# Assessing Food Security in Restricted Access Areas Using Remote Sensing: A Multi-Dimensional Analysis of Gaza from 2018 to 2024

Jasmin Jilma, Saman Ghaffarian

Department of Risk and Disaster Reduction, University College London, Gower Street, London, WC1E 6BT UK – jasmin.jilma.23@ucl.ac.uk, s.ghaffarian@ucl.ac.uk

**Keywords:** Food Security Assessment, Earth Observation, Random Forest, Land Cover, NDVI Analysis.

## Abstract

Food security assessments in conflict-affected regions face significant methodological challenges due to restricted ground access, data scarcity, and disruptions to agricultural production and food distribution networks. This study employs a multi-dimensional approach to assess food security in Gaza from 2018 to 2024, integrating Sentinel-2 satellite imagery, a Random Forest-derived land cover map, food price inflation data, and import statistics to construct a composite food security index. The findings reveal a substantial decline in agricultural productivity, evidenced by decreasing NDVI values from 0.25 to 0.16 in 2024 and increasing food imports. Furthermore, a marked rise in food prices of 180% post-October 2023 highlights the economic volatility exacerbated by conflict.

## 1. Introduction

The most recognised definition of food security originates from the 1996 World Food Summit, where it is described as "a state in which all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (Coates, 2013, pg.9). This condition is viewed as ex ante, with hunger and undernourishment being the resulting ex post outcomes (Barrett, 2002). The complex nature of food security has been acknowledged in the literature, leading to its categorization into several key pillars: availability, access, utilization, and stability (Kannan, Dev and Sharma, 2000; Coates, 2013).

Severe food insecurity is often triggered by disasters such as floods, earthquakes and war, whereas chronic food insecurity is closely linked to enduring poverty (Barrett, 2010). Displacement, destruction of agricultural infrastructure and disruption of market systems following disasters can in turn impact all aspects of food security (Holleman et al., 2017). Armed conflict has been found to severely impact food security by reducing food output through cropland abandonment and access due to the damage of physical infrastructure (Konandreas, 2012; Martin-Shields and Stojetz, 2017).

Food aid has contributed to alleviating some of these shortcomings, though with varying degrees of effectiveness (Del Ninno, Dorosh and Subbarao, 2007). While social safety nets, including remittances may offer increased relief in the short-term, prolonged conflict can diminish their effectiveness, as observed in Pakistan (Yang and Choi, 2007; Ghorpade, 2017). To counteract this, conditional cash transfers are often used by humanitarian actors including in Palestine by UNRWA (Crost, Felter and Johnston, 2016). Understanding food security in conflict situation therefore requires focusing on two key dimensions: food availability and accessibility.

An ideal measurement should holistically address the four pillars: availability, access, utilisation and stability. However, indicators that fully capture these dimensions are scarce (Petrikova, 2016). Earlier approaches, like the average national food availability, have become outdated (Porkka et al., 2013). In response, indicators like undernourishment, malnutrition and anthropometric measures (e.g. weight-for-age) have gained traction, but they still fall short in capturing food security (Leroy et al., 2015). Alternative correlates including income, poverty, and food prices have been proposed. Frankenberger (1992) encouraged composite food security indices, incorporating these dimensions alongside fears of food insufficiency and coping mechanisms. Although the best indicators are still debated, cross-referencing multiple indicators is widely accepted to enhance validity (Barrett, 2002).

Food security assessments in developing countries frequently depend on early warning systems using remote sensing (EWS) (Baruth et al., 2008). While these systems provide medium spatial resolution alerts, they often lack the granularity needed to identify local food insecurity and tend to use remote sensing qualitatively (Baruth et al., 2008). The failure of EWS to detect localized famines in Ethiopia (1999–2000), Malawi (2001–2002), and Niger (2005) highlight the challenges in accurately assessing local food insecurity, particularly regarding data accuracy and disaggregation (Devereux, 2009; Genesio et al., 2011). Other types of assessment include evaluating famine at the household level using surveys or monitoring food prices through machine learning-driven systems such as the World Food Programme's real-time price monitoring (Lentz et al., 2019). These assessments face limitations in terms of representativeness, reliability and timeliness. However, no existing approach integrates multiple methodologies for assessing food security, highlighting a critical research gap that is addressed in this study.

The recent escalation in conflict has made on-the-ground access in Gaza exceedingly difficult, complicating efforts by government and non-governmental organizations to assess food security (Saad and Dergaa, 2023). This underscores the need for alternative approaches, such as remote sensing and secondary research, to fill the gap. Machine learning has gained prominence in agricultural economics, particularly in farm risk analysis and disaster risk management (Athey, 2018). It enables automated risk assessment and is widely used for regression and classification tasks (Ghaffarian et al., 2022). Most studies focus on production risk, typically measured in crop yield or vegetation change, to enhance productivity and mitigate losses (Ghaffarian et al., 2022). These use machine learning and random forest models with simple regressions with vegetation indices, achieving an $R^2$ over 0.70 to predict yields (Toscano et al., 2019). The Normalised Difference Vegetation Index (NDVI) is one of the most used indices to study vegetation change, as it offers insights into crop growth, photosynthetic activity and vigour (Primicerio et al., 2015). Since, alternative indices have been developed to better address external factors including solar geometry, soil background, and atmospheric effects (Rondeaux, Steven and Baret, 1996). These include the soil adjusted vegetation index (SAVI), and green NDVI exploit plant reflectance properties, with low reflectance in red and blue regions and high reflectance in near-infrared (NIR) regions (Yuan and Niu, 2007). A combination of these indices is employed to best capture changes in the land cover.

## 2. Study area

In Gaza, the dynamics of food security are influenced by various factors. The coastal plain encompassing 360km$^2$ between the Mediterranean Sea and Israel has been impacted by repeated cycles of instability and violence (Roy, 1991). Past and current conflict, economic blockades and limitations in border areas have limited the agricultural sector’s capabilities (Abdelnour, Tartir and Zurayk, 2012). Historically, the agricultural sector was a key driver of economic growth. While agriculture approximately occupies 50 percent of the land within Gaza, approximately 29-35 percent of the agricultural land is within border or buffer areas, where there is highly restricted access, often leading to the abandonment of those fields (Premiere Urgence International, 2015; UNDP, 2017; Lipkind, 2024). These restrictions have a direct impact on local food production, exacerbating the dependency on imports and international aid (Reskallah, 2021). Almost 70 percent of households received humanitarian assistance in 2019 and are food insecure (UN OCHA, 2018, pg.1).
In 2022, nearly half (44 percent) of the Gaza Strip’s food consumption was derived from local production, with the remainder imported from abroad (Palestine Economic Policy Research Institute, 2023). This reliance on imports, coupled with the agricultural restrictions, leaves the region highly vulnerable to external disruptions and price fluctuations. Estimates suggest that between 50% and 66% of the population in Gaza depends on food assistance to meet their daily nutritional needs, highlighting the precariousness of the local food security situation (Palestine Economic Policy Research Institute, 2023).
There is a notable scarcity of academic literature specifically focused on food security in Palestine, with most existing studies being limited to small-scale surveys (Lin et al., 2021; El Bilbeisi et al., 2022). While there is some grey literature available on Palestine's food security situation, these reports are often restricted to isolated points in time. These studies, as conducted by Hassoun et al. (2024), for example, have failed to capture sources of food other than locally produced crops. When almost half of the food is imported, this presents a lack of comprehensive understanding of the situation, and the need to include food imports in the analysis is highlighted.

## 3. Methodology

The research adopts a multi-dimensional approach to theorise food security, recognising the key pillars needed to achieve food security: availability, access, utilisation and stability. This is achieved by integrating the Normalized Difference Vegetation Index data (Availability), a Random Forest land classifier model (Availability), with food price inflation (Accessibility) and food import data (Availability) to develop the normalized food security index. The stability pillar is achieved by creating a monthly time series analysis from 2018 to 2024. Utilisation is not captured in this analysis due the lack of frequent data and the need to measure utilisation on the ground. The methodology is summarised in Figure 1.

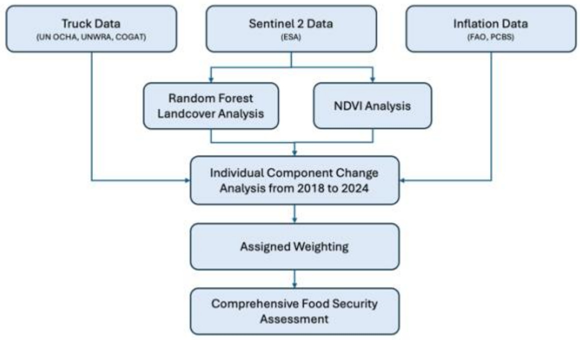

Figure 1. Methodology Summary

### 3.1 Data

Sentinel 2 satellite imagery from the Copernicus/S2 collection on Google Earth Engine (GEE) are used for the analysis. Temporal filtering is applied to the data collection to include images each month from 2018 to 2024.
UN OCHA provides the truck data prior to October 2023 until March 2024 together with UNRWA (UN OCHA, 2024; UNRWA, 2024). UNRWA then continues the data collection. UNRWA’s commercial truck data reporting continues through April 2024. Starting in May 2024, UNRWA data is no longer complete due to access issues, leaving Coordination of Government Activities in the Territories (COGAT) to be the only available dataset with commercial figures (COGAT, 2024), which is used for May.
Food prices have a crucial impact on consumer access to food in poorer countries and domestic food price volatility provides information on economic access (Naidu, Zuva and Sibanda, 2023). The study analyses the impact of food price inflation on food security, comparing local data from the Palestinian Central Bureau of Statistics (PCBS) with global data from the FAO Food Price Index (FPI) to reflect macroeconomic factors affecting all countries (FAO, 2024; PCBS, 2024). Adjustments are made to normalize the data to a common base year for comparability. The base year for the Palestinian Central Bureau of Statistics (PCBS) FPI index is 2018. The FAO FPI is adjusted to have the same base year of 2018, because it uses the years 2014-2016 as a base. The calculation to convert into 2018 as a base year are as follows.

1. Find the average index value for 2018
2. Recalculate the index value using the following formula:

$$New\ Index\ Value = \frac{Current\ Index\ Value}{Index\ Value\ for\ the\ New\ Base\ Year\ (2018)} \quad (1)$$

### 3.2 Landcover analysis

The imagery is split into five classes: buildings, fields, water bodies, dry areas, and greenhouses. These classes are selected to best reflect the classification task identifying vegetated versus dry cropland and other building types present in the Gaza Strip. The study involves defining regions of interest (ROIs) corresponding to different land cover classes within the Gaza Strip. Samples of these defined categories are displayed in Figure 2. The following classes are defined, each assigned a unique `ClassID`, as shown in Table 1.

| Class ID | Name of Class | Description of Class | Number of Polygons |
|---|---|---|---|
| 0 | Greenhouses | Areas covered by greenhouse structures | 39 |
| 1 | Buildings | Built-up and urban areas, including commercial, industrial and residential structures | 36 |
| 2 | Vegetated Fields | Agricultural fields and tree plantations which were later merged into one category | 68 |
| 3 | Water | Water bodies including rivers, the sea and reservoirs | 27 |
| 4 | Dry Fields | Barren or sparely vegetated land, often characterised by dry soil or sand | 32 |

Table 1. Class descriptions and number of samples.

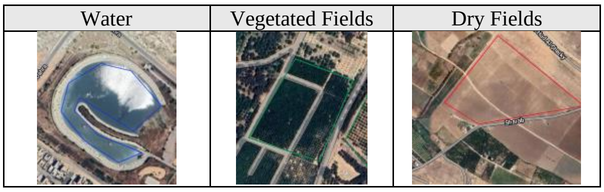


Figure 2. Sample images of classes.

### 3.3 Spectral Indices

Vegetation and surface indices (NDVI, NDTI, EVI, NDBAI2, RPGI) are computed to enhance the classification accuracy by providing additional spectral information beyond the raw bands. A composite stack is created by combining the Sentinel-2 bands with the calculated indices.

| Index | Equation | Reference |
|---|---|---|
| NDVI | $\frac{NIR - Red}{NIR + Red}$ | Genovese et al., 2001. |
| LSWI | $\frac{NIR - SWIR}{NIR + SWIR}$ | Chandrasekar et al., 2010 |
| NDTI | $\frac{SWIR1 - NIR}{SWIR1 + NIR}$ | Liu and Huete, 1995 |
| EVI | $2.5 \times \frac{NIR - Red}{NIR + 6.0 \times Red - 7.5 \times Blue + 1.0}$ | Liu and Huete, 1995 |
| NDBAI2 | $\frac{B11 - B12}{B11 + B12}$ | Balcik, Senel and Goksel, 2019 |
| RGGI | $\frac{Blue}{(1 - mean(Blue + Green + NIR)}$ | Balcik, Senel and Goksel, 2019 |

Table 2. Spectral indices used in the study.

### 3.4 Machine Learning

This stack provides a dataset for classification, with each pixel containing information from the original spectral bands and derived indices. The Random Forest algorithm is trained using the sampled regions from the ROIs. The merged ROIs is split into training (70% of the ROIs) and testing (30% of the ROIs) datasets to develop and evaluate the classification model. To ensure balanced class representation, a stratified sampling approach is used, where an equal number of samples from each class is included for the training and testing data. A Random Forest classifier, with 100 decision trees, is used to conduct the land cover classification.

### 3.5 Accuracy-weighted averaging

Given the mixed success of the classifier for some classes, a weighted averaging method for imputing missing values using the accuracy scores is used. Two datasets are combined: the original dataset received from the classifier where values are mostly complete, weighted by the provided accuracy scores and the second dataset where only values with an accuracy score of 0.70 or above were used.

The equations to compute the imputed values for each missing data point in the first dataset are as follows: For each variable (e.g., `Fields/Plantation`, `Water`, `Dry`), identify the missing values in $X_1$ and the corresponding values in $X_2$. The imputed value for a missing data point in $X_2$ for a given variable can be calculated as:

$$Imputed\ Value = A \times X_2 + (1 - A) \times \bar{X}_1 \tag{2}$$

Given:
$X_1$: Dataset with missing values (accuracy below 0.70 were removed)
$X_2$: Complete Dataset with the inclusion of lower accuracies
$A$: Accuracy Scores

The weighted average formula uses the accuracy score $A$ to determine how much weight to give to the second dataset's value versus the mean of the first dataset's available values. If the accuracy score $A$ is high (close to 1), the imputation relies more on the value from the second dataset, indicating high confidence in that data. If the accuracy score $A$ is low (close to 0), the imputation leans more on the mean of the available data in the first dataset, reflecting lower confidence in the second dataset's value.

### 3.6 Creating the Index

To improve comparability across different indices, all index values are initially normalized using the following equations, irrespective of their original dimensions and units. The Min-Max Normalisation is used, whereby 0 represents the $min_j$ and 1 the $max_j$.

$$\bar{x}_j(i) = \frac{\bar{x}_j(i) - min_j}{max_j - min_j} \tag{3}$$

The weighting and aggregation process then follows with the assigned weights, shown in Table 3.

| Food Security Category | Variable | Scenario 1 | Scenario 2 | Scenario 3 |
|---|---|---|---|---|
| Availability | Land Cover Water | 5% | 2% | 0% |
| | Land Cover: Vegetated Fields | 10% | 5% | 0% |
| | Land Cover: Dry fields | 10% | 5% | 0% |
| | NDVI | 25% | 15% | 0% |
| Physical and Economic Access | Food Price Index | 25% | 32% | 33.3% |
| | All trucks (to account for fuel needed and the delivery of food) | 5% | 9% | 33.3% |
| | Food trucks (majority of trucks are filled with humanitarian goods ensuring economic access) | 20% | 32% | 33.3% |

Table 3. Applied percentage weights in the food security index.

When values are missing for a variable in the landcover analysis due to a low accuracy score, the weights are adjusted amongst the available land cover variables, so their combined weight still adds up to 25%. These weights are applied to compute a new weighted total for each month.

Scenario 1 reflects normal circumstances where equal weighing is given to availability and physical and economic access, whereby more information on access is known. Scenarios 2 and 3 are implemented in October 2023, when the significance of availability through farming means became significantly lower (Famine Early Warning Systems, 2024).

## 4. Results

### 4.1 Consumer and Food Price Inflation

The Palestine's Consumer Price Index (CPI) is relatively stable from 2018 to 2024, with only modest fluctuations. Food tax hikes are applied to many items in 2015, 2019, 2022, and 2023 (Lipkind, 2024). The average CPI value 104.94 suggests a moderate increase in prices since 2018, but the low standard deviation indicates that these changes have been gradual and controlled. However, when the last value, 136.33 in December 2023 is recorded, a significant increase can be detected.

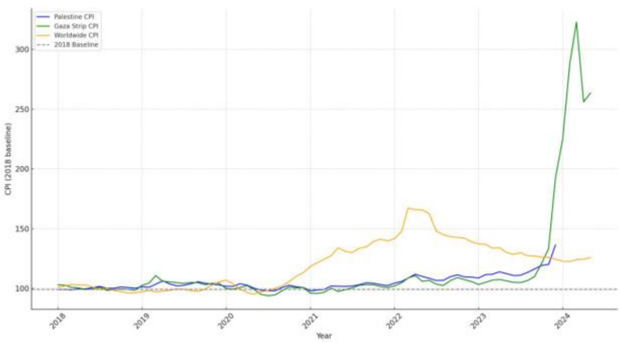


Figure 3. Food price inflation measured through components of the CPI from 2018 to 2024.

The Gaza Strip experiences considerable inflationary volatility in 2023-2024, indicating little stability, as evidenced by the rapid increase in CPI values and high standard deviation. The mean CPI of 115.18 suggests that, on average, prices were higher than in the whole of Palestine, but the extreme upper range 322.76 indicates a significant spike in prices, particularly noticeable after October 2023. This volatility shows Gaza Strip's economy high sensitivity to external shocks.

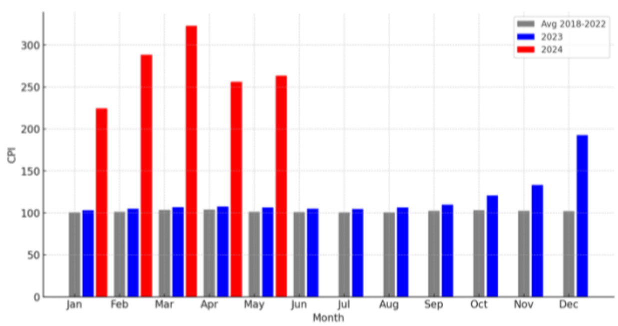


Figure 4. Food price inflation in Gaza (2018 baseline = 100).

Figure 4 shows severe economic challenges, particularly after October 2023, which leads to sharp increases over 180% in the cost of essential food items. These economic pressures are further exacerbating food insecurity, leaving the population highly dependent on food imports and humanitarian aid.

### 4.2 Truck and food imports

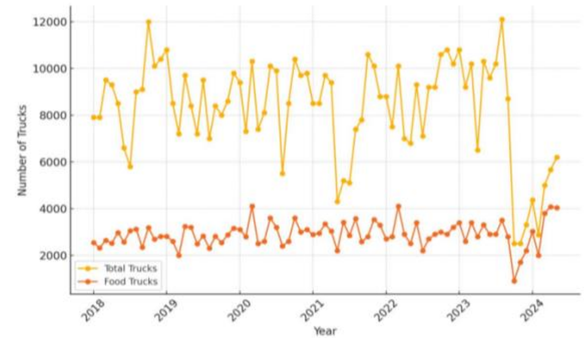


Figure 5. Total truck and food truck imports from 2018 to 2024.

Food imports declined significantly during periods of heightened conflict and instability, notably from May to August 2021 and after October 2023, as shown in Figure 5. The number of trucks remain relatively stable from 2018 to 2023, ranging from about 7,900 to 9,500 with monthly variations. Monthly truck entries range from around 9,000 from January to June, to the low of around 6,000 in the months of July and August, followed by a rise from September to December to approximately 10,000. In 2021, truck imports follow a similar trend, except in May to July/August, where imports drop considerably to 4,300 and continue to stay around 5,150 trucks for two more months. This timing coincides with the 2021 Israel-Palestine crisis, reflecting a potential role of politics in truck entries. In 2022 truck imports continues at normal levels, as well as up to September 2023. However, from October to May 2024 imports drop significantly, although they slightly increase in March and April 2024, following IPC Phase 5 famine warning release in early March 2024 (IPC, 2024).

### 4.3 Normalised Difference Vegetation Index (NDVI)

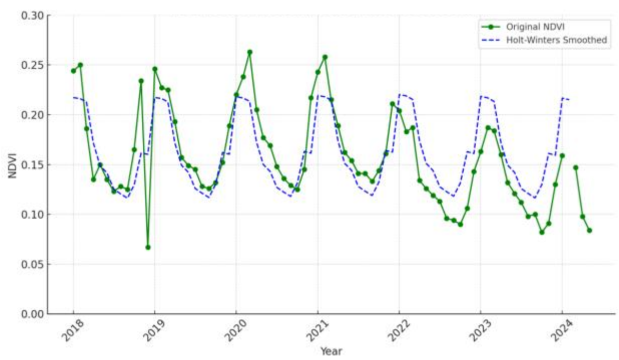


Figure 6. NDVI from 2018 to 2024.

The study reveals a significant decline in agricultural productivity in Gaza, as indicated by the decreasing maximum NDVI values from 0.25 in 2018 to 0.16 in 2024 in Figure 6. This decline points to worsening vegetation health and coverage. The cyclical nature of food production is reflected in the NDVI and Landcover Analysis, with peaks around February and troughs around September.

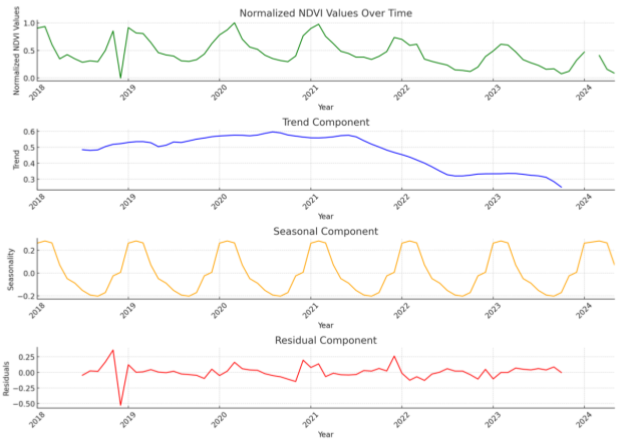


Figure 7. Component Analysis of the NDVI.

In Figure 7, the seasonal component is highlighted and found to be a variation of ± 0.25 with peak in January, the growing season, with values of 0.22 to 0.25 and lows in July-September, the off-season, with values of 0.14 to 0.17. The trend analysis reflects the gradual decline in NDVI values from the start of the series at around 0.24 to around 0.18 by the end. This suggests that a decline in overall vegetation health or coverage has occurred over the observed time period. The residuals are relatively small, mostly within the range of -0.02 to 0.02, indicating that the decomposition model captured the primary trends. There is a missing data point in February 2024 and the NDVI dropped extremely low in December 2018, which led to the high residual value. These are most likely data quality issues.

### 4.4 Land-cover Map

The land-cover map achieved an overall average accuracy of 0.82 and a kappa statistic of 0.76 from January 2018 to May 2024. The median values for these metrics remained consistent with the overall results, while the model's performance showed variability with maximum accuracy and kappa values reaching 0.89 and 0.85, respectively, and minimum values dropping to 0.76 and 0.68, respectively. These classification results are depicted in Figure 8.

| | Accuracy Assessment | Kappa Statistic |
|---|---|---|
| **Average** | 0.82 | 0.76 |
| **Maximum** | 0.89 | 0.85 |
| **Minimum** | 0.76 | 0.68 |

Table 4. Accuracy Assessment of the Landcover Model.

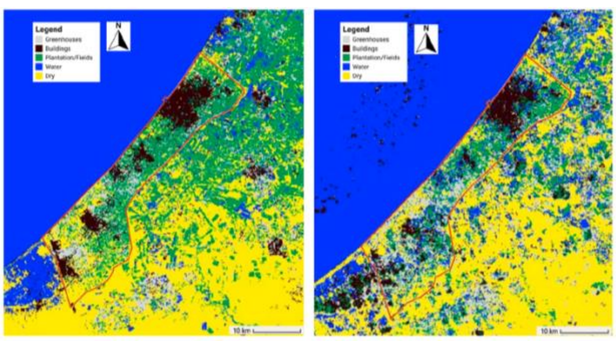


Figure 8. Maximum accuracy 0.88 (05/2022) on the left versus minimum 0.76 (10/2023) accuracy classification on the right

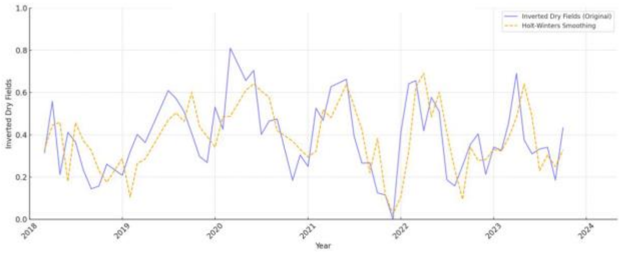


Figure 9. Inverted dry fields from 2018 to 2024.

The Inverted Dry Fields values in Figure 9 fluctuate significantly over time, showing both increasing and decreasing trends depending on the season. The Holt-Winters smoothed line reveals a more stable and predictable pattern compared to the raw data and captures the seasonal trends. The difference between the peaks and troughs in the raw data ranges from about 0.2 to 0.6, suggesting a moderate level of variability.

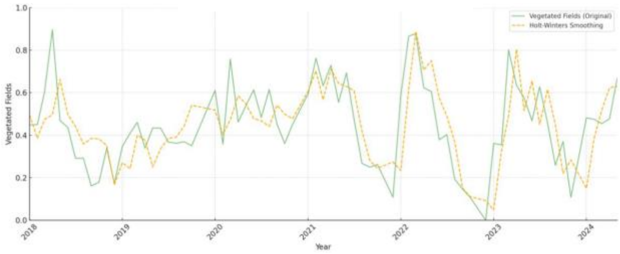


Figure 10. Vegetated fields from 2018 to 2024.

As illustrated in Figure 10, vegetated fields exhibit a distinct seasonal pattern, with elevated field levels (0.4-0.6) persisting from early January through mid-year (June-July). This period is followed by a remarkable decrease in levels, which remain low for the remainder of the year, aligning with repeated dry field conditions during these months. The amplitude in the raw data ranges from about 0.45 to 0.9 indicates significant variability. After smoothing, the amplitude reduces to a range of approximately 0.5 to 0.75. Using both vegetated and dry fields as land classification categories helps increase the certainty of the analysis, especially given the respective accuracies of analysis of the individual categories of 0.68 and 0.75. In both series, there are no significant upward or downward trends, which is most likely a result of moderate accuracies of the model. No similar analysis has been found in the literature; hence the findings cannot be triangulated. However, the two land categories present an inverse relationship and as the inverted dry fields follow the same pattern as the vegetated fields and the NDVI, some validity in the findings can be assumed.

### 4.5 Food Security Index

The developed food security index in Figure 11 reflects these key findings, showing impacts of seasonal patterns.

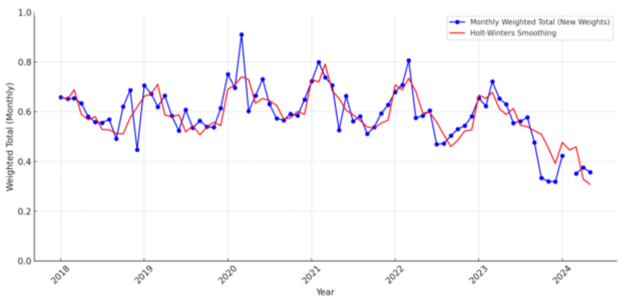


Figure 11. Developed food security index from 2018 to 2024.

From 2018 to 2022 the index fluctuates around a middle range of 0.6, with moderate peaks and troughs, reflecting the seasonal trends of local food production. From 2023 to 2024 the trend declines consistently, indicating a worsening in food security.

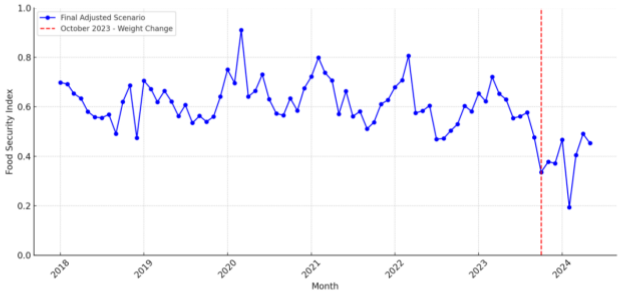


Figure 12. Scenario 2 developed food security index from 2018 to 2024.

With the changed final weights, the index values remain the same before October 2023. Post October 2023, the adjustments cause the index to reflect a stronger influence from economic and transportation factors, while decreasing the contribution from agricultural and environmental metrics including NDVI, water availability, and the vegetation of the fields. This produces a lower minimum and faster recovery, when more trucks entered Gaza.

Around 68 percent of households are found to be either moderately or severely food insecure during the latest Socio-Economic and Food Security Survey in 2019 when the food security index was around 0.60 (UN OCHA, 2018). According to the index developed in Figure 11, food security through May 2024 registered a values of 0.37, showing a 38.3% decline compared to previous levels. This percentage increase suggests that moderate or severe food insecurity levels increase to 94.0 percent according to this created index. The IPC global initiative findings show that 95 percent of the Gaza Strip's population face high levels of acute food insecurity from June to September 2024, for which 96 percent of the population is analysed (IPC, 2024). This figure aligns with the findings derived from the developed index, highlighting its utility in tracking changes in food security, particularly when a baseline survey is available for comparison.

Increased food insecurity in Gaza is primarily driven by two key drivers as findings by the IPC show, restricted humanitarian access, affecting the number of trucks allowed to enter and hostilities, directly affecting crop production, which are abandoned due to the displacement of the population. These same drivers are reflected in the developed index, reinforcing its ability to capture real-world food security dynamics, when they are accounted for (IPC, 2024).

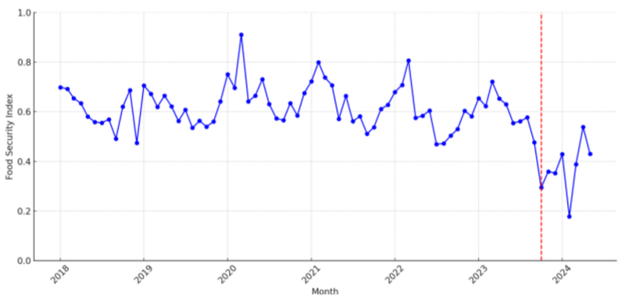


Figure 13. Scenario 3 developed food security index from 2018 to 2024.

Each hypothetical scenario post October 2023 leads to significantly different changes in food security, highlighting the need for further calibration of the model with an on-ground assessment of each variable's importance. The Scenario 1 Food Security Index decreases by approximately -12.2% from January 2024 to May 2024. The Scenario 2 index has a smaller decrease of approximately -3.1% over the same period, meaning that the reduction of vegetated fields significantly impacts the index. Scenario 3 shows a slight increase of approximately 0.5% in the index from January 2024 to May 2024, reflecting the slight reduction of inflation and increase in food trucks.

## 5. Discussion and Conclusion

Whilst this study highlights the potential of remote sensing in assessing food security, several limitations emerge, including moderate accuracy in land cover assessment, limited knowledge of distribution mechanisms, and missing data.

The accuracy of land cover analysis remains moderate due to various factors. Seasonal changes significantly impact classification accuracy, with vegetated fields showing the lowest accuracy (0.68), followed by dry fields (0.75), while water has the highest accuracy (0.98). Noise in the data and cloud cover during certain months further reduce classification performance. Additionally, the training areas within the regions of interest (ROIs) are only defined once, which does not account for seasonal variations, which results in fluctuating accuracy throughout the year. The random forest model accuracy declines in 2024 due to infrastructure destruction, which the model was not trained on.

To improve land cover classification accuracy, training data can be collected across multiple seasons. Furthermore, integrating data from multiple remote sensing sources, such as optical and SAR imagery, has been shown to improve classification results (Weiss, Jacob, and Duveiller, 2020). Higher resolution imagery may also improve classification accuracy and enable monitoring of greenhouse changes, though this objective is not pursued in the present study due to moderate classification performance. Additionally, classification accuracy is affected by seasonal variation and cloud cover, as well as unexpected infrastructural destruction in 2024, which is not accounted for in training data.

Missing data and limited knowledge of distribution mechanisms present significant constraints in assessing food security. The movement of delivered goods remains largely unknown, complicating measurements of food distribution within Gaza. Truck data is collected from UN agencies and COGAT for May 2025, for which third-party verification is not possible, nor does it exist, due to safety concerns. Additionally, detailed information on food types and kilocalories transported in each truck is unavailable, restricting the depth of analysis, particularly in terms of food utilisation.

Although remote sensing provides a cost-effective and scalable alternative to traditional field assessments, it cannot capture food utilization and intra-region distribution disparities. The spatial resolution of Sentinel-2 imagery limits the ability to monitor small-scale domestic food production and animal agriculture, thereby reducing the comprehensiveness of the analysis.

Nevertheless, the integration of socioeconomic indicators and machine learning-based forecasting can enhance early warning systems and humanitarian response strategies. Understanding seasonal patterns can allow for targeted increases in food support ahead of time. An early warning system with more than one indicator is more likely to be able to capture changes in the food dynamics, which solely remote sensing-based systems fail to pick up. Furthermore, combining remote sensing techniques with contextual analysis—such as agricultural change detection, food import data, and food inflation trends—can provide a more granular understanding of food security dynamics than a singular approach. Through tracking changes in the dimensions of food

security, policies can also be targeted specifically towards a declining dimension.
Despite its limitations, remote sensing remains a valuable tool for assessing food security in contexts where traditional data collection methods are impractical. A multifaceted approach that integrates multiple remote sensing techniques with socioeconomic and contextual analysis can offer a more comprehensive perspective on food security challenges, enabling timely humanitarian interventions.

## References

Abdelnour, S., Tartir, A. and Zurayk, R., 2012. Farming Palestine for freedom. Al-Shabaka.

Athey, S., 2018. The impact of machine learning on economics. In The economics of artificial intelligence: An agenda (pp. 507-547). University of Chicago Press.

Balcik, F.B., Senel, G. and Goksel, C., 2019. Greenhouse mapping using object based classification and sentinel-2 satellite imagery. 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics) (pp. 1-5). *IEEE*.

Barrett, C.B., 2002. Food security and food assistance programs. Handbook of agricultural economics, 2, pp.2103–2190.

Barrett, C.B., 2010. Measuring food insecurity. Science, 327(5967), pp.825–828.

Baruth, B., Royer, A., Klisch, A. and Genovese, G., 2008. The use of remote sensing within the MARS crop yield monitoring system of the European Commission. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci*, 37, pp.935–940.

Bégué, A., Arvor, D., Bellon, B., Betbeder, J., De Abelleyra, D., PD Ferraz, R., Lebourgeois, V., Lelong, C., Simões, M. and R. Verón, S., 2018. Remote sensing and cropping practices: A review. *Remote Sensing*, 10(1), p.99.

K., Sesha Sai, M., Roy, P. and Dwevedi, R., 2010. Land Surface Water Index (LSWI) response to rainfall and NDVI using the MODIS Vegetation Index product. *International Journal of Remote Sensing*, 31(15), pp.3987–4005.

Coates, J., 2013. Build it back better: Deconstructing food security for improved measurement and action. *Global Food Security*, 2(3), pp.188–194.

COGAT, 2024. Gaza Humanitarian Aid Data [Online]. Available from: https://gaza-aid-data.gov.il/main/.

Crost, B., Felter, J.H. and Johnston, P.B., 2016. Conditional cash transfers, civil conflict and insurgent influence: Experimental evidence from the Philippines. *Journal of Development Economics*, 118, pp.171–182.

DeFries, R.S. and Townshend, J., 1994. NDVI-derived land cover classifications at a global scale. *International Journal of Remote Sensing*, 15(17), pp.3567–3586.

Del Ninno, C., Dorosh, P.A. and Subbarao, K., 2007. Food aid, domestic policy and food security: Contrasting experiences from South Asia and sub-Saharan Africa. *Food Policy*, 32(4), pp.413–435.

Devereux, S., 2009. Seasonal food crises and social protection in Africa. The comparative political economy of development. Routledge, pp.137–161.

El Bilbeisi, A.H., Al-Jawaldeh, A., Albelbeisi, A., Abuzerr, S., Elmadfa, I. and Nasreddine, L., 2022. Households' food insecurity and its association with demographic and socioeconomic factors in Gaza Strip, Palestine: a cross-sectional study. *Ethiopian Journal of Health Sciences*, 32(2).

FAO, 2024. Food Price Index [Online]. Available from: https://www.fao.org/worldfoodsituation/foodpricesindex/en/.

Famine Early Warning Systems Network, 2024. Gaza Strip Food Supply Report [Online]. FEWS NET- USAID. Available from: https://fews.net/sites/default/files/2024-07/Food-Supply-Report-Gaza-202406.pdf.

Frankenberger, T.R., 1992. Rapid Food Security Assessment. Agency for International Development, Bureau for Food and Humanitarian Assistance, Office of US Foreign Disaster Assistance.

Genesio, L., Bacci, M., Baron, C., Diarra, B., Di Vecchia, A., Alhassane, A., Hassane, I., Ndiaye, M., Philippon, N. and Tarchiani, V., 2011. Early warning systems for food security in West Africa: evolution, achievements and challenges. *Atmospheric Science Letters*, 12(1), pp.142–148.

Genovese, G., Vignolles, C., Nègre, T. and Passera, G., 2001. A methodology for a combined use of normalised difference vegetation index and CORINE land cover data for crop yield monitoring and forecasting. A case study on Spain. Agronomie, 21(1), pp.91–111.

Ghaffarian, S., van der Voort, M., Valente, J., Tekinerdogan, B. and de Mey, Y., 2022. Machine learning-based farm risk management: A systematic mapping review. *Computers and electronics in agriculture*, 192, p.106631.

Ghorpade, Y., 2017. Extending a lifeline or cutting losses? The effects of conflict on household receipts of remittances in Pakistan. *World Development*, 99, pp.230–252.

Hassoun, A., Al-Muhannadi, K., Hassan, H.F., Hamad, A., Khwaldia, K., Buheji, M. and Al Jawaldeh, A., 2024. From acute food insecurity to famine: how the 2023/2024 war on Gaza has dramatically set back sustainable development goal 2 to end hunger. *Frontiers in Sustainable Food Systems*, 8, p.1402150.

Holleman, C., Jackson, J., Sánchez, M.V. and Vos, R., 2017. Sowing the seeds of peace for food security. Disentangling the nexus between conflict, food security and peace.

IPC, 2024. Gaza Strip Acute Food Insecurity June to September 2024 [Online]. (IPC Global Initiative - Special Brief). Available from:
https://www.ipcinfo.org/fileadmin/user_upload/ipcinfo/docs/IPC_Gaza_Strip_Acute_Food_Insecurity_Jun_Sept2024_Special_Brief.pdf

Kannan, K.P., Dev, S.M. and Sharma, A.N., 2000. Concerns on food security. *Economic and Political Weekly*, pp.3919–3922.

Karthikeyan, L., Chawla, I. and Mishra, A.K., 2020. A review of remote sensing applications in agriculture for food security: Crop growth and yield, irrigation, and crop losses. *Journal of Hydrology*, 586, p.124905.

Konandreas, P., 2012. Trade policy responses to food price volatility in poor net food-importing countries

Leroy, J.L., Ruel, M., Frongillo, E.A., Harris, J. and Ballard, T.J., 2015. Measuring the food access dimension of food security: a critical review and mapping of indicators. *Food and nutrition bulletin*, 36(2), pp.167–195.

Lentz, E.C., Michelson, H., Baylis, K. and Zhou, Y., 2019. A data-driven approach improves food insecurity crisis prediction. *World Development*, 122, pp.399-409.

Lin, T.K., Kafri, R., Hammoudeh, W., Mitwalli, S., Jamaluddine, Z., Ghattas, H., Giacaman, R. and Leone, T., 2022. Pathways to food insecurity in the context of conflict: the case of the occupied Palestinian territory. *Conflict and Health*, 16(1), pp.1–19.

Lipkind, S., 2024. Gaza’s Food Crisis Began Long Before the Israel-Hamas Conflict [Online]. Think Global Health. Available from: https://www.thinkglobalhealth.org/article/gazas-food-crisis-began-long-israel-hamas-conflict.

Liu, H.Q. and Huete, A., 1995. A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. *IEEE transactions on geoscience and remote sensing*, 33(2), pp.457–465.

Martin-Shields, C. and Stojetz, W., 2017. Framing the relationship between food security and violent conflict data: A clustering and typology approach. *World Development*.

Naidu, G., Zuva, T. and Sibanda, E.M., 2023. A review of evaluation metrics in machine learning algorithms. *Springer*, pp.15–25.

PCBS, 2024. Consumer Price Index [Online]. Available from: https://www.pcbs.gov.ps/site/lang__en/695/default.aspx.

Palestine Economic Policy Research Institute, 2023. Food Insecurity Bulletin [Online]. (29). Available from: https://mas.ps/cached_uploads/download/2024/03/17/fsb-29-2024-eng-1710677168.pdf.

Petrikova, I., 2016. In Pursuit of Food Security: Who Should Provide Aid Where and How. UCL (University College London).

Porkka, M., Kummu, M., Siebert, S. and Varis, O., 2013. From food insufficiency towards trade dependency: a historical analysis of global food availability. *PloS one*, 8(12), p.e82714

Premiere Urgence International, 2015. Access Restricted Area in the Gaza Strip: Farmer’s inability to access their land [ Online]. Available from: https://www.europarl.europa.eu/meetdocs/2014_2019/documents/dpal/dv/4c_pui_ara_factsheet_final_2016/4c_pui_ara_factsheet_final_2016en.pdf. Primicerio et al., 2015

Reskallah, S., 2021. Food Insecurity in Palestine: A Future for Farmers. Viewpoint Series [Online]. Available from: https://www.wilsoncenter.org/article/food-insecurity-palestine-future-farmers.

Rondeaux, G., Steven, M. and Baret, F., 1996. Optimization of soil-adjusted vegetation indices. *Remote sensing of environment*, 55(2), pp.95–107.

Roy, S., 1991. The political economy of despair: changing political and economic realities in the Gaza Strip. *Journal of Palestine Studies*, 20(3), pp.58-69.

Saad, H.B. and Dergaa, I., 2023. Public health in peril: assessing the impact of ongoing conflict in Gaza Strip (Palestine) and advocating immediate action to halt atrocities. *New Asian Journal of Medicine*, 1(2), pp.1–6.

Shanahan, J.F., Schepers, J.S., Francis, D.D., Varvel, G.E., Wilhelm, W.W., Tringe, J.M., Schlemmer, M.R. and Major, D.J., 2001. Use of remote-sensing imagery to estimate corn grain yield. *Agronomy journal*, 93(3), pp.583–589.

Sishodia, R.P., Ray, R.L. and Singh, S.K., 2020. Applications of remote sensing in precision agriculture: A review. *Remote sensing*, 12(19), p.3136.

Toscano, P., Castrignanò, A., Di Gennaro, S.F., Vonella, A.V., Ventrella, D. and Matese, A., 2019. A precision agriculture approach for durum wheat yield assessment using remote sensing data and yield mapping. *Agronomy*, 9(8), p.437.

Tomiazzi, J.S., Pereira, D.R., Judai, M.A., Antunes, P.A. and Favareto, A.P.A., 2019. Performance of machine-learning algorithms to pattern recognition and classification of hearing impairment in Brazilian farmers exposed to pesticide and/or cigarette smoke. *Environmental Science and Pollution Research*, 26, pp.6481-6491.

UNDP, 2017. Agriculture in Area C [Online]. (Resilience Series). Available from: https://www.undp.org/sites/g/files/zskgke326/files/2022-11/resilience_series_-_agriculture_in_area_c_-_final.pdf.

UNOSAT, 2024. Gaza Strip Comprehensive Damage Assessment - January 2024 [Online]. Available from: https://reliefweb.int/map/occupied-palestinian-territory/unosat-gaza-strip-comprehensive-damage-assessment-january-2024.

UN OCHA, 2018. The Monthly Humanitarian Bulletin. November 2018.

UN OCHA, 2024. Gaza crossings: movement of people and goods [Online]. Available from: https://www.ochaopt.org/data/crossings.

UNRWA, 2024. GAZA SUPPLIES AND DISPATCH TRACKING [Online]. Available from: https://www.unrwa.org/what-we-do/gaza-supplies-and-dispatch-tracking.

Weiss, M., Jacob, F. and Duveiller, G., 2020. Remote sensing for agricultural applications: A meta-review. *Remote sensing of environment*, 236, p.111402.

Yang, D. and Choi, H., 2007. Are remittances insurance? Evidence from rainfall shocks in the Philippines. *The World Bank Economic Review*, 21(2), pp.219–248.

Yuan, J. and Niu, Z., 2007. Classification using EO-1 hyperion hyperspectral and ETM data. 3. *IEEE*, pp.538–542.