Among the five Grama Niladhari Divisions (GNDs) examined, only Meewanapalana East was classified as food secure, highlighting the urgency to address food shortages in other areas. The development and deployment of a web-based GIS platform effectively mapped the spatial distribution of food security status, offering a valuable tool for local authorities to monitor and manage food availability in real time. To address these challenges, this study recommends several targeted policies and practical interventions. At the policy level, protecting agricultural land through land-use zoning regulations is crucial to prevent further conversion of farmland for non-agricultural uses. Reinstating targeted subsidies for key agricultural inputs, such as fertilizers and certified seeds, coupled with soil testing, can improve crop productivity and ensure efficient input use. Additionally, integrating climate-resilient agricultural strategies such as drought-tolerant rice varieties and water-saving irrigation methods into regional agricultural planning is necessary to mitigate the impacts of climate change. Establishing frameworks that institutionalize real-time crop monitoring using GIS and remote sensing will enhance early warning and decision-making capacities.

On the technical front, promoting crop rotation practices that include nitrogen-fixing legumes, such as soybeans, can improve soil health and reduce fertilizer dependency. Expanding access to soil health diagnostics through mobile testing and farmer education will further optimize fertilizer application and boost yields. Socio-economically, enhancing market access and stabilizing prices through cooperatives and minimum support prices will empower smallholder farmers. Strengthening household-level food storage and processing capabilities can reduce post-harvest losses and improve food availability throughout the year. Moreover, social safety nets like cash-for-work or food-for-work programs, especially during lean periods, can alleviate immediate food insecurity. Facilitating community-based seasonal planning platforms will improve synchronization of production and demand cycles, enhancing affordability and availability.

This study's findings and recommendations align with the Food and Agriculture Organization's (FAO) four pillars of food security: availability, access, utilization, and stability. By quantifying rice production deficits, identifying socio-economic barriers, and proposing spatially driven monitoring tools, this research contributes to comprehensive food security planning at the local level. Strengthening local food systems through the integration of geospatial technologies and targeted policies is essential for building resilience against future shocks, whether climatic, economic, or political. The approach presented here offers a replicable framework for sub-national food security assessment and management that can support Sri Lanka's efforts toward achieving sustainable food security.

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