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A GEOSPATIAL ANALYSIS OF FOOD INSECURITY AMONG REFUGEE HOUSEHOLDS IN LEBANON USING MACHINE LEARNING TECHNIQUES

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Abstract

This study integrates geospatial analysis with machine learning to understand the interplay and spatial dependencies among various indicators of food insecurity. Combining household survey data and novel geospatial data on Syrian refugees in Lebanon, we explore why certain food security measures are effective in specific contexts while others are not. Our findings indicate that geolocational indicators significantly influence food insecurity, often overshadowing traditional factors like household socio-demographics and living conditions. This suggests a shift in focus from labor-intensive socioeconomic surveys to readily accessible geospatial data. The study also highlights the variability of food insecurity across different locations and subpopulations, challenging the effectiveness of individual measures like FCS, HDDS, and rCSI in capturing localized needs. By disaggregating the dimensions of food insecurity and understanding their distribution, humanitarian and development organizations can better tailor strategies, directing resources to areas where refugees face the most severe food challenges. From a policy perspective, our insights call for a refined approach that improves the predictive power of food insecurity models, aiding organizations in efficiently targeting interventions.

Keywords: food insecurity, forced displacement, refugees, geospatial analysis, machine learning
JEL Classifications: I3, I32, O1, O53, R23, Q18

ملخص

تدمج هذه الدراسة التحليل الجغرافي المكاني مع التعلم الآلي لفهم التفاعل والاعتماد المكاني بين مختلف مؤشرات انعدام الأمن الغذائي. من خلال الجمع بين بيانات مسح الأسر والبيانات الجغرافية المكانية الجديدة عن اللاجئين السوريين في لبنان، نستكشف سبب فعالية بعض تدابير الأمن الغذائي في سياقات محددة بينما لا تكون تدابير أخرى فعالة. تشير النتائج التي توصلنا إليها إلى أن المؤشرات الجغرافية تؤثر بشكل كبير على انعدام الأمن الغذائي، وغالبًا ما تلقي بظلالها على العوامل التقليدية مثل التركيبة السكانية الاجتماعية المنزلية والظروف المعيشية. يشير هذا إلى تحول في التركيز من المسوحات الاجتماعية والاقتصادية كثيفة العمالة إلى البيانات الجغرافية المكانية التي يمكن الوصول إليها بسهولة. تسلط الدراسة الضوء أيضًا على تباين انعدام الأمن الغذائي عبر المواقع المختلفة والفئات السكانية الفرعية، مما يتحدى فعالية التدابير الفردية مثل FCS و HDDS و rCSI في التقاط الاحتياجات المحلية. وبتصنيف أبعاد انعدام الأمن الغذائي وفهم توزيعها، يمكن للمنظمات الإنسانية والإنمائية أن تصمم استراتيجيات أفضل، وتوجيه الموارد إلى المناطق التي يواجه فيها اللاجئون أشد التحديات الغذائية. من منظور السياسة، تدعو رؤيتنا إلى نهج محسن يحسن القوة التنبؤية لنماذج انعدام الأمن الغذائي، ويساعد المنظمات في استهداف التدخلات بكفاءة.

1. Introduction

Over 100 million people have now been forcibly displaced, a number that has more than doubled in the past decade due to recent and ongoing conflicts and crises (UNHCR, 2023). Forcibly displaced populations (FDPs) often face severe limitations in accessing adequate food and nutrition due to various factors such as the loss of their livelihoods, disruption of traditional food supply chains, and the challenges of adapting to new environments. Typically, FDPs rely on humanitarian aid for their basic needs. However, the capacity of international organizations to provide sufficient food aid is increasingly strained, especially given the rising numbers of refugees. The situation is further exacerbated in regions where the host communities also face food insecurity.

Previous research has explored the dynamics of food insecurity among refugee populations, including the impact of displacement on access to food, the effectiveness of humanitarian aid, and the long-term implications of nutritional deficiencies (e.g., Ghattas et al., 2014, 2015; Hadley et al., 2010; Lyons et al., 2023a, 2023b; Mansour et al., 2020). Recently, geospatial analysis has gained prominence in investigating food security challenges faced by FDPs (e.g., Al Shogoor et al. 2022; Çetinkaya et al., 2016; Füreder et al., 2012; Lyons et al., 2023b; Müller et al., 2016; Younes et al., 2022) and households in general (Alemu et al., 2017; Brown, 2016; Coughlan de Perez et al., 2019; Dessie et al., 2022; Lone & Mayer, 2019; Lv et al., 2022; Mathenge et al., 2023). This approach offers valuable insights into spatial patterns and factors influencing food access among disadvantaged populations. Some studies have also used machine learning techniques to predict future food insecurity (Deléglise et al., 2022; Foini et al., 2023; Lentz et al., 2019; Lyons et al., 2023b; Martini et al., 2022; Meerza et al., 2021).

This study aims to contribute to current research by harnessing advanced computational techniques to show that place-specific features and geographic specificities have a significant impact on food security outcomes. By combining both geospatial analysis with machine learning techniques, we seek to gain insights into why certain measures of food security are effective indicators in specific contexts, while others may fall short in providing accurate insights. Our approach also aims to enhance the predictive power of food insecurity models, enabling more efficient targeting of the most vulnerable refugees.

A novel and quintessential aspect of our study is the inclusion of a comprehensive set of geospatial features, which have rarely been considered in explaining food insecurity among FDPs. Previous efforts have typically relied on sociodemographic survey data obtained from a subsample of refugee households, which is then used to extrapolate key findings to the larger refugee population. These data can be time-intensive and costly to obtain (Lyons et al., 2023b). In the age of big data, new sources of easily collectable geospatial data offer an opportunity to improve the prediction of food insecurity and may even serve as a substitute for household-level sociodemographic data. At the very least, these data are likely to be a useful and necessary complement.

Understanding the interconnectedness of various measures of food insecurity and their spatial dependencies can assist in producing more effective policy recommendations. This can enhance the targeting of cash and non-cash interventions to alleviate rising levels of food insecurity among FDPs, thereby contributing valuable insights and practical tools to the ongoing research and policy-making efforts in this critical area.

For this study, we use data collected from Syrian refugees in Lebanon to better understand the interplay and spatial dependencies among key indicators of food insecurity. Lebanon presents a compelling case for examining the connection between forced displacement and food insecurity. This is due to its status as the country with the highest per capita refugee population globally, as well as recent crises that compromised the food security of both Lebanese residents and Syrian refugees. The financial and economic crisis that began unfolding in Lebanon in late 2019 has significantly heightened the vulnerability and poverty levels[8] (ESCWA, 2021). Lebanon relies on imports for most of its food and non-food needs, and the sharp currency depreciation has strained the country's capacity to pay for its imports, resulting in soaring inflation and eroding households' purchasing power. The challenges intensified with the COVID-19 pandemic and reached a critical point with the Beirut port explosion in August 2020, which limited the country's import capacity. These crises have dramatically declined the overall well-being of the country's population, exacerbating an already fragile situation for many Lebanese and refugee households. The lifting of state subsidies on medicine and energy, coupled with record-high inflation and escalating international prices, has severely impacted the ability of households to fulfill their basic needs.

Fundamentally, the crises have affected the availability of food in the country. Despite large cultivable land per capita, agricultural productivity is constrained and the country's food supply heavily depends on imports, with estimates suggesting that the country imports about 80% of its agricultural goods[9] (International Trade Administration, 2022). Between December 2019 and October 2021, the Consumer Price Index (CPI) and the Food Price Index increased by alarming 519% and 1,874%, respectively (CAS, n.d.). The cost of the Survival Minimum Expenditure Basket (SMEB), a measure of basic food and non-food necessities, also surged, with the food component increasing 11-fold between October 2019 and December 2021, and 21-fold by December 2022 (WFP, 2021, 2022a).

According to WFP (2022b), food insecurity affected 30% of Lebanon's population at the end of 2020, worsening between June and December 2021, with nearly 50% of families being food insecure. Recent data reveals that more than 35% of residents in Lebanon faced crisis-level food insecurity in the last quarter of 2022[10] (IPC, 2022a, 2022b). The crisis has hit Syrian refugees particularly hard, with food insecurity rates increasing by 21 percentage points between 2019 and 2020, reaching 67% by 2022 (UNHCR et al., 2023). North Lebanon and Akkar governorates experienced the highest rates

[8] An analysis by ESCWA (2021) based on the 2018-2019 Labour Force and Household Living Conditions Survey in Lebanon estimated that the multidimensional poverty rate in Lebanon has doubled from 42% in 2019 to 82% in 2021.

[9] The escalation of the Russo-Ukraine conflict has exacerbated food availability issues in Lebanon, as 80% of its wheat is sourced from these countries (World Bank, 2023). Recent analysis indicates that a sharp increase in currency circulation led to a decrease in food imports between 2019 and 2021.

[10] The first Lebanon IPC Acute Food Insecurity Analysis indicated that, between September and December 2022, 1.6 million people were classified in IPC Phase 3 (Crisis) requiring urgent humanitarian action to reduce food gaps and protect and restore livelihoods. Additional 306,000 people were in IPC Phase 4 (Emergency) experiencing acute malnutrition and excess mortality due to food insecurity (IPC, 2022b).

of food insecurity (79% for both), followed by Bekaa and Baalbeck-El Hermel (75% and 72%, respectively). In terms of severe food insecurity, North Lebanon and Akkar also had the highest proportions (10% and 9%, respectively). The food insecurity rates among Syrian refugees show different patterns from those of Lebanese households, as evidenced by a survey conducted between November 2020 and March 2021 (Hoteit et al., 2021). The highest incidence of food insecurity was recorded in Bekaa, where 83% of Lebanese households were estimated to have a poor Food Consumption Score (FCS), followed by Akkar at 73%, and North Lebanon at 58% (Hoteit et al., 2021).

Previous research on poverty among Syrian refugees in Lebanon, which employed machine learning techniques, revealed similar intriguing patterns in food security among Syrian refugees. Lyons et al. (2023b) found that the highest levels of food insecurity among refugees were not necessarily concentrated in the poorest localities. Further exploration of the heterogeneities across different geographic regions within Lebanon revealed certain economic dynamics that partially explained these differing patterns. In the Bekaa region, a major agricultural area, refugee households are likely to have some food security given their engagement in agriculture. In fact, it is estimated that agriculture serves as the main source of income for 90% of refugee households (Al Zoubi et al. 2019). In contrast, North Lebanon's urban and mountainous landscape offers fewer agricultural employment opportunities, resulting in higher food insecurity among refugees.

A deeper understanding of food insecurity among refugees in Lebanon necessitates further examination of the various indicators of food security and the complex interconnections between them and across different regions and refugee populations. By examining the spatial patterns of food insecurity, we aim in this study to shed light on the spatial disparities, exploring how and why certain indicators vary between areas and within specific regions. This analysis is crucial for identifying the unique challenges faced by different refugee communities and for developing tailored strategies to address them.

The remainder of this paper is structured as follows. The next section discusses the relevant literature. Section 3 provides an overview of the data, outlining our food insecurity metrics and the predictive features categorized into household sociodemographics, living conditions, and geospatial features. Section 4 explores the spatial analysis of our food insecurity measures, examining their evolution across time and regions, and identifying global and local spatial associations among the indicators. Section 5 describes our methodology, which employs machine learning (ML) techniques to predict food insecurity across all refugee households. Our findings are presented and discussed in Section 6. Section 7 concludes by highlighting important policy implications.

2. Literature Review

2.1 Measuring food insecurity: dimensions and metrics

Previous research has extensively addressed the question of assessing food security, delving into the comparability and effectiveness of various measures. According to the *Rome Declaration on World Food Security* adopted at the 1996 World Food Summit, ‘‘Food security exists when all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life” (FAO, n.d.). This widely adopted definition emphasizes the multi-dimensional nature of food security, which makes it challenging to measure comprehensively. There is still no consensus on an ideal measurement method or on the best indicators to capture food security. The choice of indicators or combination of indicators often depends on the specific context, objectives of the study, and available data. However, key dimensions have been commonly recognized.

The FAO’s reports on the annual *State of Food Insecurity in the World (SOFI)* traditionally rely on four dimensions, known as the four pillars: availability, access, utilization, and stability (FAO, IFAD, & WFP, 2015). Other frameworks, such as the Global Food Security Index (GFSI) of the Economist Intelligence Unit (EIU), focus on affordability, availability, quality and safety, and sustainability and adaptation. These frameworks, while broadly aligned, reflect a variety of conceptualizations of food security and approaches to its analysis and monitoring.

Manikas et al. (2023) discuss the use of different indicators by international agencies, summarizing commonly applied indicators according to food security dimensions and level of analysis (i.e., individual, household, and national). The authors suggest that to reflect the 1996 World Food Summit definition, an ideal food security indicator should capture all dimensions at the individual level. However, most studies that adopt a comprehensive approach focus on the national level. For instance, Caccavale and Giuffrida (2020) developed the Proteus Composite Index (PCI) to measure food security in 185 countries considering all four pillars of food security. Others have relied on the GFSI dimensions for national-level measurements (Chen et al, 2019; Izraelov, & Silber, 2019).

In their systematic literature review, Manikas et al. (2023) note that most available food security indicators focus on household-level measures of a single dimension – food access. Access reflects the demand side of food security and aligns closely with social science concepts of individual or household well-being (Barrett, 2010). Common household-level measures of food access used by international agencies include: the Food Consumption Score (FCS) developed by the WFP (2008) which is the weighted sum of food groups consumed, considering their frequency and nutritional value; the Household Dietary Diversity Score (HDDS) promoted by the FAO, which measures the number of different food groups consumed by a household over a specified period, usually 24 hours, reflecting access to a variety of foods (Swindale & Bilinsky, 2006); and the Coping Strategies Index (CSI) and reduced CSI (rCSI), which capture the various coping strategies that households employ in response to food insecurity, such as reducing meal frequency or borrowing food.

While stand-alone food security indicators are valuable for specific assessments, they often provide a narrow view, focusing on just one aspect of food security. This can result in an incomplete understanding, as they fail to capture the dynamic and interrelated elements of food security. Researchers and organizations have developed composite indices to enable a more comprehensive assessment of food security (Biederlack & Rivers, 2009; Maione et al., 2019; Mathenge et al., 2023; Reig, 2012; Santeramo, 2015; Vaitla et al., 2017; Wineman, 2016).

Several empirical studies have compared various household indicators to assess their performance in measuring food security. For example, Maxwell et al. (2013) used household data from Ethiopia to compare food security indicators, assessing inter-correlations among seven indicators and analyzing whether they detect the same or different aspects of food insecurity. The study noted that FCS and HDDS tend to capture *quality* and *diversity*, while CSI and rCSI reflect elements of *quantity* or *sufficiency*. They highlighted the importance of using more than one indicator, as food security indicators differ in the underlying aspects they capture, which can lead to potential misclassification of food insecure populations.

Similar results were found by Vaitla et al. (2017) who attempted to quantify the unique information provided by four indicators: FCS, HDDS, rCSI, and Household Hunger Scale (HHS). Using exploratory factor analysis (EFA), the study found that the selected indicators capture two distinct underlying latent dimensions related to food security, which exhibit only weak correlations with each other. The first dimension correlates strongly with HHS and rCSI, potentially capturing the *quantity* of food consumption or the costs of constrained access to food. The second correlates with FCS and HDDS, representing the *diversity* of dietary intake. The findings support the argument that multidimensional constructs like food security are best captured using a set of indicators representing key dimensions. Relying on a single composite indicator can obscure the distinct contributions and implications of each aspect (Mathenge et al., 2023; Wineman, 2016).

Recognizing the limitations inherent in both stand-alone indicators and composite indices, researchers increasingly recommend using multiple indicators. This approach enhances the depth and breadth of understanding in food security assessments, helping to better address the complexities and varied dimensions that single measures might miss (e.g., Coates, 2013; Mathenge et al., 2023; Maxwell et al., 2014; Vaitla et al., 2017).

2.2 Predictive analytics in food security

Recent studies have increasingly integrated geospatial data to assess and predict food insecurity, providing researchers and policymakers with the tools to identify and analyze patterns and trends across different regions and over time. Common sources of geospatial data used in these studies include satellite imagery (Füreder et al., 2012; Giada et al., 2003), climate data (Coughlan de Perez et al., 2019; Demeke et al., 2011; Lv et al., 2022; Mathenge et al., 2023), land use patterns (Brown, 2016; Lone & Mayer, 2019), and sociodemographic information (Alemu et al., 2017; Dessie et al., 2022; Lyons et al., 2023b). Advanced techniques like remote sensing and Geographic Information

Systems (GIS) enable the mapping of agricultural productivity, the assessment of natural resource availability, and the monitoring of environmental factors like droughts or floods that can impact food availability and access. Predictive models using geospatial data have been particularly valuable in early warning systems, anticipating food crises before they occur and enabling timely and targeted interventions. This geospatial approach offers dynamic insights into the spatial distribution of food insecurity, which is crucial for effective policymaking and resource allocation.

Geospatial data is also increasingly being used to understand the food security challenges faced by refugees and FDPs. Research in this field often includes site selection analysis for refugee camps (Çetinkaya et al., 2016; Younes et al., 2022), land use analysis (Al Shogoor et al., 2022; Müller et al., 2016), and camp monitoring (Füreder et al., 2012; Giada et al., 2003).

In Lebanon, geospatial analysis is relatively limited, especially in areas like climate change impact assessment, agricultural planning, and disaster risk reduction (Caiserman & Faour, 2021; Der Sarkissian et al., 2019; Ghoussein et al., 2018; Issa et al., 2014). Few studies have used geospatial analysis to assess food security among FDPs in Lebanon. A notable exception is the work of Lyons et al. (2023b), which used geospatial indicators as predictors of multidimensional poverty measured based on expenditures and food security (FCS and rCSI). They combined geospatial data with survey data on Syrian refugees in Lebanon and applied machine learning (ML) techniques to predict which households were more likely to be classified as poor.

Machine learning methods have become increasingly popular for predicting future food insecurity, enhancing the effectiveness of geospatial analysis in this field (Meerza et al., 2021). For example, Deléglise et al. (2022) developed the Food Security Prediction based on Heterogeneous Data ($FSPHD$) framework using machine and deep learning models to estimate FCS and HDDS from public data in Burkina Faso. Similarly, Lentz et al. (2019) predicted FCS, HDDS, and rCSI in Malawi using diverse data sources like meteorology, precipitation, market prices, and soil quality. Martini et al. (2022) applied a similar approach, relying on secondary data when primary data were not available, using "nowcasting" predictive models to estimate the prevalence of food consumption insufficiency and crisis-level food-based coping at sub-national levels across multiple countries. Among these efforts, Foini et al. (2023) developed a model using gradient boosted regression trees to forecast short-term food consumption trends in six countries, incorporating data on conflict, weather events, and economic shocks.

3. Data

In this study, we use survey data taken from the *Vulnerability Assessment of Syrian Refugees (VASyR)* jointly gathered by the UNHCR, WFP, and UNICEF for the five years spanning 2018 to 2022. The *VASyR* is a nationally representative survey of Syrian refugee households in Lebanon that includes detailed information on: (1) individual and household demographics, including work and schooling; (2) shelter, utility, sanitation, and settlement conditions; (3) income, expenditures, assets and debts;

(4) food consumption and dietary diversity; (5) health and safety; and (6) coping strategies (UNHCR et al., 2018, 2019, 2021, 2022, 2023).[11]

Our analysis is conducted at the household level. The initial sample size included 23,609 refugee households for all five survey years (4,444 in 2018, 4,687 in 2019, 4,506 in 2020, 4,968 in 2021 and 5,004 in 2022). Households with missing information for the key features related to sociodemographic characteristics and living conditions were excluded from the sample. The final sample used for our analysis consists of 22,626 refugee households (4,433 in 2018, 4,670 in 2019, 4,480 in 2020, 4,967 in 2021, and 4,076 in 2022).

In this paper, we aim to understand the relationships between different measures of food insecurity and identify which metrics are more prevalent in certain regions and which socioeconomic, environmental, and geographic characteristics are more likely to explain the different indicators and regional differences. The following presents our food insecurity metrics, and the features used to predict these, which can be broadly grouped into three categories: household sociodemographics, living conditions, and geospatial features.

3.1. Measures of food insecurity

The VASyR data include a rich set of information on food insecurity. We used these data to construct our four key measures of food insecurity: the food consumption score (FCS) and the household dietary diversity score (HDDS), as metrics of quality and dietary diversity; the reduced food coping strategies index (rCSI), as an indicator of quantity as it reflects the strategies that households use to deal with the lack of food; and households' share of food expenditures relative to their total expenditures (share of food expenditures). See Table A1 in the Appendix for a complete list of the food insecurity measures and feature variables and how they were specifically defined and constructed.

3.2. Feature data

The features included in our models to predict food insecurity were selected taking into consideration the following factors. First, we chose features readily available to humanitarian and development organizations. For the sociodemographic and living conditions, we used Lyons et al. (2023b) and Altindağ et al. (2021) as guides to identify the features likely included in official administrative data collected by UNHCR for all refugees. We then identified key geospatial features that impact the availability and accessibility of food and that are available to any organization using publicly available data from raster files. The geospatial data also needed to be linkable to the

[11] In each survey year, data were collected from Syrian refugee households who were randomly selected from the 26 administrative districts across the eight governorates of Lebanon. To ensure representativeness at the district and governorate levels, sampling was based on a two-stage cluster approach whereby clusters (villages, neighborhoods, or towns) were selected within each district, and then refugee cases were randomly selected within each cluster. Specifically, probability proportionate to size (PPS) methodology was used, where clusters with larger concentrations of refugees were more likely to be selected. Weights were also constructed at the district level based on the refugee population in each district. See UNHCR et al. (2018, 2019, 2021, 2022, 2023) for more details about the sampling and survey methodology.

sociodemographic and living conditions using the location information in UNHCR's official registry for each household.

3.2.1 Household socio-demographics and living conditions

The sociodemographic features included in our model account for a household's family structure in terms of its household size, dependency ratio, the proportion of female-headed and single-parent households, and the share of household members by age, gender, education, employment status, health and disability, and legal residency. Also included are variables that capture a household's living standards, as they pertain to basic access to electricity, sanitation, clean drinking water, cooking fuel, and shelter.

3.2.2 Geospatial features

Geographically, Lebanon is divided into 8 governorates, which can be further subdivided into 26 districts, which can be even further subdivided into "cadastres," which are the smallest administrative unit.[12] Figure 1 presents mappings of Lebanon; the left-side shows a map of Lebanon's districts while the right-side visually highlights its topographical features. Lebanon's geography is marked by a blend of coastal and mountainous landscapes with more than half of its terrain situated above 1,000 meters. The country features a narrow coastal plain along the Mediterranean Sea and two major north-south mountain ranges, and in between is the fertile Bekaa Valley (including the Bekaa and Baalbeck-El Hermel governorates). This diverse geography results in distinct climatic zones and land use patterns, even within small areas. In the western governorates, districts commonly span from coastal areas to high altitudes, encompassing both sea-level cities and elevated mountainous regions. This topographical variety significantly influences Lebanon's socio-economic dynamics. The coastal cities, especially the capital Beirut and suburbs in Mount Lebanon, are economic centers for commerce, banking, and tourism, while the Bekaa Valley is the heartland of agriculture, known for producing crops like grapes, vegetables, and grains. On the other hand, the mountainous regions traditionally support livestock rearing and cultivation of olives and fruits. Lebanon's economy is also known for its predominant services sector.

Development is not uniform across Lebanon. Peripheral areas, in particular, face significant development challenges and weak infrastructure (e.g., electricity, road networks, waste management, water supply). This infrastructure gap exacerbates regional inequalities, leading to disparities in employment opportunities, income, and the overall well-being of the population[13]. Such uneven development creates a stark contrast between these areas and the more developed regions like Beirut and its suburbs.

[12] Note the governorate of Beirut (the capital city of Lebanon) is not subdivided into districts. Also, the Akkar governorate is comprised of a single district. Cadastres in Lebanon are equivalent to Administrative Level 3 in terms of the UN Geospatial Information Section & Statistics Division's 'Second Administrative Level Boundaries' programme (UN Habitat Lebanon & ESCWA, 2021).

[13] The most recent data on the distribution of multidimensional poverty based on a 2018/2019 budget survey of Lebanese households reveal that those living in extreme poverty represented close to 50% of the population in Akkar and Baalbeck-El Hermel and Nabatieh governorates, 43% in Bekaa, 35% in South Lebanon, and 33% in North Lebanon, compared to 29% in Beirut and 27% in Mount Lebanon (ESCWA, 2021).

Thus, in the context of Lebanon, location matters such that geographical characteristics are likely to be significant predictors of food insecurity, and moreover, their importance is expected to vary across locations (Lyons et al., 2023a, 2023b). These geospatial attributes include land elevation, latitude and longitude, types of land coverage (built-up area, crop area, and permanent and seasonal water area), quality of vegetation, access to roadways and waterways, and density of refugee and host populations.

The extraction of the geospatial attributes was first conducted using the cadastral boundaries. However, to protect the safety and security of the refugees, the VASyR survey data only reports the district in which a refugee household resides and not the cadastre. In order to merge the VASyR data with the geographical feature data, we needed to aggregate the cadastral level values for each geographical feature at the district level using the geographic boundaries for the 26 districts in Lebanon. See Table A1 in the Appendix for a description of the geospatial features and how they were constructed. For more information on the source and availability of each feature, see Table A2 and Lyons et al. (2023b), who we followed in obtaining our data and constructing the features.

4 Spatial Analysis of Food Insecurity Measures

4.1 Changes in food insecurity over time

Table 1 presents the descriptive statistics for the food insecurity measures by survey year; p-values are reported to identify which metrics differed significantly across the years[14]. The mean values for our key food insecurity variables were found to significantly vary across the years. In general, total expenditures per capita more than tripled between 2018 and 2021 and more than quadrupled between 2021 and 2022, due to severe currency depreciation and hyperinflation.[15] Similarly, we observe an even more pronounced surge in food expenditures per capita, with the share of total expenditures spent on food rising from 41% in 2018 to 58% in 2022. The percentage of refugee households with expenditures below the Survival Minimum Expenditure Basket (SMEB) went from 50% in 2018 to nearly 100% by 2022. While this measure alone provides an indication of the growing and stark rise in food insecurity among refugee households, additional evidence also points to rising food insecurity levels. Food consumption scores and diet diversity scores have worsened, with FCS and HDDS decreasing by 18% and 8%, respectively (FCS: from 53.3 in 2018 to 43.7 in 2022; HDDS: from 9.1 in 2018 to 8.4 in 2022). Refugee households' use of reduced food coping strategies (rCSI) increased between 2018 and 2022 as well. More specifically, we see increases across the board in the percentage of households who reduced the number of meals per day, reduced portion sizes of meals, relied on less preferred or less expensive food, borrowed food or relied on help from friends or relatives, and restricted consumption by adults in order for young-small children to eat. Thus, all indicators denote

[14] The p-values were calculated using t-tests by category when the variables were continuous. These p-values were adjusted for multiple pairwise comparisons following the Benjamini-Hochberg method using the R package "compareGroups." When the variables were categorical, the p-values were based on a chi-square test.

[15] Lebanon's local currency has lost more than 95% of its value, driving inflation to triple digits since July 2020 and impacting mostly the poor and vulnerable (World Bank, 2022).

a dramatic rise in food insecurity, which is not surprising given the severe economic crisis and reports by humanitarian agencies (e.g., UNHCR et al., 2021, 2022, 2023).

4.2 Geospatial differences in food insecurity

The mappings presented in Figures 2 and 3 highlight several significant geospatial differences in food insecurity across the districts within Lebanon and over time. Note that darker shading indicates higher levels of food insecurity, and hence, worsening conditions. For the various measures of food insecurity, there are considerable geographical heterogeneities. In Figure 2, we find that, while FCS, HDDS, and rCSI worsened in general for refugee households across Lebanon, there were specific geographical areas that fared worse than others. For example, FCS worsened in the southern districts between 2018 and 2020, then improved and worsened again between 2021 and 2022. Aside from the southern districts, we also observed a worsening trend in FCS in the west, and especially in the northwestern districts, which was offset by worsening conditions in the east between 2021 and 2022. Similar trends were also observed for HDDS between the east and west as well as for northwest and southern districts. In terms of rCSI, food insecurity in the west was consistently worse than in the east. See Figure A1 in the Appendix for a breakdown and comparison of the five subcomponents of rCSI.

Figure 3 presents the mappings for changes in share of food expenditures and share of refugee households below the SMEB. In general, we find that the share of total expenditures refugee households spent on food increased over time for almost all districts. In particular, refugee households located in the northern-most district of Akkar and the southern-most district of Bint Jbeil experienced the largest increases in the share of food expenditures, reaching over 60% in 2022. Additionally, with the onset of the economic crises and hyperinflation, the percentage of households below the SMEB also increased, with a noticeably higher increase in the western districts compared to the eastern districts (this percentage was high in the east since 2018). From 2020 onwards, almost all refugee households were below the SMEB, regardless of the district. The exception was the Matn district adjacent to Beirut, where fewer households were below the SMEB. However, in 2022, even in Matn, almost all households were below the cutoff.

4.3 Testing for spatial dependencies

To test for spatial dependencies, we first calculated a Global Moran's I to evaluate the existence of a global spatial association among the food insecurity indicators at the district level.[16] The existence of a global spatial structure indicates the degree to which food insecurity in a given district *(i)* is similar to food insecurity in the immediate neighboring districts, indicating that the underlying factors impacting food security are anchored to that particular geographical area. The results of the Global Moran's I were tested against the null distribution which represented complete spatial randomness,

[16] Spatial dependence pertains to the extent of spatial autocorrelation among independently measured values within a geographic area. Global indicators of spatial autocorrelation, such as Moran's I, provide a singular measure of spatial dependence. In parallel, local indicators of spatial association, such as LISA, serve a comparable purpose but yield multiple location-specific measures of spatial dependence, enabling researchers to examine the spatial variation in dependence across different locations.

where the food insecurity scores were not correlated for neighboring districts (Anselin, 1995).[17] The null distribution was estimated numerically using conditional permutation of the food insecurity scores.

The results of the Global Moran's I (GMI) are presented in Table 2. As expected, we find evidence of spatial correlation, confirming the descriptive findings presented in Figures 2 and 3. However, the findings vary significantly across indicators and across time for specific indicators. The scores for the FCS show moderate but significant spatial association, and this spatial association is centered around the southern districts, which in Figure 2 appear to have lower levels of food insecurity (higher FCS). Although this pattern seems to be persistent, it changed in the year 2020, where more spatial randomness was observed in the geographical arrangement of the scores for FCS.

We also tested for local spatial association using the local version of the Moran's I test. The analysis tested the spatial association between a given district *(i)* and the immediate neighboring districts that share a boundary or at least a single point with the district (i.e., Queen neighbor criterion). The local Moran's I test identifies four different scenarios by comparing the indicator value at a given district and the spatially weighted average values at all the neighboring districts of that particular district. Four different scenarios are identified through this comparison: both the value of the district and its neighbors is high (hot spot); both values are low (cold spot), and the other two scenarios deal with outliers when the district value and the average value of its neighbors are opposite. In our analysis, we only considered any of the four scenarios if they were very extreme (p-value ≤ 0.01). Otherwise, the results were ignored and considered to be artifacts produced by spatial randomness. The significance level was tested using a random permutation method to derive a null hypothesis (i.e., spatial randomness) and the extremeness of the observed hot spots, cold spots, or outliers were tested if they exceeded the set p-value threshold. The analysis was conducted using the pygeoda python library (Anselin et al., 2022)[18].

The results from the Local Moran's I are presented in Figure 4 and compared to those presented in Table 2 for the Global Moran's I. In general, the results from the Global Moran's I were confirmed by the Local Moran's I. Evidence of a global spatial structure was found for FCS for 2019, 2021, 2022. In Figure 4, the Local Moran's I reveals a significant hotspot of districts in the south (mostly in the Nabatieh governorate) with high FCS scores, particularly for years 2019 and 2022.[19]

[17] Previous research has almost always assumed spatial independence prevails such that food insecurity and poverty among FDPs tends to be randomly distributed over geographical units – in our case, districts. However, it is reasonable to expect that food insecurity may not be spatially independent such that levels of food insecurity among FDPs within neighboring districts may be significantly related to those within a particular district, especially given the geospatial heterogeneities across Lebanon that can impact availability, access, and utilization of food.

[18] We acknowledge that districts have different population sizes, which could result in outliers when mapping the food indicators, especially over sparsely populated districts. In addition, the local Moran's I calculation ignores differences in population sizes between the geographic units. Nevertheless, this is the first step to visualize and analyze the spatial structure of food insecurity indicators.

[19] In Figure 4, gray areas indicate districts where there is spatial randomness and no evidence of a spatial structure. Blue indicates "cold spots" and districts where food insecurity is significantly low, whereas red indicates "hot spots" where food insecurity is significantly high such that the spatial arrangement of food insecurity within that district is unlikely due to chance. Cyan represents outlier districts with a low score surrounded by relatively high scoring neighbors, and vice versa, orange indicates outlier districts with a high score surrounded by relatively low scoring neighbors.

In comparison, we see in Table 2 that the scores for HDDS tended to lack a global spatial structure. In 2018, the Global Moran's I value for HDDS was approaching 0 (complete spatial randomness) with a p-value of only 0.301. This finding was confirmed using the Local Moran's I. In fact, no clear trend for HDDS was observed over the five-year period, with the exception of 2019, where we found a cluster of HDDS high scores in the southern districts of Lebanon, specifically in Nabatieh.

With regards to rCSI, Figure 4 shows a clear and significant spatial structure, characterized by higher rCSI scores in the northwest districts compared to lower rCSI scores in the southeast districts. The spatial pattern appears to be persistent over time, and breaks only in year 2022, where the differences between the northwest and southeast districts become less distinct. Again, the findings from the Local Moran's I support the persistent pattern revealed by the global test results presented in Table 2.

In terms of the share of food expenditures, the scores showed a global spatial association that is likely high and radiates from the north. Further testing using the Local Moran's I reveals that the share of food expenditures was high (more food insecure) in the districts of Bsharri (North Lebanon governorate) and El Hermel (Baalbeck-El Hermel governorate).

Finally, the percentage of refugee households below the SMEB also revealed the existence of a spatial structure, although it was less significant than the geographic patterns produced by mapping the rCSI scores. Still, the spatial patterns indicated a contrast between the high percentages below the SMEB in the northern and eastern districts compared to those in the southern and western districts. We also observe that spatial trends in the percentage below the SMEB diminish over time, as indicated by the decrease in spatial correlation and subsequent increase in spatial homogeneity and its insignificance over time, especially in year 2022. This result confirms our earlier descriptive finding that almost all refugee households were below the SMEB by 2022.

Overall, the descriptive analysis in this section underscores the presence of spatial differences in food insecurity among Lebanon's districts. This observation, supported by the outcomes of the Global and Local Moran's I analysis, reinforces the notion of substantial spatial dependence, particularly evident in measures like FCS and rCSI. Consequently, it is plausible to posit that these spatial variations in food insecurity stem from diversities in geospatial features across Lebanon and within specific districts.

5 Methodology

The descriptive findings raise the following questions: What are the specific geospatial features that are likely driving the spatial differences in food insecurity that we are observing, and what is their importance in predicting current and future food insecurity? To provide insight into these questions, we predicted food insecurity using machine learning (ML) techniques, pooling the observations for all refugee households for all five survey years. Specifically, we conducted a comparative analysis of the predictive power of three ML models – Random Forest (RF), Gradient Boosting (GB), and Lasso. The models were trained to predict food insecurity by classifying whether a refugee household fell

within the bottom 30% for each measure. The cutoff values for the bottom 30%, derived from the pooled sample, were as follows: FCS ≤ 37; HDDS ≤ 8; rCSI ≥ 24; and Share of food expenditures ≥ 60.4%. We compared the results of these models to those generated using a logistic model, which served as our benchmark. The steps we followed to conduct our analysis are described below and are consistent with standard ML techniques (e.g., Han, Kamber, & Pei, 2012).

5.1 Model calibration and tuning

We first conducted our training validation strategy, which involved an 80/20 split (80% training data and 20% testing data) (Gholamy et al., 2018).[20] To do this, we ran a 5-fold cross-validation strategy using the training data to optimize the parameters for each model while safeguarding against overfitting.[21] The data were divided into five equal folds, with the models trained on four partitions and tested on the remaining one. This process was repeated five times. Models were fitted to obtain the best values for the parameters. We performed different calibration procedures for RF, GB, and Lasso depending on the algorithm that was used.[22]

We then used the testing data to assess model performance and identify the best model at predicting food insecurity (Pedregosa et al., 2011). The metric used to assess model performance was the recall score, which measures a model's ability to identify positive instances among all true positives. We prioritized this metric to maximize the inclusion of districts with severe food insecurity in our predictions. Models were calibrated, tuned, and assessed in Python using the "sklearn" package (Pedregosa, et al., 2011).

5.2 Feature selection

The features incorporated into our food insecurity models, as detailed in the data section, encompass three broad categories: household sociodemographics characteristics, living conditions, and geospatial features. We tested to ensure the selected features were not redundant using a judicious feature selection process following the methodology outlined in Han, Kamber, and Pei (2012) and Lyons et al. (2023b). It is important to avoid redundancy in models caused by an excessive number of features, which can hinder effective model learning. In our feature selection, we also employed an evidence-based approach, drawing on existing literature and considering socioeconomic, environmental, and geographical conditions. As outlined in the data section, feature selection was

[20] The choice of an 80/20 split is a common rule of thumb, but it can be adjusted based on the specific characteristics of the dataset. Our decision to use the 80/20 split strikes a balance between providing the model with enough data for effective training and having a sufficiently large validation set for robust performance evaluation.

[21] Overfitting happens when the model memorizes the training dataset and performs well in terms of goodness of fit. However, model quality degrades when applied to external data other than the training dataset (e.g., an out of sample testing dataset). The solution for overfitting is using cross-validation, which is a resampling method that uses different portions of the data to test and train a model on different iterations (Han et al., 2012).

[22] For RF, we used a parameter grid that included different values for 'n_estimators' (100, 200, 300) and 'max_depth' (None, 5, 10, 15, 20), which controlled the number of trees and their maximum depth. For GB, we used a parameter grid that included different values for 'n_estimators' (100, 200), 'max_depth' (3, 5, 7), and 'learning_rate' (0.01, 0.1, 0.2), which influenced the number of boosting stages, depth of individual trees, and step size (Kuhn, 2022). For Lasso, we used a parameter grid that included different values for the regularization parameter 'C' (0.1, 0.5, 1.0). For Logistic, we used a parameter grid that included different values for the regularization parameter 'C' (0.1, 1, 10), different solvers ('liblinear', 'lbfgs'), and different maximum iterations ('max_iter' of 750 and 1000).

guided by insights from relevant studies such as Lyons et al. (2023a, 2023b) and Altindağ et al. (2021). The features selected were deemed particularly relevant to food insecurity and readily available publicly to be downloaded and used. This approach ensured that the selected features were not only statistically significant but also contextually meaningful in capturing the dynamics of food insecurity in the Lebanese context, particularly concerning refugee populations.

6 Results

6.1 Model performance and selection

We conducted a comparative analysis of the predictive power of the three machine learning (ML) models – RF, GB, and Lasso. Table 3 presents the percentage of accurate predictions by each model identifying households in the bottom 30% for specific food insecurity measures according to the recall score. To enhance model accuracy, we applied balanced class weights to account for the skewed distribution resulting from classifying households as either 0 or 1 based on food insecurity. Each ML model incorporated all the feature variables encompassing household sociodemographic characteristics, living conditions, and geospatial features.

The RF and GB models generated the highest accuracy with comparable results. GB outperformed RF for three out of the four measures, except for the share of food expenditures, where RF exhibited slightly superior results (60.7% for RF compared to 57.9% for GB). RF displayed consistent performance across all food insecurity measures, ranging from 62.1% for FCS to 67.7% for rCSI, outperforming GB in terms of overall consistency.

In contrast, Lasso exhibited subpar performance, which is consistent with expectations. Random Forests tend to outperform individual decision trees like Lasso due to their ability to combine multiple trees, reducing overfitting and enhancing predictive performance and robustness. RF was selected as our preferred model, motivated by its common usage in ML algorithms, flexibility, ease of tuning, and reduced susceptibility to overfitting. Additionally, RF tends to perform well when models involve multiple 0/1 features or a diverse range of features based on different scales and value ranges.

Using the RF method, we refined the calibration of the food insecurity models and determined feature importance. As a robustness check, the results obtained from the RF models were compared to those from the GB models, ensuring a comprehensive evaluation of model performance.

6.2 Feature importance

Figure 5 presents the RF results regarding the feature importance for the three broad categories of features. Three key findings are worth noting. First, geographical features emerged as the most important predictors for three of the four food insecurity measures (FCS, rCSI, and the share of food expenditures). Second, and of notable significance, geographical features played a decisive role in predicting over 50% of the models for FCS and the share of food expenditures, and over 90% for the rCSI model. Intriguingly, household demographics and living conditions were found to be the least

important predictors for rCSI when compared to the other food insecurity metrics. Third, although household demographics were identified as the most important predictors for HDDS, geographical features held nearly equal importance (approximately 44.9% and 44.5%, respectively). Basically, geographical features emerged as the most crucial predictors of food insecurity. Moreover, rCSI was notably more influenced by geospatial feature data, while HDDS leaned more towards being influenced by household demographics than the other models.

The results for the GB models can be found in Figure A2 in the Appendix. Despite similarities with the RF results, some differences can be observed. For instance, geographical features exhibited heightened importance for the rCSI model using GB. The predictive importance of the household demographics and living conditions were negligible. For the share of food expenditures, geographical features slightly diminished in importance, with living conditions becoming more important than household characteristics. Notably, geographical features became the most important predictors of HDDS, contrasting with the RF method where household characteristics were the most important predictors.

Figure 6 displays the results detailing the top 20 most important features. There are several common predictors across the four measures of food insecurity. Among the geospatial features, population density, the number of refugees in the district, NDVI (indicating the health of vegetation), latitude, and permanent water coverage area consistently ranked among the most important features.[23] In fact, population density was among the top six predictors for all four models. Additionally, household characteristics such as lack of electricity and the share of non-working household members emerged as important predictors for all four measures of food insecurity. However, these were the only sociodemographic and living condition features that were consistently among the top predictors.

For three of the four measures (FCS, rCSI, and share of food expenditures), several other geospatial features were identified as key predictors. These features predominantly pertained to the physical landscape and land coverage within a district, encompassing crop and seasonal water coverage areas, river zones, and incoming roadways. Additionally, population size was also among the top predictors for all of the models. Other features that were consistently among the top predictors for three of the four measures included three household characteristics – namely, the household size, the ratio of dependent to total household members, and the percentage of household members with no education.

A particularly interesting finding to note is the distinct difference in the top 20 predictors for HDDS compared to the other three food insecurity measures. Unlike the other measures, HDDS is less linked to the "external" physical location and more tied to the "internal" household characteristics. The majority of the top predictors for HDDS (15 out of the top 20) were related to the structure and sociodemographic composition of the household. These factors include the share of household members with various age and education levels, as well as their employment status, health condition, and legal residency status. In contrast, only three of the top 20 features for FCS, six for rCSI, and

[23] When comparing the relative importance of each individual predictor across the four food insecurity measures, note that the scales on the x-axis reflecting the percentage of importance vary and are not the same across the graphs.

eight for the share of food expenditures were related to household demographics. Given that HDDS serves as a micro-level indicator of food usage, offering real-time reporting of the household's consumption of various food groups in the past 24 hours, it may not be surprising that its predictors align more closely with internal sociodemographic features than external locational features. This distinction is worth mentioning, considering that the other measures are more broadly oriented towards assessing food access and availability over longer periods of time, such as the past week or year.

Figure A3 in the Appendix presents the top 20 most important features for food insecurity using the Gradient Boosting (GB) method. Broadly, the findings align with those derived from RF method. Although the ranking of top predictors may vary, the overall consistency in the selection of top predictors is evident. In particular, the top predictors for each model generally remain the same when comparing the GB and RF results for each food insecurity measure. The most noticeable difference lies in the increased importance of geospatial characteristics and living conditions as predictors of HDDS.[24] In contrast, the sociodemographic features and living conditions assume greater importance when it comes to the share of food expenditures. Interestingly, a robust association between rCSI and geospatial features persists. While fewer geospatial features appear in the top 20 predictors using the GB method compared to the RF method (11 versus 14), the dominance of geospatial relevance for rCSI remains evident. Of the remaining nine features for rCSI using GB, four are associated with living conditions (no electricity, damaged shelter, lack of sanitation, and shelter crowdedness), while the remaining five are tied to sociodemographic factors (legal residency status, employment status, disability status, and health condition of household members, along with dependency ratio).

6.3 Model accuracy versus model stability

While the results of the RF and GB models were fairly consistent, there were variations in the findings. These differences may raise concerns about the reliability of the models and their predictions. One explanation for these differences is that our calibration process prioritized model accuracy over model stability. However, ensuring the stability of predictive models is also crucial for their reliable deployment in real-world applications. Small perturbations in the input data should not lead to significant changes in model predictions, as this can indicate overfitting or sensitivity to noise. Yet, achieving greater model stability often comes at the cost of model accuracy. Researchers need to determine what that balance or tradeoff between model accuracy versus model stability should be.

We conducted sensitivity analysis by perturbing the input features of the dataset with random noise (Yu, 2013). The perturbed data was then used to make predictions with the trained model, and the difference in predictions between the original and perturbed data were calculated. This process was repeated for multiple levels of noise to assess the model's sensitivity. The methodology was applied to the four different predictive models: RF, GB, Lasso, and logistic regression.

[24] When comparing the GB to the RF results in Figure 6 and Figure A3, note that the scales on the x-axis reflecting the percentage of importance vary not only across the four food insecurity measures but also for the GB and RF models.

The sensitivity analysis revealed varying levels of stability among the different models.[25] RF and GB models demonstrated lower sensitivity, indicating higher stability, while the Lasso and logistic models exhibited higher sensitivity, suggesting lower stability. Taking into consideration the results for both model accuracy and stability, RF remains the preferred model.

7 Conclusions

In this study, we developed a foundational understanding of the interconnections and relationships among various measures of food security in Lebanon over the period from 2018 to 2022. Using survey data collected from Syrian refugee households by the UNHCR, WFP, and UNICEF, we investigated four common measures of food security: the food consumption score (FCS), household diet diversity score (HDDS), reduced food coping strategies index (rCSI), and food consumption expenditures per capita. A novel aspect of the study was the integration of the refugee survey data with geolocational features to predict and analyze food insecurity. The analysis was conducted in three phases utilizing geospatial analysis and machine learning techniques.

In the first phase, our descriptive analysis revealed significant and dramatic increases in food insecurity across all measures, which is not surprising given the severe economic crisis and humanitarian reports (e.g., UNHCR et al., 2021, 2022, 2023). Distinct spatial variations were observed, particularly in the northwest and southeast districts, where agricultural suitability and employment opportunities for refugees are likely to be more limited. Food insecurity was also found to be more prevalent in less developed and less urbanized districts. However, the degree of food insecurity across districts and over time was found to vary considerably depending on which measure was used.

Our findings highlight the challenges that researchers have encountered in defining and measuring food insecurity, as well as the difficulties faced by humanitarian and development organizations when using individual measures such as FCS, HDDS, and rCSI to capture localized needs. Relying on a single measure of food insecurity may prove inadequate in capturing the diverse nuances associated with the availability, access, and usage of food. Conversely, a composite index comprising various metrics might obscure these nuances and result in misleading conclusions, especially if the underlying relationships and importance of the metrics are not well understood and if geographic conditions vary considerably within the location. Therefore, composite measures of food insecurity, which typically aggregate indicators of food insecurity, may also fall short in adequately capturing locally expressed needs.

In the second phase of our analysis, we tested for spatial dependencies among our food insecurity indicators. Our results confirmed the presence of spatial dependencies, with food insecurity scores showing correlations with neighboring districts. Notably, non-random patterns were identified within specific districts, particularly those in the northwest and southeast regions. Significant heterogeneities persisted across food insecurity measures and over time for specific indicators. The most robust and

[25] These results are not presented in the paper but are available from the authors upon request.

consistent spatial dependencies were associated with rCSI, followed by FCS. These findings reinforce the earlier descriptive observations and again underscore the intricate nature of food insecurity. This led us to hypothesize that spatial variations in food insecurity likely arise from differences in geospatial features across Lebanon and within specific districts.

We used machine learning methods in the third phase to assess the importance of the geospatial features in predicting food insecurity. Most notably, geolocational indicators emerged as the top predictors of food insecurity, overshadowing traditional factors like household sociodemographics and living conditions. These results suggest that future analyses aiming to evaluate the food security needs of forcibly displaced populations (FDPs) should consider integrating geospatial features into the models, especially when forecasting future vulnerabilities to food insecurity. Geospatial data, being readily available, can supplement or offer a more efficient alternative to the labor-intensive process of collecting household socioeconomic survey data from highly vulnerable populations like FDPs.

The results on feature importance highlight key distinctions between "internal" characteristics specific to individuals and households, such as sociodemographics and living conditions, and "external" characteristics such as geospatial features dependent on location. As shown in this study, the topography of a location holds significant importance, and perhaps more so than traditional demographic characteristics, in relation to food insecurity of refugee households in Lebanon. Geospatial features associated with refugee and host populations, vegetation, and type of land coverage were among the top predictors of food insecurity, particularly influencing FCS, rCSI, and share of food expenditures. Having noted this, the machine learning (ML) analysis assumes the independence of features. It is plausible that certain geographical features may be highly correlated with demographic characteristics, especially those linked to economic development and urbanization of a location, as well as the employment and education levels of subpopulations in that locale. However, correlation analysis did not reveal any strong associations between specific geospatial features and the sociodemographics and living conditions.

Future research can build upon our work to deepen the understanding of the relationships between key geospatial features and food insecurity among FPDs not only in Lebanon but also in other crisis situations. It is crucial to explore the various dimensions of food security and their complex interconnections across different locations and refugee populations. Our analysis demonstrated that geolocational indicators are perhaps the most crucial drivers of food insecurity. Consequently, these geospatial features hold critical value for humanitarian and development organizations when making impactful decisions about which locations may be most vulnerable and what food security needs to prioritize in those locations. From a policy perspective, our insights suggest a more nuanced approach to tackling food insecurity among refugees, incorporating geospatial data as an informative tool in this process.

By disaggregating the various dimensions of food insecurity and understanding their geospatial distribution, humanitarian and development organizations can better tailor their strategies, directing

resources to areas where FPDs face the most severe challenges, thereby enhancing the effectiveness of food security measures. These organizations should leverage geospatial data to identify regions with the highest food insecurity levels. This geo-targeted approach ensures efficient resource allocation to areas most in need. Geospatial analysis can assist in optimizing the allocation of limited resources by identifying where interventions can have the most significant impact. This can include not only food aid but also support for agricultural development, infrastructure improvements, and economic opportunities. Additionally, as this study has shown, integrating geospatial features with traditional sociodemographic data can provide a more comprehensive understanding of food insecurity. This holistic approach can guide more nuanced policy decisions and help design interventions that better address both immediate and underlying causes of food insecurity.

Finally, our analysis also points to the usefulness of machine learning techniques in incorporating geospatial data to improve the accuracy of food insecurity predictions. These enhanced models can help anticipate future food security crises, allowing for proactive measures and better preparedness. Combined with geospatial data, these techniques can be instrumental in ongoing monitoring and evaluation of food security interventions. By tracking changes over time and across locations, humanitarian and development organizations can assess the effectiveness of their strategies and anticipate future adjustments as conditions change.

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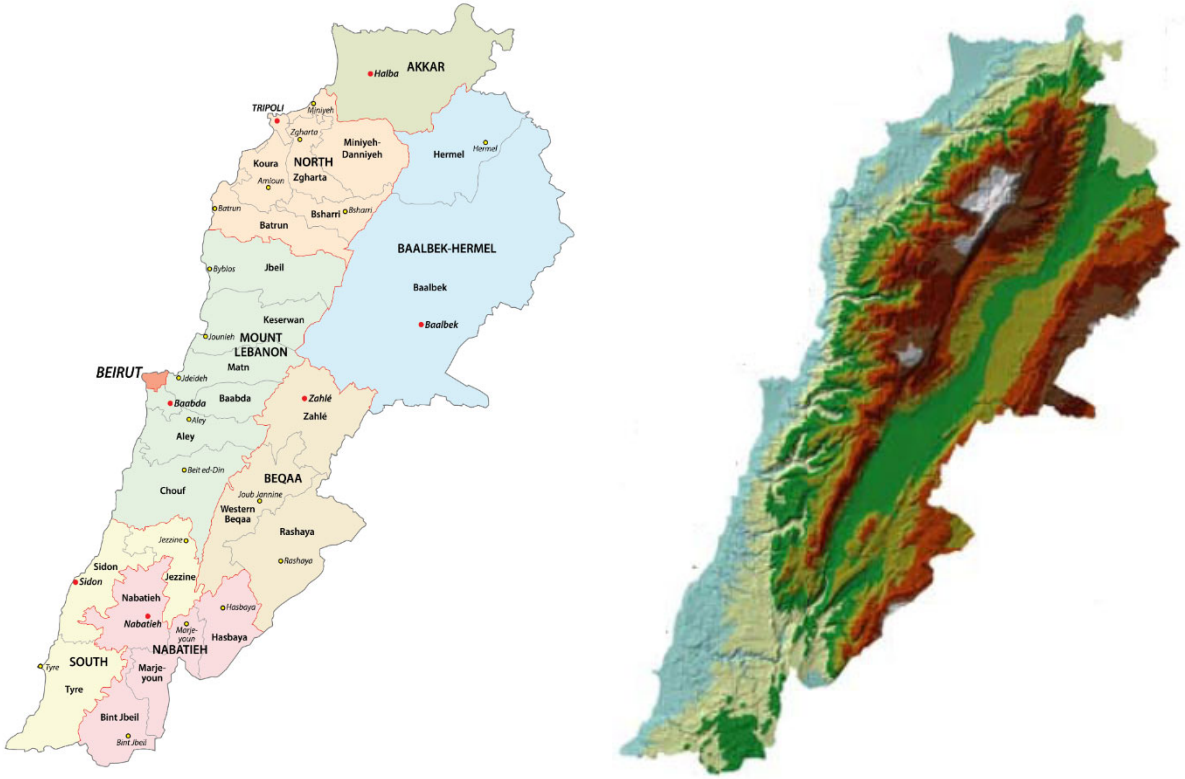
Figure 1. Geography and Topography of Lebanon



Sources: *World Atlas (2020)*. Retrieved from https://www.worldatlas.com/maps/lebanon; *Lebanon's Council for Development & Reconstruction (2005)*

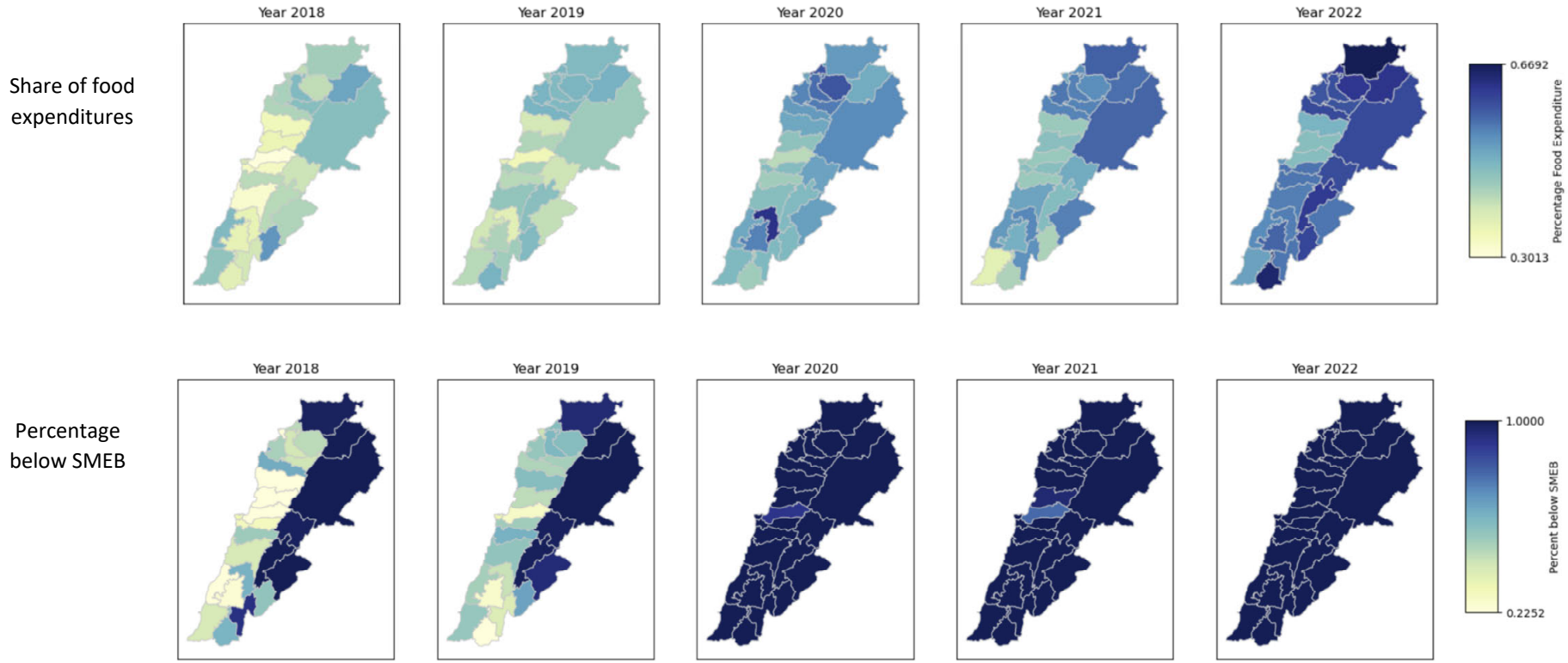
Table 1. Changes in food security by year

Food security measures	2018 (N=4,433)	2019 (N=4,670)	2020 (N=4,480)	2021 (N=4,967)	2022 (N=4,076)	p-value
Total expenditures per capita (LBP)	170,857.90	180,346.60	196,254.00	345,410.0	1,600,000.00	<0.001
Food expenditures per capita (LBP)	62,218.65	71,589.30	91,963.30	161,054.30	864,089.10	<0.001
Share of food expenditures	0.41	0.43	0.50	0.50	0.58	<0.001
Expenditures < SMEB	0.50	0.52	0.88	0.84	0.99	<0.001
FCS	53.34	55.12	44.98	48.29	43.74	<0.001
HDDS	9.12	9.42	8.14	8.46	8.41	<0.001
rCSI	17.77	18.81	17.25	20.08	20.61	<0.001
rCSI1 (reduced meals)	0.59	0.62	0.66	0.70	0.74	<0.001
rCSI2 (reduced portions)	0.55	0.60	0.64	0.73	0.78	<0.001
rCSI3 (consumed less expensive food)	0.86	0.88	0.88	0.93	0.95	<0.001
rCSI4 (borrowed food)	0.36	0.38	0.40	0.42	0.47	<0.001
rCSI5 (restricted consumption)	0.37	0.37	0.33	0.33	0.42	<0.001

Note: The sample size is reduced for share of food expenditures, because some households reported total expenditures equal to 0 (n=4,362 for 2018; n= 4,604 for 2019; n=4,413 for 2020; n=4,912 for 2021; n= 4,076 for 2022). The cutoffs for the Survival Minimum Expenditure Basket (SMEB) were as follows for each year: 87 USD for 2018 and 2019 (equivalent to 131,153 LBP); 308,722 LBP for 2020, 490,028 LBP for 2021, and 8,156,858 LBP for 2022.

Figure 2. Changes in food insecurity for FCS, HDDS, and rCSI by district and across years (darker shading indicates higher levels of food insecurity)

Figure 3. Changes in share of food expenditures and share of refugee households below the SMEB by district and across years (darker shading indicates higher levels of food insecurity)



Note: The SMEB cutoffs were as follows for each year: 87 USD for 2018 and 2019 (equivalent to 131,153 LBP); 308,722 LBP for 2020, 490,028 LBP for 2021, and 8,156,858 LBP for 2022.

Table 2. Global Moran's I (GMI) and simulated p-values (PSIM)

Food security measures		2018 (N=4,433)	2019 (N=4,670)	2020 (N=4,480)	2021 (N=4,967)	2022 (N=4,076)
FCS	GMI	0.080	**0.519**	-0.045	**0.321**	**0.292**
	PSIM	0.147	**0.001**	0.500	**0.010**	**0.007**
HDDS	GMI	0.018	**0.349**	0.072	0.194	0.170
	PSIM	0.301	**0.001**	0.190	0.045	0.059
rCSI	GMI	**0.327**	**0.566**	**0.358**	**0.402**	0.090
	PSIM	**0.008**	**0.001**	**0.003**	**0.001**	0.158
Share of food expenditures	GMI	0.169	**0.354**	0.245	0.284	**0.306**
	PSIM	0.064	**0.004**	0.019	0.012	**0.009**
Expenditures < SMEB	GMI	0.232	**0.366**	**0.337**	0.152	0.017
	PSIM	0.030	**0.006**	**0.002**	0.067	0.263

Note: GMI represents the Global Moran's I. PSIM represents the simulated p-values for each measure of food insecurity. Bolded values indicate significance at $p<0.01$.

Figure 4. Local Moran's I (LMI)

FCS

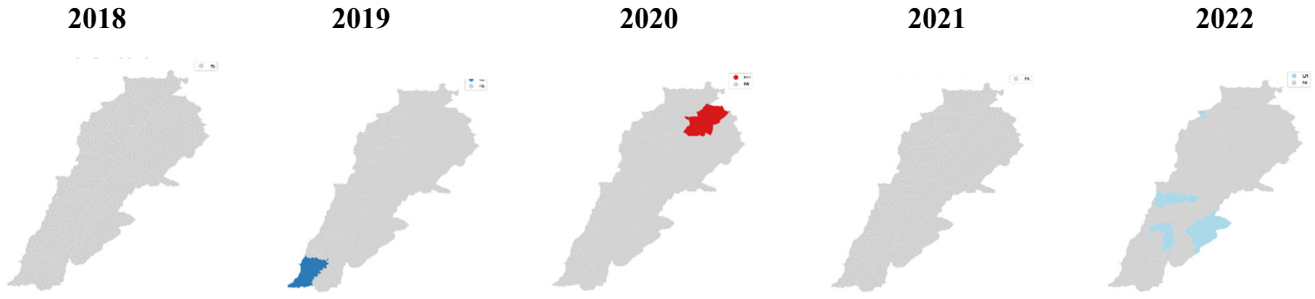
HDDS

rCSI

Share of food expenditures

Figure 4. Local Moran's I (LMI) (continued)

Expenditures < SMEB



Note: Gray areas indicate districts where there is spatial randomness and no evidence of a spatial structure. Red represents a "hot spot" where there is a high score district surrounded by high score neighbors (i.e., high levels of food insecurity). Blue represents a "cold spot" where there is a low score district surrounded by low score neighbors (i.e., low levels of food insecurity), Cyan represents an outlier district with low score surrounded by a relatively high score neighbors, and vice versa, orange indicates an outlier district with high score surrounded by a relatively low score neighbors.

Table 3. Predictive power of the machine learning models for food insecurity measures

Target variable	Cutoff value for bottom 30%	Accuracy of prediction			
		Logistic	Random Forest	Gradient Boosting	Lasso
FCS	≤ 37	0.6189	0.6208	0.6467	0.0989
HDDS	≤ 8	0.6045	0.6277	0.6850	0.4565
rCSI	≥ 24	0.6835	0.6769	0.7111	0.2078
Share of food expenditures	≥ 60.4%	0.5787	0.6073	0.5788	0.1362

Note: This table shows the percentage of times the model accurately predicted food insecurity for each measure. The predictive power of the models was determined using the recall value. Predictions are based on the classification of whether the household was in the bottom 30% for each measure. To improve model accuracy, balanced, class weights were applied to account for the skewed distribution resulting from the classification of households as either 0 or 1 depending on whether they are food insecure. Each ML model also includes all the features (the household characteristics, the living conditions, and the geospatial features).

Figure 5. Random Forest Models: Categorical feature importance for each food insecurity measure (years pooled)

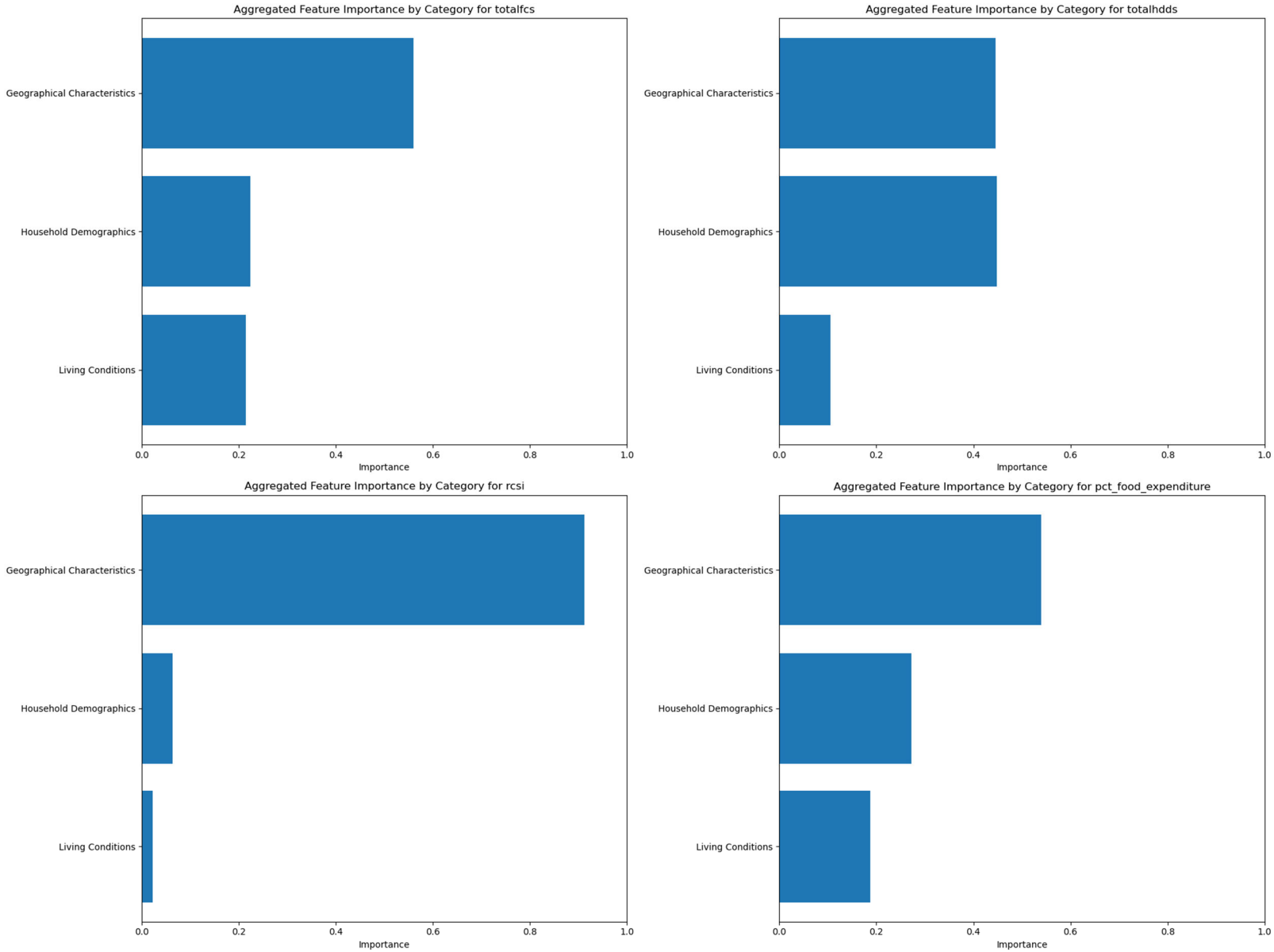
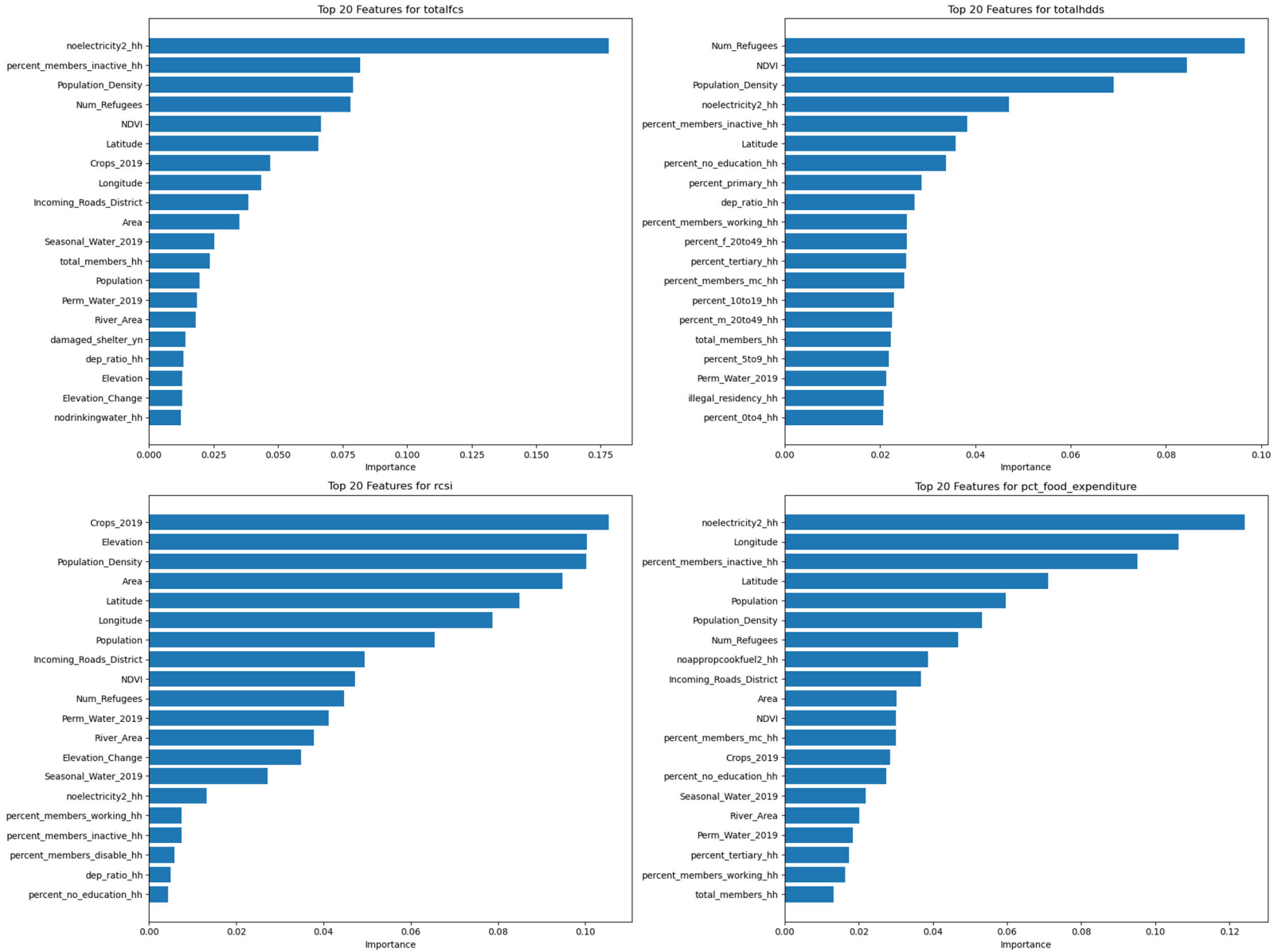


Figure 6. Random Forest Models: Top 20 most important features for each food insecurity measure (years pooled)



Appendix

Table A1. Variable definitions

Variables	Variable name	Definitions
Food insecurity measures		
FCS	totalfcs	The Food Consumption Score (FCS) measures the diversity and frequency of households' diets in the week prior to the survey. Scores range from 0 to 112, with lower scores indicating less diet diversity; the FCS is grouped into three categories: acceptable (>42), borderline (28-42), and poor (<28)
HDDS	totalhdds	Household's dietary diversity score measures the number of food groups consumed during the last 24 hours. The index ranges from 0 to 12 (the total number of food groups). A score lower than 6 is considered as low diversity, 7-8 borderline, and 9 or higher acceptable.
rCSI	rcsi	Reduced food coping strategies index (rCSI) measures the strategies that households use to cope with the lack of food and the severity of the strategies used to compare the hardship faced by households due to a shortage of food. The index ranges from 0 (no coping strategies) to 56 (severe level of coping strategies), with higher scores indicating more food coping strategies are being used. Households are classified as having a low (0-3), medium (4-18), or high (≥19) rCSI.
Share of food expenditure per capita	pct_food_expenditure	Expenditures per capita in Lebanese Pounds (LBP) on food as a share of total expenditures per capita
Survival Minimum Expenditure Basket (SMEB)	Povertyindicators1	=1 if the household's monthly expenditures per capita is below the Survival Minimum Expenditure Basket (SMEB) cutoff. This cutoff varies by year. For 2018 and 2019, it was equal to 87 USD (equivalent to 131,153 LBP); for 2020, it was equal to 308,722 LBP; for 2021, it was equal to 490,028 LBP, and 8,156,858 LBP for 2022.
Food insecurity measures (cutoffs for bottom 30% for GB models)		
FCS ≤ 37		=1 if Food Consumption Score (FCS) score is less than or equal to 37, indicating "poor" diet diversity that is at an unacceptable level (poor and borderline food consumption) and in the bottom 30% of households.
HDDS ≤ 8		=1 if the household's dietary diversity score was less than or equal to 8, indicating "poor" diet diversity in terms of the number of food groups consumed by the household in a 24-hour period.
rCSI ≥ 24		=1 if the Reduced Coping Strategies Index (rCSI) is greater than or equal to 24, indicating a "high" number of food coping strategies are being used and that the household is in the bottom 30% of households.
Share of food expenditure per capita ≥ 60.4%		=1 if the share was greater than 60.4%, indicating that the household is in the bottom 30% of households.
Household demographics		
Household size	total_members_hh	Number of household members
Dependency ratio	dep_ratio_hh	Ratio of dependent household members (below 15 or above 60 years of age) relative to total household members
% HH members aged 0-4	percent_0to4_hh	Percentage of children aged 0 to 4 in each household
% HH members aged 5-9	percent_5to9_hh	Percentage of children aged 5 to 9 in each household
% HH members aged 10-19	percent_10to19_hh	Percentage of household members aged 10 to 19 in each household
% Male members aged 20-49	percent_m_20to49_hh	Percentage of male adults aged 20 to 49 in the household
% Female members aged 20-49	percent_f_20to49_hh	Percentage of female adults aged 20 to 49 in the household
% HH members older than 60	percent_60_hh	Percentage of household members aged 60 and above
% HH members education unknown		Percentage of household members who do not report any educational level
% HH members no education	percent_no_education_hh	Percentage of household members who did not go to school
% HH members primary education	percent_primary_hh	Percentage of household members who completed primary education
% HH members secondary education	percent_secondary_hh	Percentage of household members who completed secondary education
% HH members above secondary education	percent_tertiary_hh	Percentage of household members with high school, technical, or college diploma
% HH members working	percent_members_working_hh	Percentage of household members who are working
% HH members unemployed	percent_members_unemployed_hh	Percentage of household members who are unemployed
% HH members inactive	percent_members_inactive_hh	Percentage of household members who are inactive
% HH members with disability	percent_members_disable_hh	Percentage of household members with any disability (seeing, hearing, walking, etc.)
% HH members with medical condition	percent_members_mc_hh	Percentage of household members with a chronic illness or unable to care for themselves
Child not attending school	schoolage_notatt_hh	=1 if household has a child who is of school age (5 to 14 years of age) who is not attending school
Disabled Head	disable_head	=1 if the head has a disability

Disabled dependent member	disable_dependent	=1 if at least one member of the household other than the head has a disability
% Illegal residency	illegal_residency_hh	Percentage of household members aged 15 or older who do not have legal residency in Lebanon
Living conditions		
No electricity	noelectricity2_hh	=1 household does not have access to electricity or has access for less than 16 hours
Lack of sanitation	nosanitation_hh	=1 if household does not have access to basic sanitation (i.e., no access to flushed toilets or improved pit latrines with a cement slab, and are not sharing the toilets with other households)
No clean drinking water	nodrinkingwater_hh	=1 if household does not have access to clean drinking water
No cooking fuel	noappropcookfuel2_hh	=1 if household does not have access to electric or gas stove and cooks only with dung, wood, or charcoal
Shelter crowdedness	overcrowding	=1 if household is living in an overcrowded shelter with less than 4.5m^2 per person
Damaged Shelter	damaged_shelter_yn	=1 if the shelter is damaged in any way
Geographical Characteristics		
Latitude	Latitude	Geographical coordinates
Longitude	Longitude	Geographical coordinates
Elevation	Elevation	Average elevation (km)
Elevation Change	Elevation_Change	Difference between highest and lowest elevation (km)
NDVI	NDVI	Normalized Difference Vegetation Index (NDVI) is a standardized measure of healthy vegetation and how sensitive vegetation in a particular area may be to drought (agriculture); the average NDVI was calculated for each district using the years 2018, 2019, 2020, and 2021.
Area	Area	Area of the district km^2
Population		Average total population was calculated for each district using the years 2018, 2019, and 2020; based on the population counts taken from the WorldPop adjusted to match the UN estimation count. Population counts for 2021 and 2022 are based on the most recently available data for 2020
Number of refugees	Num_Refugees	Manually extracted from UN maps; Number of refugees in each district
Built area	Built_Up_2019	Average fraction coverage of built-up area was calculated for each district using the years 2018 and 2019
Crop area	Crops_2019	Average fraction coverage of crop covered area was calculated for each district using the years 2018 and 2019
Permanent water	Perm_Water_2019	Average fraction coverage of permanent water area was calculated for each district using the years 2018 and 2019
Seasonal water	Seasonal_Water_2019	Average fraction coverage of seasonal water area was calculated for each district using the years 2018 and 2019
Population Density	Population_Density	Divide population by area to get population density (persons/km^2)
Area near river	River_Area	Area of land within 500 meters of a river
Incoming roads	Incoming_Roads_District	Number of incoming roads within each district

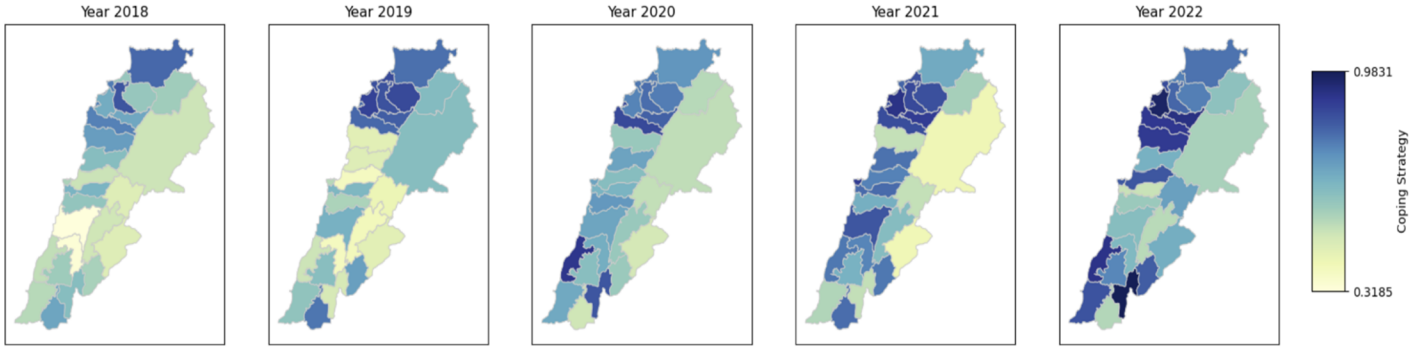
Sources: 2018, 2019, 2020, 2021, and 2022 Vulnerability Assessment of Syrian Refugees (VASyR).

Table A2. Overview of geospatial feature data

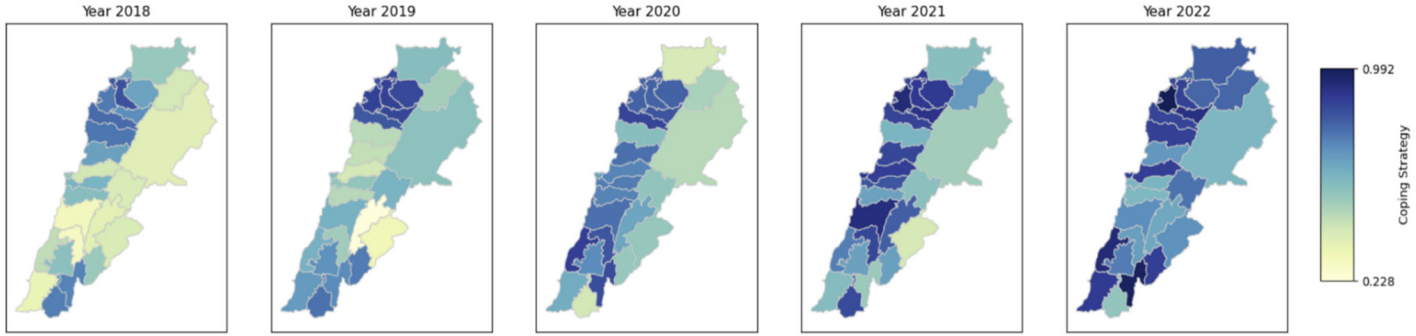
Geospatial feature	Aggregation from cadastral to district level	Source	Weblink
Latitude	Mean	USGS/NGA Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010)	https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-multi-resolution-terrain-elevation
Longitude	Mean	USGS/NGA Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010)	https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-multi-resolution-terrain-elevation
Elevation	Mean	USGS/NGA Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010)	https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-multi-resolution-terrain-elevation
Elevation Change	Mean	USGS/NGA Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010)	https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-multi-resolution-terrain-elevation
NDVI	Mean	Copernicus Global Land Service (CGLS), NDVI Collection 300m (Versions 1 and 2)	https://land.copernicus.eu/en
Area	Sum	USGS/NGA Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010)	https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-multi-resolution-terrain-elevation
Population	Sum	WorldPop rasters	https://www.worldpop.org/
Number of refugees	Sum	United Nations High Commissioner for Refugees (UNHCR)	https://data.unhcr.org/
Built area	Sum	Copernicus Global Land Service (CGLS) portal	https://land.copernicus.eu/global/
Crop area	Sum	Copernicus Global Land Service (CGLS) portal	https://land.copernicus.eu/global/
Permanent water	Sum	Copernicus Global Land Service (CGLS) portal	https://land.copernicus.eu/global/
Seasonal water	Sum	Copernicus Global Land Service (CGLS) portal	https://land.copernicus.eu/global/
Population Density	Sum	WorldPop rasters	https://www.worldpop.org/
Area near river	Sum	International Steering Committee for Global Mapping	https://maps.princeton.edu/catalog/stanford-wn533df2039
Incoming roads	Sum	United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA)	https://data.humdata.org/dataset/wfp-geonode-lebanon-road-network-main-roads

Figure A1. Changes in the 5 components of the reduced coping strategies index (rCSI) across districts and years

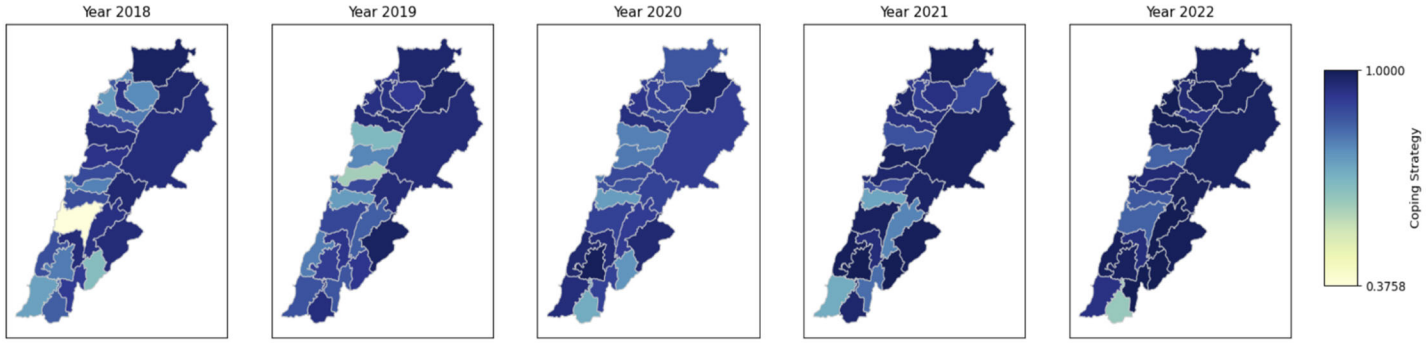
rCSI 1: Reduced number of meals per day



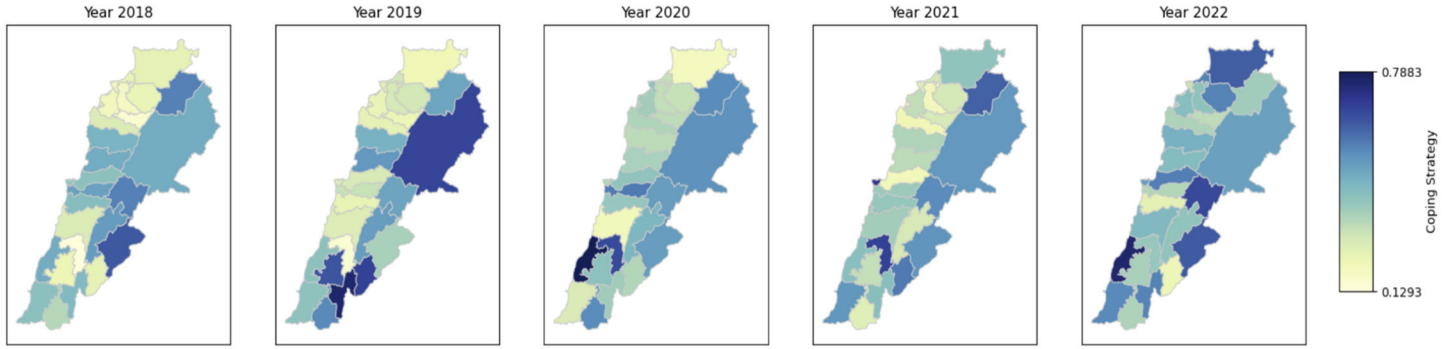
rCSI 2: Reduced portion size of meals



rCSI 3: Relied on less preferred, less expensive food



rCSI 4: Borrowed food or relied on help from friends or relatives



rCSI 5: Restricted consumption by adults in order for young-small children to eat

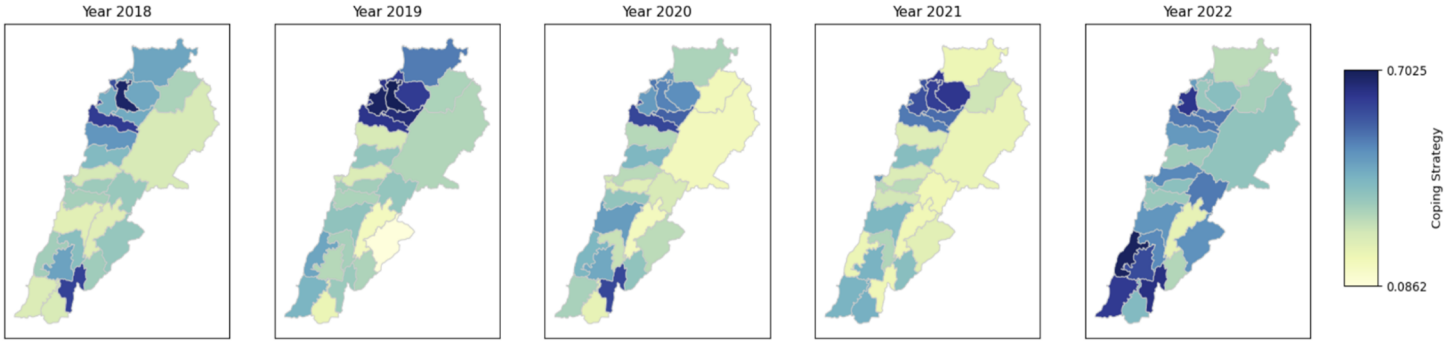


Figure A2. Gradient Boosting Models: Categorical feature importance for each food insecurity measure (years pooled)

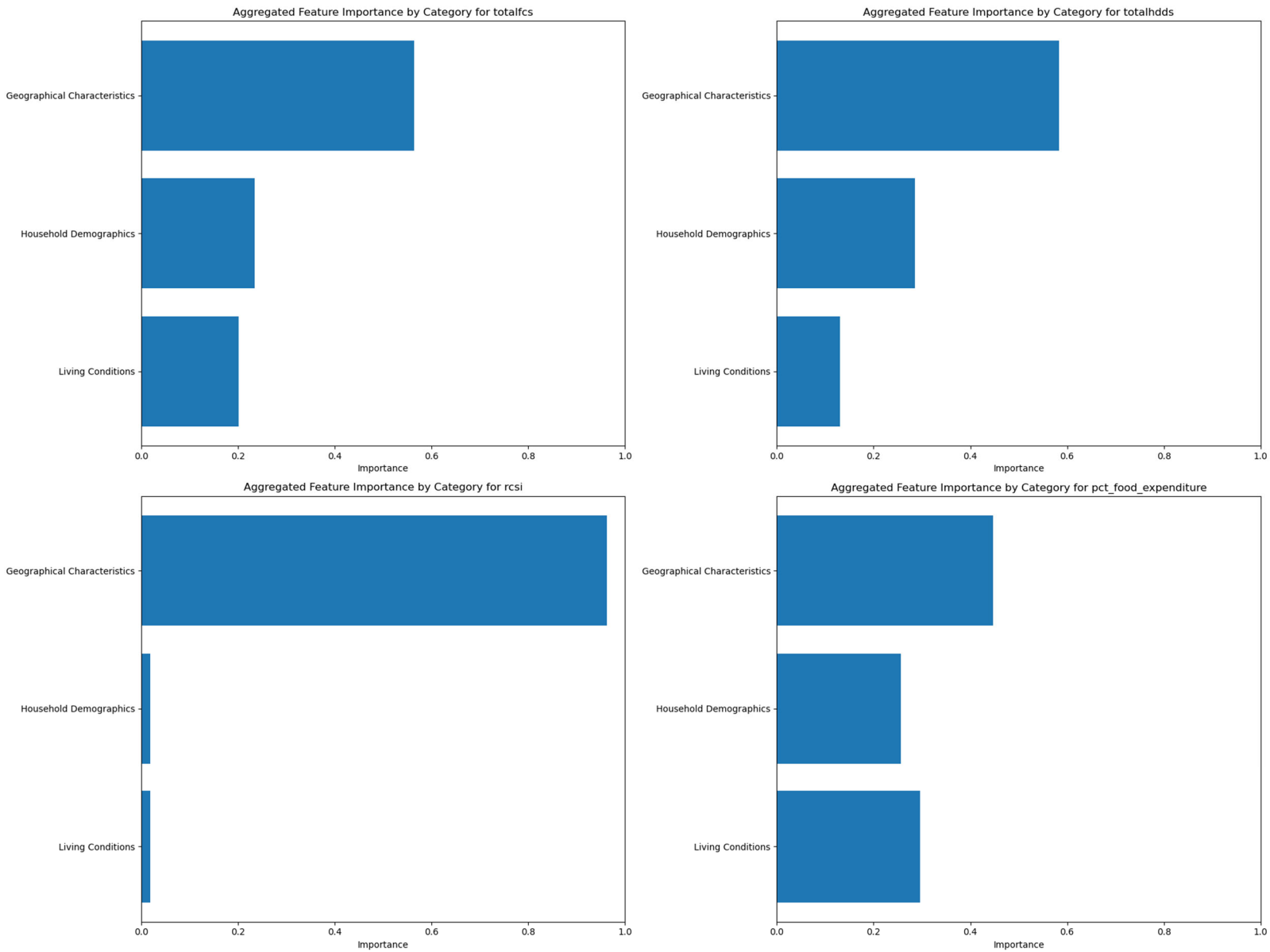


Figure A3. Gradient Boosting Models: Top 20 most important features for each food insecurity measure (years pooled)