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The Household Food Security Implications of Disrupted Access to Basic Services in Five Cities in the Global South

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Abstract: COVID-19 has caused significant disruptions regarding the extent to which households can access basic services and resources in cities around the world. Previous studies have indicated a predictive relationship between the consistency of resource access and food access among urban households. These investigations, however, have predominantly been isolated to Southern Africa and have not accounted for other dimensions of food security. To test whether these results are observable outside Southern Africa, and with a more multidimensional measure of food security, this investigation proposes a method for building an index of urban household food access, utilization and stability. The scores for the constructed index are then compared across household survey samples collected from five cities in the Global South. The investigation then assesses the predictive relationship between the consistency of household resource access and this more multidimensional index of food insecurity. While the general trend of inconsistent resource access predicting food insecurity is confirmed, there are geographic differences in the strength and quality of this relationship. These findings suggest that the resource access disruptions inflicted by COVID-19 will likely have a heterogeneous impact on urban food security dependent upon the affected resource and the city in which a given household resides.

Keywords: COVID-19; urban food security; infrastructure; basic services; Global South; cities

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1. Introduction

1.1. The Impacts of COVID-19 on Urban Food Insecurity and Resource Access

As COVID-19 and its variants continue to spread across the world, it has become apparent that, in addition to health problems, there are far reaching adverse impacts. One key sector impacted is food systems which support the food security and nutrition of urban populations. Food security is a fundamentally important measure for determining the health and wellbeing of people [1]. Considering that the majority of the world's people currently live in urban areas, and urban populations will continue to increase [2], attention must be given to urban food systems and food security [3]. Urban areas consume up to 70 percent of global food supply and the pandemic has created disruptions that have hindered access to food and increased the food insecurity of vulnerable populations [4]. Notably, measures such as lockdowns and the restriction of movement to contain the virus have concurrently affected the operation of actors within urban food systems, particularly consumers; as such, the COVID-19 pandemic has had a direct effect on urban food security [5].

The pandemic has also resulted in widespread unemployment and loss of income, thus, affecting the overall purchasing power of consumers and exacerbating underlying socio-economic inequalities [6,7]. Already, poor urban households spend a large proportion of their income on the food they consume [8], meaning that households have had less income to secure food. In addition, demand and consumption has been adversely impacted by the general closure of eating outlets, including restaurants, and as such, the majority of food preparation and consumption has been concentrated in households [9]. Households dependent on meals away from home prior to the pandemic were more impacted as food preparation abilities have been associated with dietary intake and food security of households [10]. The pandemic is, therefore, a wake-up call for understanding the challenges contributing to the vulnerability of urban households to food insecurity. Even prior to the COVID-19 pandemic, food systems and food insecurity were key issues of concern, as the number of food insecure people has been increasing globally, as well as drivers of food system change [11].

Managing the effects of COVID-19 on urban food systems should involve decision-making by all stakeholders to ensure food systems are more equitable, inclusive and resilient [12,13]. However, apart from low preparedness in addressing the pandemic, there was poor consultation with key stakeholders, especially those in the food system in making decisions regarding COVID-19 containment measures [5]. This begs the question of how to reduce the impacts of restrictive measures on food system actors, such as consumers, so that their vulnerability is not worsened? Knowledge of the sources of vulnerability to food insecurity by knowing who, where and why people are food insecure may guide management actions to reduce them [14]. Measuring food security and determining these vulnerabilities is, therefore, very important but doing so has proven to be challenging. The reasons are that the food security construct is inherently latent, difficult to define and even operationalize [15,16].

Historically, food insecurity has been addressed by producing more food to increase availability and meet the needs of increasing populations [17]. However, Sen (1981), through his seminal work on the causes of famine and starvation debunked this approach by indicating that even when food was available, poor households could not access it because of the lack of entitlements to obtain food [18]. This influenced the definition of food security at the 1996 World Food Summit, defined as a condition which 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*" [19] (p. 1). Such conceptualization addressing food insecurity should include demand and consumption factors, which result in the loss of entitlements (e.g., loss of employment) and negatively impact food access [15]. For instance, the food security crisis of 2007, which triggered political riots, resulted from the lack of access to food for masses living in poverty [20]. According to the Food and Agriculture Organization [21], food security can be thought of as a multidimensional construct encompassing food availability, access, utilization and stability.

Food insecurity, therefore, refers to the lack of one or more of these dimensions [8]. With the COVID-19 pandemic, availability has been affected by food supply disruptions, food access and food utilization are affected as consumers opt for lower quality food being limited by price, access to health and sanitation services. Finally, stability is affected by physical distancing measures and the lockdown of informal markets, affecting the food security of poor urban households whilst behavioral responses such as panic buying and hoarding have been identified in better off households [22,23]. Some pandemic-related interventions in addressing food insecurity, such as improved food distribution, have been based on the monitoring of food availability and prices in markets [24]. This implies that, despite the broader definition of food security, a focus on food availability and supply has continued to influence the measurement of food security and interventions [25,26]. This also highlights increased calls for the appropriate measurement of food insecurity because of serious implications for health, development programs, nutrition evaluations, vulnerable group identification and informing various government policies [8,27].

Understanding the unfolding impacts of COVID-19 on the food security of urban households should be based on examining the existing drivers of vulnerability and all dimensions of food security not just availability. Within cities, emerging research has identified a potential relationship between infrastructure access and food access [28,29]. McCordic (2016) first established a predictive relationship between infrastructure access and household food access in a study of Maputo. Subsequent studies have also indicated that access to public resources (e.g., water, electricity, medical care) is predictive of household food insecurity [30–32]. That said, these studies established this relationship by focusing almost exclusively on measures of food access, begging the question of whether this relationship would exist if a more multidimensional measure of food security were used. Sustainable cities need the improved measurement of indicators in order to reduce vulnerabilities and increase resilience [33]. Furthermore, these studies have predominantly focused on Southern African cities, begging the question as to whether this relationship is generalizable to other cities outside of this geographic context. In order to address this gap in the literature, this study will build a multidimensional index of food security, assess its relationship to broader household resource access in multiple cities (within and outside the Southern African context) and review the implications of these findings for research and policy.

1.2. Measuring Urban Food Security

One of the great obstacles in food security research has been deciphering clear narratives around the drivers of food insecurity while appreciating the complexity of this development challenge [34–36]. The multidimensional nature of food security impacts [37] obstructs the precision of social research methods and analytical approaches. The multi-scaler and collateral impacts of climate change have exacerbated both national food supply and household incomes, rendering opaque images of food security vulnerabilities and obstructing effective mitigation measures [38]. This challenge begins with the conceptualization of food security as a development challenge. Foran et al.'s (2014) interdisciplinary analysis of food security frameworks found several conceptual paradigms, often in tension with one another, and confounding effective food security interventions [39]. As a result, there is a pressing need to develop innovative decision support mechanisms to support food security policy and research [40].

Without the appropriate diagnostic tools, public policymakers can be left with the unenviable task of clarifying the nuanced narratives derived from social research. Previous approaches to overcoming this challenge have distilled satellite imagery into timely and relevant famine early warning systems [41]. Scenario-based simulations have provided helpful visualizations to support policy decisions on food security impacts [42]. Other researchers have developed novel metrics to account for the combined influences of multidimensional factors underlying sustainable food and nutrition security [43]. Each of these approaches attempt to capture the dynamic and complex nature of food security [44] by simplifying that complexity into a metric that is both valid and reliable.

The nature of this challenge is amplified in urban environments where food access, utilization and stability are often subservient to global economic and climate pressures translated through the local dynamics of market access and household entitlements [45–47]. The complexity of urban food security challenges can hamper the effective translation of research into policy, often because of miscommunications arising from the nuance of urban food research findings [48]. As a result, there is an urgent need for research tools that can effectively capture the complexity of urban food security in support of statistical modeling and public policy formation.

The complexity of modern urban food systems (encompassing food production, distribution and retail) can create significant governance challenges, particularly among cities in developing countries [49]. The multitude of actors engaged in the urban food system creates a disaggregated network that is difficult to manage through centralized governance [50]. Among developing countries in Sub-Saharan Africa, Maxwell (1999) further notes that the lack of formal safety nets can offload the responsibility of urban food security to the household [27]. In response to this challenge, localized food systems (integrating rural and urban food production) have emerged as a solution to bolster urban food security has become a common theme in urban food studies [51]. While complicating the urban food system, these alternative systems of food supply are a response to social justice concerns for equitable household access to food [52]. As a result, Haysom (2015) notes the need for clear urban food research narratives to help coordinate urban policy action by multiple actors in municipal government [50].

The importance of multidimensionality in food security paradigms has been further underscored by the growing recognition of vulnerability and risk in assessing food security [53–55]. This new conceptualization of food security has supported research into the diverse set of drivers underpinning inconsistent food access among cities [56]. Several authors have noted the crippling effects of household poverty on food security in cities of the Global South [27,57], which has been abundantly observed during food price shocks [45]. Research has also indicated that poor households in cities can face disrupted food security under the strain of both communicable [58] and non-communicable diseases [59,60]. Inconsistent access to infrastructure resources may also predispose poor urban households to food insecurity [28]. It is important to remember, however, that stable food access in cities rests upon a functional urban food system connecting food producers to consumers. That supply of food can occur through both formal markets and supermarkets [61] or informal markets and urban food production [62–65].

In order to inform urban food security policy, Haysom and Tawodzera (2018) have urged a renewed focus on building food security metrics that are applicable to the unique characteristics of urban food systems [66]. Survey-based methods to examine experienced food security have provided a foundational platform to guide policy interventions in household food security issues [67]. Freedman and Bell (2009) further note that, based on a survey of the urban poor, self-reported measures of perceived food in-accessibility can be accurate and provide a valid basis for food security interventions [68]. Three widely used self-report food security scales were developed by USAID's Food and Nutrition Technical Assistance (FANTA) programme. These measures include the Household Dietary Diversity Score (HDDS) [69], the Household Food Insecurity Access Scale (HFIAS) [70] and the Months of Adequate Food Provisioning (MAHFP) [71]. For the purposes of this investigation, each of these scales are discussed and assessed independently as measures of food utilization, food access and food stability.

1.2.1. Household Dietary Diversity Score

The Household Dietary Diversity Score (HDDS) measures the number of food groups consumed by any member of a household in the previous 24 h [69]. The score is calculated based on the report of the household member in charge of food preparation or who can reliably describe the consumption patterns of the household. The scale can be adapted to the local food consumption patterns using the following food groups as a guide:

1. Any bread, rice, noodles, biscuits or any other foods made from millet, sorghum, maize, rice, wheat or any other locally available grain;
2. Any potatoes, yams, manioc, cassava or any other foods made from roots or tubers;
3. Any other vegetables;
4. Any fruits;
5. Any beef, pork, lamb, goat, rabbit, wild game, chicken, duck, other birds, liver, kidney, heart or other organ meats;
6. Any eggs;
7. Any fresh or dried fish or shellfish;
8. Any foods made from beans, peas, lentils or nuts;
9. Any cheese, yoghurt, milk or other milk products;
10. Any foods made with oil, fat or butter;
11. Any sugar or honey;
12. Any other foods such as condiments, coffee, tea [69] (p. 4).

If the household has consumed any given food group in the past 24 h, a one is inputted for that food group. Otherwise, a zero is inputted for all food groups not consumed by the household in the past 24 h. The HDDS is then calculated by summing the number of food groups consumed by the household in the previous 24 h (thus, higher scores on the HDDS represent greater dietary diversity).

$$\text{HDDS} = \sum \text{Food Groups Consumed in the Last 24 h} \tag{1}$$

The HDDS was designed to measure dietary diversity, specifically focusing on the nutritional diversity in household food consumption [69]. That said, the HDDS can also be administered to individuals rather than households. Dietary diversity makes up a key component of effective food utilization [36] and has been used as a proxy measure of food utilization by other studies [72,73]. As a result, the HDDS can provide insight into effective household food utilization in social survey research. The HDDS is also supported by a growing body of evidence for its external validity. Cordeiro et al. (2012) found a strong correlation between the HDDS and energy intake in a survey of Tanzanian adolescents [74]. The HDDS also demonstrated a strong correlation with the Food Consumption Score across several surveys [8]. Faber et al. (2009) also found a strong correlation between the HDDS and the HFIAS in a survey of Limpopo in South Africa [75]; however, this finding was not replicated in a study performed by Maxwell et al. (2014) [76]. It is important to note (as was suggested by Maxwell et al.) that this finding may have arisen from the different dimensions of food security measured by these two scales. In summary, however, the HDDS provides important insights into a key facet of effective food utilization (dietary diversity).

1.2.2. Household Food Insecurity Access Scale

The Household Food Insecurity Access Scale (HFIAS) is a survey instrument designed to measure the frequency and intensity of food access challenges experienced by a household [70]. The scale comprises nine Likert questions meant to measure a diversity of physical, economic and social dimensions of food access challenges. The questions range from minor to more severe experiences of these food access challenges. The Likert scale accompanying each question ranges from never in the last month to more than ten times in the last month. The questions in the scale include:

1. In the past four weeks, did you worry that your household would not have enough food?
2. In the past four weeks, were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?
3. In the past four weeks, did you or any household member have to eat a limited variety of foods due to a lack of resources?
4. In the past four weeks, did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food?
5. In the past four weeks, did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?
6. In the past four weeks, did you or any household member have to eat fewer meals in a day because there was not enough food?
7. In the past four weeks, was there ever no food to eat of any kind in your household because of lack of resources to get food?
8. In the past four weeks, did you or any household member go to sleep at night hungry because there was not enough food?
9. In the past four weeks, did you or any household member go a whole day and night without eating anything because there was not enough food? [70] (p. 5).

If the household has experienced any of the included food access challenges in the past month, the respondent is asked to rank the frequency with which the food access challenge was experienced in the past month using the following scale: One = Rarely (once or twice in the past four weeks), Two = Sometimes (three to ten times in the past four weeks) or Three = Often (more than ten times in the past four weeks). The scores are then summed up to provide an overall HFIAS score from zero to twenty-seven, where higher scores represent greater frequency of experienced food access challenges.

$$\text{HFIAS} = \sum \text{Frequency of Food Access Challenges in the Past 4 Weeks} \quad (2)$$

The HFIAS is likely the most implemented of the three scales reviewed here and has assembled a strong body of evidence to support its use. Knueppel et al. (2009) confirmed that the HFIAS scores were supported by key informants in a study of rural Tanzania [77]. Similarly, the HFIAS was also associated with increased odds of undernutrition among children in surveys carried out in Bangladesh, Vietnam and Ethiopia [78]. That said, some studies have questioned the effectiveness of the scale. As an example, Dietchler et al. (2010) found that the HFIAS was less accurate in its classification of food security status than the Household Hunger Scale (citing potential challenges in translating the concepts of the HFIAS) [79]. As with other measures of food security, the over-riding recommendation has been to use the multiple food security measures rather than attempting to rely solely on one food security scale and disregard other dimensions of food security [76]. Among the multiple food security scales available for measuring different dimensions of food security, the HFIAS remains an effective survey measure of household food access.

1.2.3. Months of Adequate Household Food Provisioning

The Months of Adequate Household Food Provisioning (MAHFP) provides a measure of the stability with which households have maintained adequate food provisioning over the previous year [71]. As with the other scales reviewed here, the scale is meant to be administered to the household member in charge of food preparation. The scale is administered using the following instructions:

> "Now I would like to ask you about your household's food supply during different months of the year. When responding to these questions, please think back over the last 12 months, from now to the same time last year. Were there months, in the past 12 months, in which you did not have enough food to meet your family's needs? If yes, which were the months in the past 12 months during which you did not have enough food to meet your family's needs?" [71] (p. 4)

If a given month is identified by the respondent, one is inputted for that month, otherwise, zero is inputted for any months not identified by the respondent. The scale is calculated by subtracting the sum of the inputted numbers for each month from 12 (thus, higher scores on the scale are associated with greater household food stability).

$$\text{MAHFP} = 12 - \sum \text{Months of Inaadequate Food Provisioning the Last Year} \quad (3)$$

Unlike the HDDS and the HFIAS, there have been fewer studies assessing the validity or reliability of this measure in spite of its widespread implementation in studies of urban food security [28,80,81], many of which have identified common predictors of the MAHFP and other food security scales [82]. As a result, this measure remains an empirically supported measure of food stability but without the same empirical support as the other measures reviewed here.

1.2.4. Index Development Considerations

While each of the reviewed food security scales provide measures of different dimensions of food security, they still represent distinct measures. In order to collapse the measures into one over-arching index, there are a number of considerations that must be taken into account. First, the relative weighting of each food security scale's contribution to the overall index score should be decided [83]. While this is usually a decision made on theoretical grounds, the index may either weight each scale's contribution equally or disproportionately weight each scale's contribution based on theoretical considerations. Second, given that the HDDS, HFIAS and MAHFP are measured on different scales, the scales need to be normalized to ensure that each scale is comparable [84]. This is important because of its implications for the third consideration: aggregation. The means by which the scores are aggregated (averaged) can significantly impact the stability of the overall index. Decisions when aggregating scales in an index predominantly revolve around the theoretical implications of compensability (the extent to which performance on each scale can be traded off) [85]. Some means of aggregation (such as arithmetic mean or Bordo ranking procedures) are perfectly compensable in that poor performance on one scale can be traded off for improved performance on another scale. Alternatively, Condorcet ranking procedures ensure that performance on each scale cannot be traded off for performance on another scale.

To support clear policy narratives and statistical modeling, an index of urban food access, utilization and stability will need to be comparable and theoretically address issues of compensability and weighting. Such an index will need to provide a means of normalization that is not relative, a weighting scheme that ensures equal priority to all included measures, and a means of aggregation that is consistent with the theory underlying food security measurement. Therefore, in order to assess whether the identified relationship between resource access disruption is applicable to a more multidimensional measure of food security, this investigation will construct an index of urban household food access, utilization and stability using the HDDS, HFIAS and MAHFP measures. Using the constructed index, the investigation will then assess the extent to which the previously observed relationship between household food access and resource access is present in cities outside of the Southern African context. Given the novelty of the multidimensional index constructed in this investigation, the investigation will also include a Southern African city to replicate earlier findings on this relationship and for comparison with the other cities included in the data set.

2. Materials and Methods

2.1. Research Objectives

1. Create an internally consistent index of urban household food access, utilization and stability;
2. Assess the relationship between urban household resource access and household food security.

In order to achieve these objectives, this investigation will, first, create an index of urban food access, utilization and stability using the HDDS, MAHFP and HFIAS measures and then, second, use that index to analyze the relationship between food insecurity and inconsistent resource access in the selected cities.

2.2. Sample

The sample for this investigation was drawn from household surveys conducted by the Hungry Cities Partnership (led by Jonathan Crush, the Principal Investigator of the partnership) between 2014 and 2016 in five purposively selected cities: Maputo, Mozambique; Kingston, Jamaica; Nairobi, Kenya; Mexico City, Mexico; Nanjing, China. These cities were selected for this investigation in order to account for multiple geographic regions (North America, the Caribbean, Africa and Asia). These city surveys administered the same household survey instrument which included the same household food security scales, administered in the same manner to adult household respondents in each selected household. That said, there was variation in the language with which the scales were administered. The household survey scales were administered in English (for the Kingston and Nairobi surveys), Portuguese (for the Maputo survey), Spanish (for the Mexico City survey) and Mandarin (for the Nanjing survey). Each of these surveys sampled households from across the city using a combination of random systematic sampling with sample sizes distributed across city sub-districts using approximate proportionate allocation (based on the most recently available census data for the city). In each of these cities, the household sample size was stratified across randomly selected wards (across the entire city) using proportionate allocation based on the most recently available census data. Households were then selected for the survey using a combination of random and systematic sampling. All surveys were carried out as in-person household surveys with trained enumerators speaking with adult representatives for the entire household. The original sample sizes varied between the cities but, for this investigation, 500 households were randomly selected from each data set in order to provide an equal contribution of each city to the effects observed in this study (Table 1). Among the final household samples included in this investigation, the response rates for the included food security scales varied from 96 percent to 99 percent.

Table 1. Frequency distribution of household city sample.

Cities	n
Maputo	500
Kingston	500
Nanjing	500
Nairobi	500
Mexico City	500
Total	*2500*

2.3. Scale Normalization

The HDDS, MAHFP and HFIAP scores included in this investigation all differed in magnitude and direction. Therefore, prior to aggregating the scales together into an index, all three scales had to be normalized so that they could be expressed on the same numeric scale. Given this investigation's focus on building an index to support comparisons of household food security across geographic regions and time, relative normalization techniques (standardization, ranking, etc.) were not viable approaches. Instead, this investigation implemented min–max normalization to transform each food security score to a scale of 0 to 1. As a reminder, the HDDS and MAHFP scales range from 0 to 12. All transformed scales are denoted with the superscript ′ notation (e.g., HDDS′). The HDDS and MAHFP scores were transformed using the following equations:

$$\text{HDDS}' = \frac{\text{HDDS} - 0}{12 - 0} \tag{4}$$

$$\text{MAHFP}' = \frac{\text{MAHFP} - 0}{12 - 0} \tag{5}$$

While this approach easily converted the magnitude of each scale, min–max transformation does not account for the reversed direction of the HFIAS (where, unlike the HDDS and MAHFP, higher scores denote more severe food insecurity). Furthermore, as a reminder, the HFIAS scale ranges from 0 to 27. In this case, the min–max normalization equation was modified in order to reverse the direction of the HFIAS scale in addition to its magnitude:

$$\text{HFIAS}' = \frac{\text{HFIAS} - 27}{0 - 27} \tag{6}$$

2.4. Index Aggregation

The Food Security Geometric Mean (FSGM) index provides a means of aggregating the food security scales in an unweighted fashion. In this case, the mean is calculated as the nth root of a product of n scales. The geometric mean has a few advantages over the arithmetic mean. First, the geometric mean is more sensitive to the improvement of weak scores than to the improvement of high scores (displaying imperfect compensability). This is because positive increases in low scores have a greater impact on the geometric mean than would positive increases among high scores [86]. Second, the geometric mean is a unitless measure and can aggregate scales with varied degrees of magnitude. Finally, geometric means are the preferred method of aggregation for ratios. That said, there is one important caveat to the use of geometric means when aggregating multiple scales. The inclusion of a score of 0 for any of the scales included in the index will result in a geometric mean of 0 (regardless of the scores for the other scales). In order to overcome this challenge, the scale for each of the food security scales was shifted by 1 before calculating the geometric mean of the food security scales (providing FSGM′). Once the geometric mean was calculated, 1 was subtracted from the geometric mean to provide the FSGM. While this approach is not optimal in that the mean produced is not technically the geometric mean of the original normalized scores (given that each normalized score was shifted by 1), it provides an efficient approach to aggregating ratios that include 0. In order to preserve comparisons across households in the data set, this approach was consistently applied to each food security score in the data set. The approach is expressed as follows:

Step (1). Add 1 to each normalized HFIAS, MAHFP and HDDS score, multiply the sums together and find the cube root of the product:

$$\mathrm{FSGM}' = \sqrt[3]{(\mathrm{HFIAS}' + 1) \times (\mathrm{HDDS}' + 1) \times (\mathrm{MAHFP}' + 1)} \tag{7}$$

Step (2). Subtract 1 from the resulting cube root:

$$\mathrm{FSGM} = \mathrm{FSGM}' - 1 \tag{8}$$

2.5. Index Internal Consistency

The index constructed in this investigation represent aggregated measures of urban household food access, utilization and stability. Given the multidimensional nature of the scale, it is not necessary for the scales to consistently measure one domain (as would be indicated by tests of internal consistency). That said, in order to preserve the linear aggregation of the scales, it is important to determine whether there is a positive linear relationship between the scales that would support the aggregation of the scales. A negative linear relationship between any of the scales would indicate that increasing scores on one food security scale was associated with decreasing scores on another food security scale in the index (creating internal inconsistency in the index). As a result, one or more of the sub-scales may not be positively correlated with the overall index score. To assess whether this is the case, this investigation calculated descriptive statistics of the index scores per the different aggregation methods. Pearson's R correlation analysis were used to determine the linear strength and direction of the correlation between each of the underlying scales and the overall index score using each aggregation method. This correlation analysis was supported by bootstrapped 95% confidence intervals (calculated via percentiles), which were calculated based on 1000 samples drawn using simple random sampling.

2.6. Assessing the Relationship between Resource Access and Household Food Security

In this investigation, resource access was measured according to the consistency of household access to water, electricity, medicine, cooking fuel or a cash income over the previous year (where higher scores indicate increasingly inconsistent access to these resources). These analyses were performed within each of the cities included in this investigation. This data was collected using a Likert-scale poverty measure taken from the Lived Poverty Index. The index measured the frequency with which households have gone without access to these resources via the following questions:

- Over the past year, how often, if ever, have you or your household gone without enough clean water for home use?
- Over the past year, how often, if ever, have you or your household gone without medicine or medical treatment?
- Over the past year, how often, if ever, have you or your household gone without electricity in your home?
- Over the past year, how often, if ever, have you or your household gone without enough fuel to cook your food?

- Over the past year, how often, if ever, have you or your household gone without a cash income?

In response to these questions, and on behalf of the respondent's entire household, the respondent can select from the following answers: never, just once or twice, several times, many times, and always. The relationship between the resulting index in this investigation and household resource access was first established through Spearman's Rho correlations. This correlation analysis was supported by bootstrapped 95% confidence intervals (calculated via percentiles), which were calculated based on 1000 samples drawn using simple random sampling. These correlations assess the relationship between the FSGM scores and measures of the consistency of household access to these resources (Table 2).

Table 2. Correlation Variable Descriptions.

Correlation Variables	L.O.M.	Values
FSGM	I/R *	0 (Food Insecure)–100 (Food Secure)
Household Cooking Fuel Access	Ordinal	never, just once or twice, several times, many times, always
Household Cash Income Access	Ordinal	never, just once or twice, several times, many times, always
Household Medical Care Access	Ordinal	never, just once or twice, several times, many times, always
Household Water Access	Ordinal	never, just once or twice, several times, many times, always
Household Electricity Access	Ordinal	never, just once or twice, several times, many times, always

I/R *: Interval/Ratio.

This assessment also included the creation of a decision tree to better understand how household resource access might be used to identify households in the sample according to their food security scores on the FSGM. This decision tree was built using a classification and regression tree algorithm method that was designed to ensure the splits produced would separate the sample into homogenous pieces with respect to the FSGM scale created. That homogeneity is determined using a least-squared deviation measure to assess for homogeneity within each category created. In order to avoid overfitting, the model, the tree was set to a maximum tree depth of five levels with a minimum threshold of 100 cases in any given parent node and 50 cases in any given child node. Any missing values were excluded from the model and all variables included in the model had at least 97% of their values recorded.

To support this analysis, the resource access variables were dichotomized into binary variables. This dichotomization allowed for a more objective interpretation of the consistency of resource access. In order to further investigate any city-specific decision tree splits, the sampled cities were included as dummy variables indicating whether or not a given household was sampled from each respective city (Table 3).

Table 3. Decision Tree Variable Descriptions.

Decision Tree Variables	L.O.M.	Values	
FSGM	I/R	0 (Food Insecure)–1 (Food Secure)	
Household Cooking Fuel Access	Binary	Consistent Access	Inconsistent/No Access
Household Cash Income Access	Binary	Consistent Access	Inconsistent/No Access
Household Medical Care Access	Binary	Consistent Access	Inconsistent/No Access
Household Water Access	Binary	Consistent Access	Inconsistent/No Access
Household Electricity Access	Binary	Consistent Access	Inconsistent/No Access
Kingston	Binary	No	Yes
Maputo	Binary	No	Yes
Mexico City	Binary	No	Yes
Nairobi	Binary	No	Yes
Nanjing	Binary	No	Yes

I/R: Interval/Ratio.

2.7. Limitations

The samples used in this investigation should not be taken as representative of each city, given the sampling methods used in this investigation. Instead, these samples were derived in order to provide the approximately equivalent contribution of each city toward each analysis presented in this investigation. In addition, this investigation only provided analyses for a limited number of cities for comparisons. As a result, further research should be undertaken to confirm whether the properties of these indices hold in other cities. The MAHFP scores included in the sample demonstrated a high degree of skewness (−3.560) and kurtosis (14.245). Data transformations to reduce this level of skew and kurtosis to within acceptable levels, however, resulted in little change to aggregated scores (approximately 75 percent of scores were unchanged with an average difference of 0.05 between scales with and without the transformation), correlation analysis (less than a 10 percent change in correlations between the scales) or factor analyses. Consequently, to maintain interpretability, the MAHFP scores were normalized but not transformed in this analysis. Given the observational nature of this investigation, the analysis of the relationship between the inconsistency of household resource access and food insecurity should not be interpreted as causal. It is also important to note that, while the variables were binned in order to provide objective comparisons, the relationships observed may have changed if other cut-points were used in the binning process. Finally, as with all survey research, this investigation is premised upon the accurate and reliable recall of survey respondents. All enumerator teams that collected the survey data analyzed in this investigation underwent the same survey administration training to limit the potential for bias and support accurate respondent recall. In order to test for a potential common method bias that may have arisen from these issues, Harmon's single factor test (via both Principal Component Analysis and Principal Axis Factoring) was applied to all variables included in this investigation. This analysis indicated that a single factor extracted less than 50% of the variance, providing counterevidence for a common method bias in this investigation.

3. Results

3.1. Index Internal Consistency

The differences observed in the variation of these three indices across the cities may be the result of a combination of factors: the predominant clustering of high scores in a given city (as observed in Nanjing) or the reduced spread of scores (as observed in Nanjing and Nairobi). It is interesting to note the association between the clustering of scores within and between the three index scores in each sampled city, which may give an indication of the spread inherent in the underlying food security scales in these cities (Table 4).

Table 4. Descriptive Statistics of the FSGM Scores Across Cities.

Statistics	Maputo (n = 484)	Kingston (n = 474)	Nanjing (n = 488)	Nairobi (n = 493)	Mexico City (n = 494)	Total (n = 2433)
Mean	0.6357	0.6648	0.8716	0.7072	0.7584	0.7281
Median	0.6711	0.6782	0.8821	0.726	0.7686	0.7472
Std. Dev.	0.17832	0.15539	0.07842	0.1488	0.1232	0.16415
Min	0.05	0.03	0.55	0.2	0.05	0.03
Max	0.97	1	1	1	1	1

The Pearson's R correlations of the indices and sub-scales revealed significant and high positive linear correlations across the three indices (Table 5). In addition, each of the underlying food security scales also demonstrated significant and positive correlations with the three indices. Interestingly, however, while the relative strength of the relationship between these sub-scales and the three indices did not vary substantially across indices, the relative strength of these relationships did vary by city. As an example, Maputo, Nairobi, Mexico City and Kingston all indicated very strong linear correlations between the food security scales and the three indices. That said, in Nanjing, the MAHFP and HFIAS indicated weak to moderate positive relationships with the overall food security scale. This observation likely resulted from the fact that few households received less than a perfect food security score on these scales in the Nanjing household sample.

Table 5. Pearson's R Correlation of Normalized HFIAS, MAHFP and HDDS Scores with FSGM Scores Across Cities (with bootstrapped 95% confidence intervals).

Scales	Maputo (n = 489)			Kingston (n = 478)			Nanjing (n = 488)			Nairobi (n = 493)			Mexico City (n = 494)		
		95% C.I.			95% C.I.			95% C.I.			95% C.I.			95% C.I.	
	r	Low	High	r	Low	High	r	Low	High	r	Low	High	r	Low	High
HDDS′	0.683 **	0.638	0.721	0.684 **	0.632	0.736	0.966 **	0.954	0.976	0.738 **	0.689	0.783	0.677 **	0.601	0.753
HFIAS′	0.857 **	0.828	0.879	0.818 **	0.786	0.845	0.415 **	0.312	0.513	0.859 **	0.838	0.879	0.729 **	0.676	0.775
MAHFP′	0.790 **	0.747	0.825	0.645 **	0.561	0.714	0.244 **	0.136	0.346	0.715 **	0.668	0.759	0.631 **	0.538	0.704

** $p < 0.01$.

3.2. Assessing the Relationship between Resource Access and Household Food Security

The three indices also demonstrated solid external validity in their relationship with inconsistent household access to water, medicine, electricity, cooking fuel and a cash income. The Spearman's Rho correlations indicated significant and negative relationships between each of these indices and the household measures of resource access (indicating that increasing food security was associated with decreasing inconsistency in household access to these resources). Interestingly, while all of the correlations were negative in the Nanjing sample, the sampled households in Nanjing only indicated significant correlations between inconsistent access to medicine/cash income and the three indices. Weaker correlations (when compared to the other sampled cities) were also observed with the HFIAS, HDDS and MAHFP against the FSGM in Nanjing. While a fascinating finding, given the imbalance in the variables collected from the Nanjing data, these correlations should be interpreted with caution (Table 6).

Table 6. Spearman's Rho Correlation of FSGM with Consistency of Household Resource Access Across Cities (with bootstrapped 95% confidence intervals).

City		95% C.I.	
Maputo	**Rho**	**Low**	**High**
Inconsistent Access to Water (n = 476)	−0.147 **	−0.048	−0.234
Inconsistent Access to Medicine or Medical Care (n = 479)	−0.336 **	−0.244	−0.413
Inconsistent Access to Electricity (n = 478)	−0.215 **	−0.12	−0.301
Inconsistent Access to Cooking Fuel (n = 478)	−0.412 **	−0.331	−0.495
Inconsistent Access to Cash Income (n = 477)	−0.428 **	−0.349	−0.498
Kingston	**Rho**	**Low**	**High**
Inconsistent Access to Water (n = 467)	−0.119 *	−0.01	−0.202
Inconsistent Access to Medicine or Medical Care (n = 459)	−0.264 **	−0.164	−0.346
Inconsistent Access to Electricity (n = 466)	−0.335 **	−0.249	−0.419
Inconsistent Access to Cooking Fuel (n = 468)	−0.438 **	−0.342	−0.51
Inconsistent Access to Cash Income (n = 467)	−0.453 **	−0.354	−0.526
Nanjing	**Rho**	**Low**	**High**
Inconsistent Access to Water (n = 484)	−0.019	0.083	−0.111
Inconsistent Access to Medicine or Medical Care (n = 487)	−0.270 **	−0.189	−0.338
Inconsistent Access to Electricity (n = 487)	−0.033	0.059	−0.12
Inconsistent Access to Cooking Fuel (n = 486)	−0.087	0.003	−0.162
Inconsistent Access to Cash Income (n = 486)	−0.223 **	−0.143	−0.297
Nairobi	**Rho**	**Low**	**High**
Inconsistent Access to Water (n = 487)	−0.305 **	−0.216	−0.382
Inconsistent Access to Medicine or Medical Care (n = 488)	−0.363 **	−0.284	−0.447
Inconsistent Access to Electricity (n = 488)	−0.320 **	−0.241	−0.409
Inconsistent Access to Cooking Fuel (n = 489)	−0.430 **	−0.356	−0.509
Inconsistent Access to Cash Income (n = 486)	−0.416 **	−0.341	−0.488
Mexico City	**Rho**	**Low**	**High**
Inconsistent Access to Water (n = 492)	−0.274 **	−0.198	−0.355
Inconsistent Access to Medicine or Medical Care (n = 493)	−0.235 **	−0.15	−0.321
Inconsistent Access to Electricity (n = 493)	−0.187 **	−0.102	−0.27
Inconsistent Access to Cooking Fuel (n = 492)	−0.251 **	−0.153	−0.337
Inconsistent Access to Cash Income (n = 492)	−0.270 **	−0.181	−0.349

* $p < 0.05$; ** $p < 0.01$.

When the independent variables in this investigation were dichotomized into binary variables representing consistent or inconsistent access to these resources, interesting trends emerged (Table 7). Very few of the sampled households in Nanjing reported inconsistent access to a cash income, cooking fuel or medical care access. The sampled households in Nanjing also reported the highest frequency of consistent access to water and electricity. These frequency distributions may help to account for the weak correlations observed between resource access and food security among the sampled households in Nanjing (since so few households experienced these challenges). Outside of the sampled households in Nanjing, the sampled households in Mexico City also reported consistent access to the resources under investigation. The sampled households in Maputo, Kingston and Nairobi reported the lowest frequencies of consistent resource access. It is important to note that these city samples are not necessarily representative of these cities and further work (with larger samples to account for any data imbalances) will be needed to confirm these findings.

Table 7. Sample Distribution of Household Resource Access Across Cities.

Variables	Values	Maputo	Kingston	Nanjing	Nairobi	Mexico City
		%	%	%	%	%
Household Water Access	Consistent	67.8	80.2	82.1	67.4	75.7
	Inconsistent	32.2	19.8	17.9	32.6	24.3
Household Medical Care Access	Consistent	77.6	81.5	95.4	82.6	88.4
	Inconsistent	22.4	18.5	4.6	17.4	11.6
Household Electricity Access	Consistent	48.7	66.8	78.6	50.1	85.1
	Inconsistent	51.3	33.2	21.4	49.9	14.9
Household Cooking Fuel Access	Consistent	68.1	63.3	97.4	79.0	85.5
	Inconsistent	31.9	36.7	2.6	21.0	14.5
Household Cash Income Access	Consistent	68.4	60.1	96.2	64.3	76.5
	Inconsistent	31.6	39.9	3.8	35.7	23.5

Across the board, consistent household access to each resource was associated with higher FSGM scores (better food security). When the sampled households were assessed according to their city of residence, some geographic specific differences emerged. Households sampled from Nanjing had an average FSGM score that was almost 20 percentage points above the rest of the sample. Households sampled from Mexico similarly had an average FSGM score that was 4 percentage points above the rest of the sample. The remaining cities represented in the sample indicated lower FSGM scores when compared with the rest of the sample. The lowest FSGM scores were observed in Maputo, Mozambique, where the sampled households had an average FSGM score of 63% (Table 8).

Table 8. FSGM Summary Statistics for Dichotomized Independent Variables.

Variables	Values	FSGM			
		Mean	Median	St.Dev.	n
Household Water Access	Consistent	0.75	0.77	0.15	1798
	Inconsistent	0.67	0.70	0.18	608
Household Medical Care Access	Consistent	0.75	0.77	0.15	2052
	Inconsistent	0.59	0.60	0.18	354
Household Electricity Access	Consistent	0.76	0.78	0.14	1591
	Inconsistent	0.66	0.69	0.18	821
Household Cooking Fuel Access	Consistent	0.77	0.78	0.14	1905
	Inconsistent	0.58	0.61	0.18	508
Household Cash Income Access	Consistent	0.77	0.78	0.14	1771
	Inconsistent	0.61	0.63	0.17	637

Table 8. *Cont.*

Variables	Values	FSGM			
		Mean	**Median**	**St.Dev.**	**n**
Maputo	No	0.75	0.77	0.15	1949
	Yes	0.64	0.67	0.18	484
Kingston	No	0.74	0.77	0.16	1959
	Yes	0.66	0.68	0.16	474
Nanjing	No	0.69	0.71	0.16	1945
	Yes	0.87	0.88	0.08	488
Nairobi	No	0.73	0.75	0.17	1940
	Yes	0.71	0.73	0.15	493
Mexico City	No	0.72	0.74	0.17	1939
	Yes	0.76	0.77	0.13	495

The classification and regression tree that was built using these independent variables provided some fascinating insights (Figure 1). Amongst the included independent variables, household cooking fuel access provided the best indicator for splitting the FSGM score. Among those households that reported inconsistent access to cooking fuel, the next best indicators for splitting the FSGM scores were inconsistent access to a cash income and then medical care. Among the households that had inconsistent access to all three of these variables, their FSGM score was 0.492. Among households with consistent access to cooking fuel, the situation was more complicated. First, the sampled households from Nanjing were split into a separate branch. Among the remaining households, the best indicator was inconsistent access to a cash income. Those households with inconsistent access, then split into Mexico City or not (households in Mexico City having better food security than the households in the remaining cities). The remaining households were split into Maputo and then Kingston.

The decision tree model indicated that the subset of households with the worst mean FSGM scores were those that had inconsistent access to cooking fuel, a cash income and medical care access in the previous year. This subset of households had a mean FSGM score of 0.495 with a standard deviation of 0.191. The subset of households with the highest mean FSGM score were those that had maintained consistent access to cooking fuel and were from the Nanjing sample. These households had a mean FSGM score of 0.872 with a standard deviation of 0.078. The model indicates that inconsistent access to an increasing number of resources was associated with lower FSGM scores, regardless of city of origin. That said, the extent to which consistent access to an increasing number of resources was associated with higher FSGM scores was dependent upon the city in which the household was located. For the subset of households with consistent access to cooking fuel in the previous year, city of origin appeared to be a more significant splitting variable than for households with inconsistent access to cooking fuel.

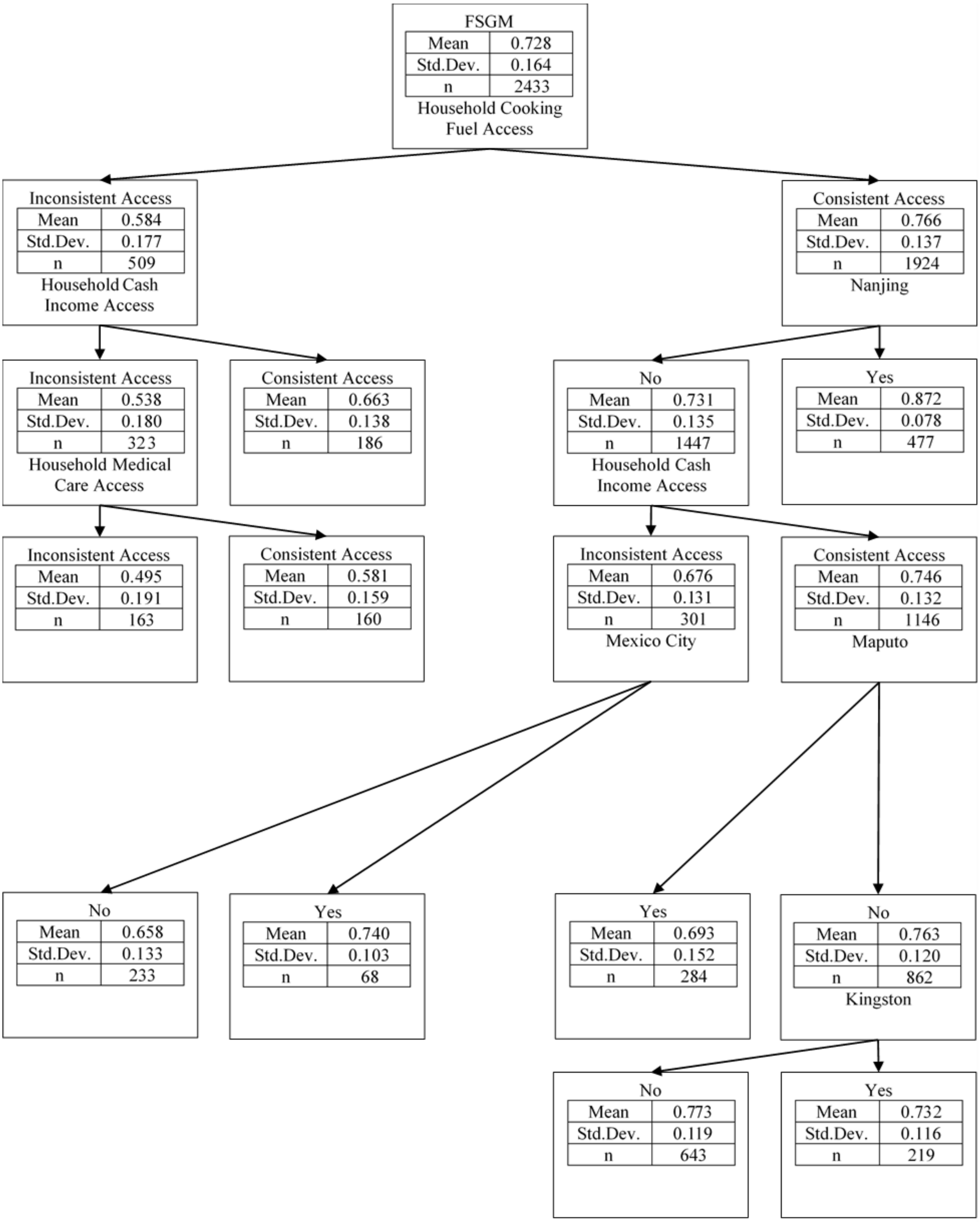

Figure 1. Decision Tree of Food Security Scores by Resource Access and City Variables.

4. Discussion

This paper proposed an index of urban household food access, stability and utilization via min–max normalization and geometric means for index aggregation. Using the constructed index, the investigation found that among the sampled households, inconsistent household access to water, cooking fuel, electricity, medical care and a cash income were significantly correlated with food insecurity (though with a moderate strength) in all of the sampled cities except for the Nanjing sample. In the Nanjing sample, only inconsistent access to a cash income and medical care access (the strongest correlates from other city household samples) were correlated with food insecurity. The decision tree model confirmed that finding. While the worst food security scores were recorded by households with inconsistent access to multiple resources (regardless of city of origin), the highest food security scores were recorded by households from specific cities in addition to a specific configuration of consistent resource access. Given the findings presented by the investigation, it appears that the observed correlations between the consistency of household resource access and food security may be contextually dependent upon a household's city of origin. In other words, the observed relationships between disrupted resource access and household food insecurity may only be heterogeneously present under COVID-19. Given these findings, it will be important for policymakers responding to COVID-19-related disruptions to account for the unique characteristics of each city. The findings align with broader work on sustainable development, which point to the network of trade-offs and synergies that can exist across development outcomes (linking food security to broader resource access) [87]. It is important to note that, given the aggregated sample approach used in this investigation, these findings are not generalizable to the population in each city. Further research will be required to assess the generalizability of these findings.

5. Conclusions

The COVID-19 pandemic has created challenges within the food system and revealed the lack of preparedness by national and local governance as well as stakeholders in responding to them. Furthermore, the pandemic has resulted in the worsening of food insecurity through public health measures, which have impacted physical and social infrastructure access and also worsened the socioeconomic status of households. However, management of food security is dependent on measurement which has been subject to several definitions and data collection tool constraints. The pandemic provides a unique opportunity for managing the direct and indirect impacts as well as preparedness for future disruptions to food systems in already food insecure populations. Developing interventions better suited to address food insecurity-related impacts of the COVID-19 pandemic in urban households may benefit from measurements of existing dimensions and underlying vulnerabilities. Given the relationship identified in this paper between inconsistent resource access and household food insecurity, there may be a network of cascading impacts from COVID-19-related resource disruptions that could have implications for household food insecurity. Given the complexity of the pandemic, however, further empirical research should assess whether and how these food insecurity impacts have unfolded.

This paper proposed an index of urban household food access, stability and utilization via min–max normalization and geometric means for index aggregation. Geometric means are partially non-compensable and the preferred method of aggregation for ratios and skewed data. The issue of compensability is also an important theoretical consideration among these index aggregation techniques. Perfect compensability (as allowed by an arithmetic mean) would allow households to trade-off their performance across their food access, utilization and stability. These pillars of food security are likely meant to be interpreted as fundamental necessities for food security to exist (rather than compensable entities). As a result, from a theoretical perspective, it is unlikely that arithmetic means would be preferable as a means of measuring across urban household food access, utilization and stability. While perfect non-compensability is not likely to be helpful (given that available methods, such as Condorcet methods, would only support household ranking rather than scoring), Geometric means may provide a more reasonable conceptual grounds for the index, given that the approach supports imperfect compensability.

This index should not be interpreted as a comprehensive measurement of household food access, utilization and stability, but rather as an indication of these food security characteristics. As examples, the definition of food utilization covers a broader set of features than what is measured by the HDDS and the scale by which food stability is measured can vary from the 12-month recall period covered by the MAHFP. As a result, this index provides one proxy for the measurement of these food security concepts. With the development of more refined food security scales, it may be possible to develop more sophisticated indices of food security to better account for the characteristics not covered by the current proposed index. There are some important caveats to the use of this index in the field. Depending on the population of interest, some of the food security scales (HDDS, HFIAS and MAHFP) may demonstrate varying degrees of skewness and kurtosis. In such cases, researchers should evaluate the potential benefits of transforming the distribution of these scales prior to normalization. The index was designed with a focus on maintaining the theoretical equal weighting of food access, utilization and stability. That said, the equal importance of these three pillars of food security may not be generalizable across cases. Future research should consider whether food security metrics should shift based on contextual factors in order to more precisely discriminate among households. Finally, the utility of this index is bolstered by the validity of the scales it comprises. As such, future research should continue to assess the reliability and validity of these measures across development contexts.

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