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POLICY-ORIENTED FOOD INSECURITY ESTIMATION AND MAPPING AT DISTRICT LEVEL IN PAKISTAN

Purpose. *Food insecurity maps reveal the spatial variability of relevant indicators in relevant units in geographically disaggregated levels. This study is based on a systematic analysis of the least studied areas related to food insecurity in Pakistan, such as district-level Small Area Estimation (SAE) analysis of food insecurity by integrating several well-established datasets, including PSLM 2014–2015 and HIES 2015–2016.*

Methodology / approach. *We investigate the food insecurity situation at the district level in Pakistan by applying the household level technique of SAE method. The geographically disaggregated indicators of welfare are estimated by using SAE that integrates the census and survey datasets. This study estimates incidence and density indictors at the district level of food insecurity. The accessibility aspect of food security is taking into account by calculating monthly equivalent food expenditure per adult. In addition, the food insecurity headcount ratio is calculated to identify the food insecurity incidence at district level, and density are visualized using 'spmap' in STATA 14.*

Results. *The results of this study indicate that the districts with low food insecurity incidence are dense in terms of food insecure people. The second least food insecure district, according to food insecurity incidence estimates, has become the most food insecure in terms of food insecurity density. However, the most food insecure district with respect to food insecurity incidence has been identified as one of the least food insecure districts in terms of food insecure people. For instance, Washuk district in Balochistan, has been identified as the most food insecure district with almost 93 % food insecurity incidence. However, Washuk has only 0.17 million food insecure people according to food insecurity density estimates.*

Originality / scientific novelty. *The study highlighted the importance of food insecurity density estimates in addition to the food insecurity incidence for targeted policy interventions. In this study we have integrated a large and relatively smaller data set that covers most of the districts from all provinces of Pakistan for addressing the small sample issue which have been identified in previous studies. The variables that are common to both data sets are included after a screening process that include Variance Inflation Factor for multicollinearity, forward – backward selection criterion with model adjustment criterion either adjusted R^2, Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC), least absolute shrinkage and selection operator (LASSO).*

Practical value / implications. *The results of the study indicate that the policy makers should consider both the density and incidence of food insecurity for targeted policy interventions. This is because several districts with low food insecurity incidence are found to be dense with food insecure people. Moreover, the obtained results can be complemented by the results of the Integrated Food Security Phase Classification (IPC) which is based on relatively very small samples from few districts of three provinces. This can be useful in efficient implementation of food security policy and programs in targeted areas. Furthermore, the results highlight that the efforts reduce food insecurity should be targeted at district level in Pakistan.*

Key words: *small area estimation, food insecurity, spatial mapping, food expenditure, district level, Pakistan.*

Introduction and review of literature. Food insecurity mapping is a widely used technique for visually representing food insecurity issue. Food insecurity maps reveal spatial variability of relevant indicators within concerned units in geographically disaggregated levels. In addition, food insecurity maps help in spatial targeting of low-income households characterized with food insecurity incidence or else high income households may benefit from the programs initiated for supporting poor, while low-income households remain underprivileged [1–3].

Currently, the developing countries are overwhelmed with the issue of food insecurity. The unaffordability of healthy diet caused by its high costs, poverty and income inequality is associated with severe food insecurity. In 2020, about 928 million people faced severe food insecurity, an increase of 148 million from 2019. Additionally, 2.37 billion people, i.e. one out of three people on the globe was lack adequate food access in 2020. Most of such people have been located in Asia and Africa. Furthermore, 50 % of the world's undernourished people also belong to Asia. Subsequently, child malnourishment is a challenging fact, especially in Asia and Africa, as nine out of ten children suffer from stunting and wasting in these regions. Moreover, in 2020, food insecurity among women was found to be 10 % higher than among men. This whole scenario raises fears that food insecurity may not be resolved by 2030 unless inequalities in access to food are addressed [4].

Most of the developing countries are confronted with the challenge to ensure food security for all [5] and Pakistan is no exception in this regard. According to a report on food insecurity condition of Asian countries [6], Pakistan has worst performance after Afghanistan in reducing food insecurity during 2011–2015. Also, Pakistan ranked 77th in Global Food Security Index (GFSI) [7]. Similarly, Pakistan is reported under top ten countries with very high prevalence of undernourishment in children [8].

It is evident from the literature that food supply/availability is not the main issue. As, the estimated value of caloric availability based on major food items is 2485 kcal per capita/day [9], which is far above the daily requirement of 2350 kcal per person person/day [10]. Despite this fact, the poor hardly get around 1848 kcal [11]. Different studies [11; 12] have identified access or utilization issues related to food in Pakistan. Sufficient food availability is not a guarantee of food security. As, physical and especially economic access to food is also an important aspect of food security. Therefore, different measure of economic access have been used such as household income [13], 2450 kcal/day/person [14; 15].

Empirical studies conducted to analyse the food insecurity situation in Pakistan have penned a troublesome picture of Pakistan. Trends in food insecurity incidences at national and sub-national levels in Pakistan have been found in a study [16] taking household level dietary energy consumption as food security measure. At provincial level, food insecurity incidence is found to be the highest in Sindh followed by Balochistan, and lowest in KP.

Various studies have considered calorie intake, food diversity score, and food consumption as the indicators of food security [17–20]. Malik, Nazli [21] estimated Linear Approximate Almost Ideal Demand System (LA-AIDS) on the data derived from Household Integrated Economic Survey (HIES) 2010–2011. The analysis results indicated that majority of households consume calories less than minimum requirement. In addition, the up serge in wheat prices has adversely affected the food security levels in Pakistan through reducing the purchasing power of the consumers. Haider and Zaidi [22] used seven rounds of Household Income Expenditure Survey (HIES) over the period 2000–2001 to 2013–2014. The results based on the Quadratic Almost Ideal Demand System (QUAIDS) revealed the inter-provincial differences in household consumption patterns. Per adult equivalent average calories intake is found to be less than the 2350 kcal threshold in spite of increase in per capita income and food availability. Using the Household Integrated Income and Consumption Survey 2015–2016 of Pakistan, Hameed, Padda [23] estimated the calorie intake patterns at national and provincial level. The study found that the highest number of calorie deficient households are located in Balochistan followed by Sindh.

Additionally, approximately two-third of Pakistani households are unable to afford a nutritious diet with their current food expenditures [24]. Limited food access is an important issue in attaining household food security. Moreover, four out of ten Pakistanis are experiencing multidimensional poverty [25]. The food and nutrition security have been given top priority in the government's development programs from 2015 to 2025. All the facts presented above highlight the importance of accessibility aspect of food security. This study incorporates food accessibility as the monthly per adult equivalent food expenditures below the subsistence level referring to food insecurity of the particular household.

Nonetheless, the food insecurity problem can be addressed by emphasizing and refining the national, regional and household food security condition in a country [26]. In addition, aggregate indicators often misrepresent as they may fail to uncover the massive dissimilarities among the different regions or areas. Therefore, identifying food insecurity maps can be a source of guidance for the policy makers in selecting best intervention strategies from multiple policy options. Similarly, finding the most vulnerable zones can significantly help in concentrating on areas, which are resulting in an accurate understanding of the targeted areas [27]. However, household surveys provide limited disaggregation levels, e.g., *HIES* – urban/rural and within province. One of the major underlying reason is that household surveys represent some regions, therefore, the analysis conducted on the basis of such datasets cannot accurately identify the targeted or vulnerable areas [28]. Contrarily, census, being a large data source, gathers insufficient data on welfare variables. Similarly, visual representation of food insecurity estimates helps in efficient planning through quantifying patterns of targeted areas using spatial analysis, which gives visual methods an obvious advantage over traditional tabular analysis. In addition, spatially variable factors determining food poverty can be highlighted to suggest required policy interventions in different localities accordingly [27].

As far as Pakistan is concerned, some estimates of food insecurity at district level are available based on smaller datasets [29; 30]. For instance, the integrated context analysis (ICA) of vulnerability to natural hazards and food insecurity by WFP [30] provides beneficial information for policy purpose. However, there are certain limitations underlined in the report itself, which makes it difficult to formulate a comprehensive strategy. First limitation includes the exclusion of 33 districts due to data constraints from the analysis. Secondly, food insecurity is not associated directly with Multidimensional Poverty Index (MPI) and only some indicators of MPI are related to food security access and utilization aspects. Thirdly, the population estimates are based on projected values and the growth rates were taken from 1991 census. Finally, the small sample issue, which can be resolved using PSLM or population census datasets. The most recent example is Integrated Food Security Phase Classification [31]. The Integrated Food Security Phase Classification (IPC) headed by the Ministry of National Food Security and Research includes stakeholders from Government, United Nations (UN) agencies and Non-Government Organizations (NGOs). The IPC is a process of classifying the characteristics and severity of chronic food and nutrition insecurity according to international standards. Whereas, the acute food insecurity is defined in terms of the severity threatening the lives and livelihood of the residents of a specified area in specific time period. Sudden shocks negatively affecting the food insecurity determinants may cause the prevalence of acute food insecurity within short span of time. The objective of the IPC is to alert the government for emergency response in addition to the food security policy formation. The first round of IPC for analyzing chronic food insecurity was conducted in 2017 in vulnerable districts of Sindh province. The results of IPC analysis are used in decision making by the government and NGOs to target the food insecure zones. However, the IPC analysis faces some serious limitations. Firstly, the data sets used for the analysis are small including rural areas of only 25 districts of Sindh, KP and Balochistan. Urban areas are ignored in this regard, therefore, the results of the analysis cannot be generalized for the whole population except on rural level. Secondly, Household Hunger Score (HHS) module is utilized as an indirect outcome indicator with less reliability score [31].

On the other hand, the SAE method provides valid geographically disaggregated estimates of food insecurity by combining survey and census datasets, as compared to the estimates based on smaller coverage survey data [2]. SAE methods allow reliable estimations at the desired disaggregated levels, regarding the targeted areas [32]. To the best of our knowledge, no such study has been conducted in the context of Pakistan. In addition, food insecurity density estimates are significant for successful targeted interventions and food insecurity incidence [33] as a large number of food insecure people may be located in low food insecurity incidence area. This aspect also requires further investigation of studies based on food insecurity mapping in Pakistan.

The critical requirement of food insecurity reduction in relevance to the Sustainable Development Goals highlights the importance of geographic variability of food insecurity and availability of natural resource [34]. Mapping can lead to the assessment of hot spots for targeting the most affected areas, as well as, the information related to the socio-economic factors affecting the food insecurity situation in such areas. Moreover, the spatial distribution of food insecurity and poverty proves to be important for the researchers and policy makers to quantify the regional discrepancies in terms of food security and welfare [34]. Additionally, targeted programs for poverty and food insecurity alleviation can be facilitated on the basis of geographical disaggregated information. Subsequently, the food insecurity and poverty maps point out the resource deficient areas and provide guidance in efficient deployment of resources by the government as well as international organizations. It will have effective impact on food insecurity and poverty reduction in such affected areas [34; 35]. The identification of the food insecurity and its locations may lead to the formulation of least cost and rapid solution oriented policies [36].

In the existing literature, food security concerns have been investigated from various aspects. The food security policies and the relevant studies have experienced major modification processes across time in terms of unit and the scope of analysis as well as the food security perception [37]. The objectively assessable indicators of food security have been complemented by the subjective perceptions ranging from state to household and from availability to sustainability [37]. However, it has been identified that combining qualitative and quantitative indicators can result in high precision and validity [37]. Some of the most relevant studies are have discussed in the following: Food insecurity is a complex, multidimensional phenomenon and diverse factors affect food insecurity at national, provincial, district and household levels. Food security encompasses the availability, access, sufficient level of consumption, and above all, proper utilization features surrounded by a healthy environment [38]. Due to the complex nature, the measurement of food security necessitates an index of the relevant indicators [39].

The Food Insecurity and Vulnerability Information and Mapping Systems (FIVIMS) were formulated in 1996 at World food summit (WFS) for observing the global as well as national forces to attain the food security objective [40]. In addition, the food insecurity and poverty maps at disaggregated geographic levels are highly constructive for researchers and policymakers as census or household surveys alone do not fulfil this objective of targeting food insecurity. For instance, the income related data from the census is not a closer substitute of the average income or poverty rates at disaggregated geographical levels. Therefore, it entails the optimal usage of census data that is not optimally utilized in many developing countries. Furthermore, suggestions based on analysis on smaller geographical units contribute in successful allocation of resources to the poor [41]. Similarly, census data incapacitate small sample problems, however, there are limitations of inadequate income or expenditure information.

On the other hand, it has become indispensable for policy makers to derive the alternate welfare indicators as such indicators cannot be a good substitute for consumption or income like welfare indicators [42]. Consequently, the limitations of household surveys and census data stimulated the combination of required information from the above two sources for originating the consumption-based poverty estimates at disaggregated geographical units. For instance, Hentschel, Lanjouw [2] assessed the Ecuador household consumption patterns by combining the household survey and census data. The authors conceived a process for deriving household probability to confront with poverty in the census and utilized that process for analyses at the disaggregated geographical units via merging the survey and census data. The methodology of Hentschel, Lanjouw [2] can estimate poverty at any geographically disaggregated level. Subsequently, the amended methodology contains first stage regression topographies of disturbances [43]. Furthermore, there are systematic variances in the results of income and poverty estimations obtained from the census and household survey datasets. In a study based on South Africa October Household Survey (OHS, 1995) and associated Income and Expenditure Survey (IES) in combination with Population Census (1996), substitute imputed income estimates for all households in the census were computed and results were consistent with the survey estimates [44]. The imputed values of the consumption, which are not available in the census data, serve as income proxy that is available. On the other hand, consumption is collected in the household surveys with higher accuracy as compared to income, therefore, consumption gets higher validity as a welfare measure [45].

The poverty mapping supports the equitable distribution of wealth, as the direct evaluation of the number of individuals is difficult for significant allocation. For instance, systematic bias in census income may result in underestimating the poverty in some areas and overestimating in others. Therefore, the income information gathered in census does not prove to be a good proxy for mean expenditures at different geographical levels. On the other hand, poverty mapping aims to disaggregate the wealth-based data at smaller geographical levels i.e., municipalities or districts. Therefore, poverty maps contribute to the decentralization procedure of government services through priorities of the government resource allocation. However, in many developing countries the valuable information contained in census data is not being used properly. It requires the easy access of policy makers and researchers to the census data for fruitful efforts. The geographic and socio-economic factors are of great significance in formulating relevant policies [46] as food security at national level does not guarantee food security at geographically disaggregated levels i.e., districts or households. Therefore, poverty or food insecurity mapping at geographically disaggregated level provides guidance to distribute rationally the resources through targeting the victims using income or consumption-based welfare indicators.

Similarly, food insecurity and poverty related case studies have highlighted the developments in poverty and food insecurity mapping such as small area estimation, measures of physical accessibility and distance, environmental information, and the spatial relationships [47]. Though, such developments are not widely used in available literature regarding food insecurity and poverty mapping except for some studies. For instance, in Bangladesh, food insecurity and poverty were mapped using an SAE approach at the lowest geographical levels using distinct factors, which trigger the very problem of food insecurity [48]. Subsequently, a robust model was formulated based on the explanatory variables, which are common to census and the survey datasets [48]. The overall poverty line was attained through combining the food and non-food expenditures. The upper threshold was 2112 kcal whereas the lower threshold slightly decreased to 1800 kcal. The estimates showed that approximately 45 % Bangladeshi rural households suffered from poverty, whereas 18 % lived under extreme poverty.

Subsequently, in Ecuador, a spatial analysis of food poverty was conducted at the district level [27]. However, Ecuadorian analysis is based on FGT poverty indices, including headcount ratio, severity and gap [49]. These indicators were estimated for the upper and lower bounds of food poverty and the estimates highlighted the specific spatial units with food poverty concentration. On the other hand, in Kenya, community level poverty rates was estimated using spatial analysis technique [32]. For deep geographical coverage, the information related to food and non-food expenditures from Kenya welfare monitoring survey (1997) and Kenya population census was merged using SAE techniques [32].

Later, in a case study in Malawi, spatial regression analysis identified that high yields link rainfall to lower poverty levels [50]. Similarly, other economic activities such as crop diversity and average maize yield can effectively determine the poverty level. Moreover, maximum educational attainment and dependency ratio significantly determine the prevalence of poverty. On the other hand, the case study on Mexico revealed that all variables except potable are significant in the rural household expenditures model [51]. On the other hand, education, poor housing and inadequate access to potable water inversely related to variance of per capita expenditures. Similarly, spatial variability was observed at municipality level with a concentration of extreme poverty in rural segments of southern Mexico. Nonetheless, at rural community level, almost forty thousand of communities were living below the food poverty line [51].

On the other hand, the case study of Nigeria, highlighted three key areas with acute rural poverty [52]. The case study is based on livelihood indicators for food insecurity and poverty mapping. A strong correlation was found among the development indicators, including piped water, distances to educational and health facilities. Similarly, the incidence and density of poverty in Vietnam were mapped using SAE [33]. The threshold was defined as food expenditures to acquire 2100 kcal per person per day along with other expenditures. The estimation results highlighted the importance of density mapping was emphasized as a lot of poor were located in areas with a low incidence of poverty. The importance of density mapping presented a trade-off between targeting policy interventions centered on poor people and poor areas.

Global and regional food security condition can be improved through food production modifications based on climate change. Recent literature related to food security has widely analyzed the climate change impact on food security in Pakistan. Localized floods have resulted in lowering the cereal crop yields and income of households, thus have a significant adverse impact on the food security of farming households in Pakistan [53]. Climate change also affects the physical accessibility dimension of food security in Pakistan through affecting the yield of major food crops [54]. Similarly, flash floods highlight the importance of exposure i.e. the households' sensitivity is determined by the dependence on agricultural income from crop production and livestock. Additionally, the household vulnerability significantly affects the livelihood vulnerability of households [55]. Moreover, the areas of southern Punjab are found to fall under different food insecurity risk categories based on the nature of climate change, where, low climate variability areas are found to have a moderate risk of food insecurity, whereas, high climate variability is associated with high food insecurity risk [56]. Climate change adaptation strategies are crucial in assessing the food security impact. Non-adapters of such strategies experience very low food security status in comparison to the adapters [19]. Therefore, the more adaptation strategies are chosen, the higher the level of food security. Thus, in case of Pakistan, the climate adaptation strategies positively affect food security [54].

Additionally, Integrated Context Analysis **(**ICA) of vulnerability to food insecurity and natural hazards [30] have ranked districts of Pakistan using food security and natural calamities. ICA is based on a Multidimensional Poverty Index (MPI) as a proxy of the vulnerability to food insecurity for all provinces, except FATA [30]. The MPI consisted of 15 variables with three broad categories: education, health and living standard. According to the results, ICA has categorized 123 districts and 7 agencies from FATA into five ICA groups from most vulnerable to less vulnerable to natural disasters and food insecurity.

Finally, based on the analysis of rural sample from nine districts of Balochistan, IPC [31] marked Balochistan as highly food insecure with high rates of poverty and malnutrition. Eight districts, including Chagai, Kharan, Kech, Killa Abdullah, Panjgur, Loralai, Washuk and Pishin were indicated in crisis while, Nushki district in a stress situation. The possible deriving factors for poor food security mentioned by IPC are drought, fuel and food price hikes, livestock diseases and COVID-19. Food access is projected to be a serious challenge. Similarly, while analyzing the KP's seven districts namely Bajaur, Kurram, Khyber, Mohmand, Orakzai, North Waziristan and South Waziristan, IPC [31] found all of the analyzed districts under food insecurity crisis. Multiple shocks are reported as a cause of poor food security conditions, including conflicts/ terrorism, food price hikes, poor weather and COVID-19. Food access is also challenging in the analyzed districts of KP. While analyzing the food insecurity situation in Sindh, IPC [31] reported that in all of the nine districts included in the analysis about 0.8 million people in an emergency and 2.26 million in crisis phase. Such outcome is a result of natural calamities, price hikes and COVID-19. In case of districts from all three provinces analyzed IPC recommends to reduce food consumption gaps [31].

Overall review of food security studies, especially in context with Pakistan indicates some gaps to be filled by this study. Some studies on food security estimates at district level are based on relatively smaller datasets [29; 30] as reviewed in this section. Such studies are beneficial, but under certain limitations. For instance, 33 districts are excluded from the ICA study due to data constraints. Also, few indicators of MPI are related to food security. Moreover, population estimates are projected on the basis of 1991 census growth rates. Finally, IPC and ICA studies face small sample issues.

In this study, we used SAE with multiple datasets that cover most of the districts from all provinces of Pakistan. The study incorporates the importance of food insecurity density estimates that has been emphasized in earlier studies in addition to the food insecurity incidence for targeted food security interventions. A comprehensive screening process identifies the variables that are common to the datasets. Therefore, the results of this study can be complemented with the results of IPC that is based on a relatively small sample including few districts of only three provinces. Consequently, a higher level of efficiency relating to food security programs and policy can be achieved in targeted areas. The contribution of this study can be summarized as following:

1. Integration of multiple datasets in varying sizes to overcome small sample issues in previous studies;
2. Generation of final model by combining variables that are common to both the datasets by utilizing state-of the-art screening process;
3. Analytical coverage of maximum possible districts of Pakistan that indicates the food insecurity situation at disaggregated level;
4. Comparison of food insecurity incidence and density estimates that emphasizes the policy significance of both types of estimates.

Rest of paper is organized as follows: Section 2 provides the details on model, methodological framework and datasets used in this study. Section 3 contains detailed analysis of SAE estimation results with tables and maps of food insecurity incidence and density at the provincial and district level. Finally, section 4 concludes the findings of this study along with the policy implications and future research.

The purpose of the article. This study highlights the targeted food insecure districts of Pakistan based on spatially disaggregated food insecurity incidence and density estimates through combining a larger (PSLM 2015–2016) and a smaller (HIES 2015–2016) dataset to avoid the small sample issue. As, the areas with a low food insecurity incidence may be dense in terms of food insecure people. Additional purpose is to display the facts associated with the food insecurity spatial distribution at district level in Pakistan through map visualization of the obtained results.

Material and methods. This study included household and geographical characteristics variables, which were common to both the PSLM 2014–2015, and HIES 2015–2016 data. For food insecurity mapping, the shape files for Pakistan are used. Both the datasets and shapefiles are obtained from the Pakistan Bureau of Statistics. Threshold limit of food security is Rs. 2275.67 as computed using the given datasets, it is defined as monthly subsistence per adult equivalent food expenditures. Operationally, the food insecurity incidence is measured as the food insecurity headcount in Pakistan. The expenditures required to meet per adult equivalent monthly caloric requirement are taken as food insecurity threshold level. The expenditures required to meet the monthly per adult equivalent caloric requirement as calculated are Rs. 2275.67.

Dataset. The first dataset used in this study Pakistan Social and Living Standard Measurement (PSLM) 2014–2015 [57] is sixth round, which provides district level estimates of social indicators and improvements as required according to the MDGs. It encompasses intermediary and output measures for the performance assessment of social sector. In addition, multiple outcome measures for assessment of population welfare are included in PSLM 2014–2015. The PSLM Survey data is useful for formulating the development plans and poverty reduction policies by the government. The district level indicators include education, health, water and sanitation, household assets, and satisfaction to service delivery sectors. The PSLM 2014–2015 comprises 78635 households.

The second dataset used in this study is Household Integrated Expenditure Survey (HIES) 2015–2016 [58]. HIES 2015–2016 data consists of 24238 households. The information on household income, consumption expenditures, saving, consumption patterns and liabilities is collected at national and provincial level for rural/urban households.

In both the PSLM 2014–2015 and HIES 2015–2016 datasets universe is comprised of all the provinces, rural and urban areas of Pakistan, except for FATA and the military restricted areas. Every town/city is disaggregated into enumeration blocks consisting of 200 to 250 households. These enumeration blocks are assigned the name of Primary Sampling Units (PSUs). A sample size of 12 households from each of the urban PSU and 16 households form every rural PSU is denoted as Secondary Sample Unit (SSUs).

A representative sample is taken by using Stratified random Sampling technique for reliable results. Therefore, the sampling limitations of HIES 2015–2016 were not so strict. However, 63 PSUs were dropped from the total of 1668 PSUs due to law and order situation specially in Province of Balochistan. Additionally, about 1442 households were excluded due to Non-contacted or refusal [59]. Similar sampling technique is used for PSLM 2014–2015 for reliable results. However, Panjgur and Kech district including 82 PSUs of Balochistan, 13 PSUs from KP, and 7 PSUs from Sindh were dropped due to the prevalent law and order situation there [60].

Methodology. Broadly used methods of food insecurity or poverty mapping include small area estimation (SAE), combination of qualitative information and secondary Data, multivariate weighted basic need index, direct measurement of household-survey data, extrapolation of participatory approaches, and Direct Measurement using Census Data [61]. In addition, the method to construct SAE through regression models and simulation technique are used for interpolating from comprehensive to general datasets [47]. SAE is still efficient as compared to other contemporary techniques despite econometric and computational challenges as well as large volume of census data and non-normality [62]. One advantage of SAE is that the reliability of the estimates can be easily checked by the built in program 'SAE' an improved version by World bank in replacement of POVMAP 2.0. Additionally, this approach is institutionally backed by a team of researcher who is engaged in the development of this methodology and relevant training on behalf of World bank [61]. In addition, the standard error size depends upon the disaggregation level and the power of predictor variables for prediction of the dependent variable. Furthermore, SAE allows the comprehensive examination of statistical properties [61]. Therefore, this study uses SAE for food insecurity estimation and mapping. SAE method was popular because of the availability of the software for the relatively easy implementation of the method to the real data. The implementation process has been evolved starting with the SAS implementation by Alderman, Babita [44], then PovMap by Zhao [63] and final Stata version 'SAE' package by Nguyen, Corral [64; 65].

SAE is a process, which estimates for the indicators of welfare at geographically disaggregated level by combining the census and survey datasets. Basically, SAE applies the parameters of predicted models to similar variables from census data based on the assumption that the relationship is true for the population and *t*-sample [66]. SAE has been utilized in many countries for obtaining disaggregated poverty estimates [67–72].

The SAE method consist of two main techniques, namely using census data on household units [3] and community level averages on Household level units. This study uses the technique of census data on the household units [3]. Household level method (HLM) was designed by Hentschel, Lanjouw [2] and Elbers, Lanjouw [62]. However, HLM was presented by Deichmann [73] and [3]. The HLM utilizes the census data and the household survey for the period similar to that of the census. HLM has been used in several studies [2; 27; 68; 74; 75]. This study uses HLM of SAE for food insecurity estimation. The SAE based food insecurity mapping framework is depicted in Figure 1. The process consist of five main steps, including Data Preparation, Modelling for Household Welfare, Simulation, Validation and Mapping.

Step-1. Data preparation mainly focuses on combining the PSLM 2014–2015 and HIES 2015–2016 datasets via variables common to the both datasets. The process of combing the two datasets goes through location code matching, variable definition matching, statistical matching and creation of location variables.

Calculation of Per Adult equivalent Monthly household Food Expenditures. Per adult equivalent monthly household total food expenditures are obtained by dividing the deflated monthly food expenditure by the number of adult equivalents per households. For this purpose, the household per adult equivalents are calculated using the Nutrition Based Adult Equivalent Scales issued by the Nutrition Cell of Planning Commission [76].

Adult Equivalent Scales are defined as:

$$A_{ij} = S_i\,(a_j, s_i), \tag{1}$$

where A_{ij} is the *jth* individual's and the *ith* commodity's scale value, the *jth* individual's categorization is based on age a_j and sex s_i [77].

Calculation of Threshold Food Expenditures. The threshold food expenditures are defined here, as the monthly subsistence per adult equivalent calorie based food expenditures for meeting the caloric requirements. The national food basket, with the minimum indispensable common food items developed in 2011 by the Nutrition Section of Planning Division is used as a reference to calculate the monthly subsistence per adult equivalent food expenditures to get the officially indorsed minimum per day 2350 kcal.

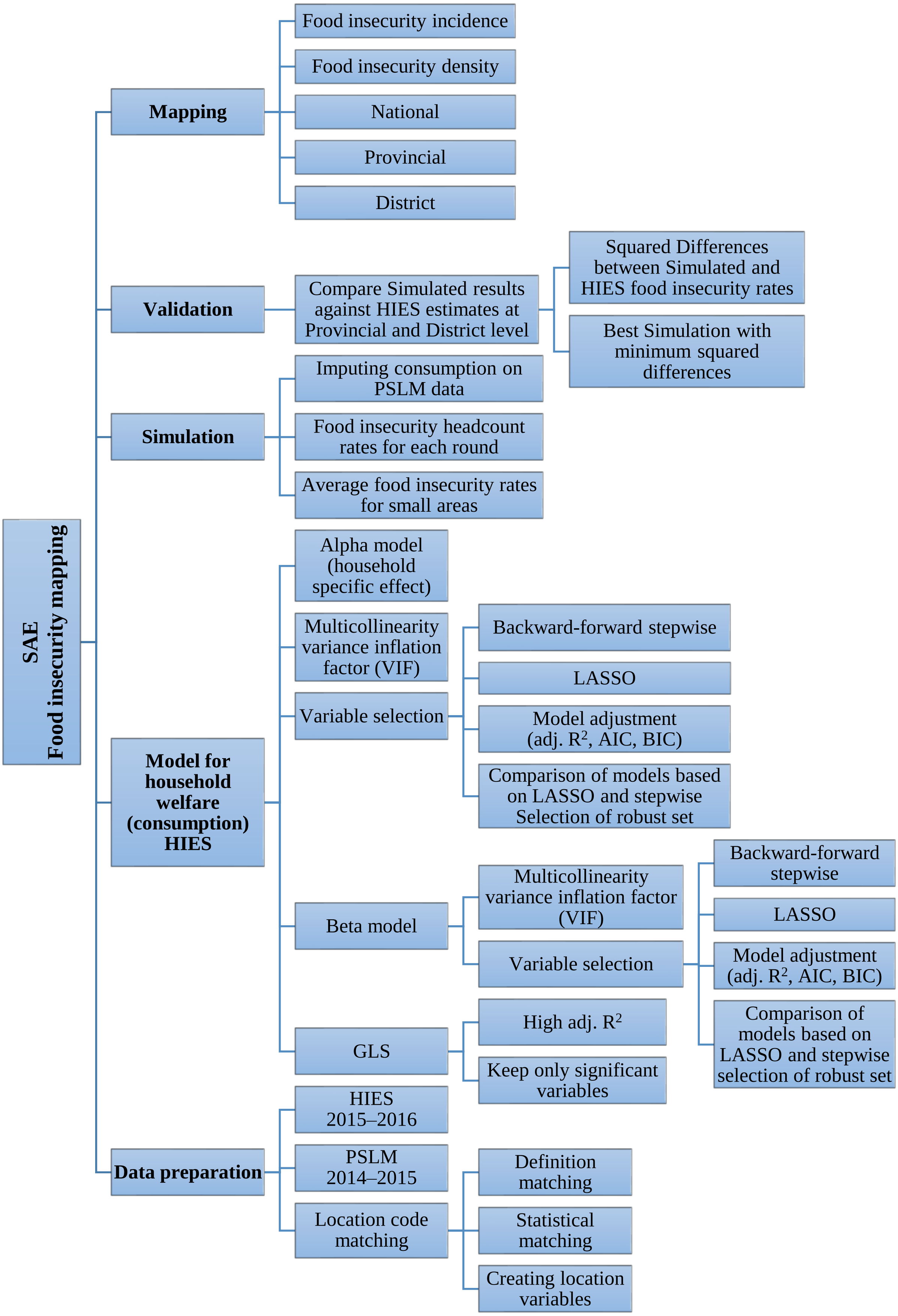

Figure 1. SAE based food insecurity mapping framework

Source: authors' adaptation from World Bank SAE workshop on poverty mapping, 2019.

The basket consisted of monthly consumption of wheat (10 kg), rice (2.3 kg), pulses (1 kg), milk (4.5 ltr), meat (1.3 kg), fats and oils (1.25 kg), sweetener (1.5 kg), and fruits and vegetables (10.5 kg) [21].

Per day quantities are converted into values on the basis of prices of 2015–2016 [78]. It was found that an adult requires Rs. 2275.67 to purchase food providing 2350 kcal per day. Thus, monthly subsistence per adult equivalent food expenditures of Rs. 2275.67 are taken as the threshold food expenditures.

Step-2. The next step of modelling household welfare starts with the estimation of model for household welfare given in equation (2) using the HIES 2015–2016.

$$lnC = \alpha + \beta 1X + \beta 2V + \varepsilon \quad (2)$$

Here, lnC represents the food consumption expenditures (per adult equivalent) taken as a food security proxy. Similarly, X is the matrix of household characteristics, whereas V represents the matrix of geographical characteristics.

For the best model specification, beta model, alpha model and generalized least square (GLS) models are estimated.

Beta model is an OLS regression that is estimated with highest adjusted-R^2 and significant coefficients of multicollinearity free predictor variables [79]. Beta model, in its general form, is represented as:

$$ln(y_{ch}) = X_{ch}\beta + u_{ch\,,} \quad (3)$$

where $ln(y_{ch})$ represents log per adult equivalent food expenditures of household h in cluster c, X_{ch} indicates a predictor variable vector for household h in cluster c and u_{ch} is the error term decomposable into two sub-components as described in the following:

$$\hat{u}_{ch} = \hat{u}_c + (\hat{u}_{ch} - \hat{u}_c) = \hat{\eta}_c + \hat{e}_{ch} \quad (4)$$

Here, $\hat{u}_c$ represents a weighted average of $\hat{u}_{ch}$ for a specific cluster c, $\hat{\eta}_c$ shows the location or cluster effect and $\hat{e}_{ch}$ indicates the household specific effect. The error term $\hat{u}_{ch}$ in equation (4) is obtained through running OLS regression in equation (3) and $\hat{u}_{ch}$ is used to model the location-specific, $\hat{\eta}_c$ and household-specific $\hat{e}_{ch}$ effects. Beta model is formulated using *Xs* which is obtained from household survey leading to the prediction of consumption.

Similarly, the computation of Variance Inflation Factor (VIF) is used for selecting best predictors and a better assessment of the multi-collinearity in explanatory variables of the beta model [80]. Furthermore, least absolute shrinkage and selection operator (LASSO) [80] process is performed by shrinking the impact of specific variables until the coefficients of such variables become zero. Subsequently, adjusted-R^2, Bayesian Information Criterion (BIC) or Akaike Information Criterion (AIC) are used to reduce significantly chances of over-fitting model by imposition of penalty on newly added variables as compared to using p-values.

On the other hand, adjustment process using backward stepwise criteria, first, the model is run inclusive of all k variables and the value of either BIC or adjusted-R^2 is noted. Secondly, each of k variables are dropped one by one (i.e., dropping the lowest impact variable at first) and the goodness of fit of k – 1 regressions is recorded. If the model fit is not affected by dropping a specific variable, then the variable is excluded and the same process is repeated, taking a new group of k – 1 variables unless the remaining variables have an impact on the model's goodness of fit. This process is repeated until none of the remaining variables effects on the model's goodness of fit. Finally, the models are compared for selecting the robust set of variables.

After getting the variables for the Beta model, household specific effect is modelled which requires estimating the Alpha model. Initially, the OLS regression based on Beta model is run and the residuals are obtained along with $\hat{y}_{ch}$. Subsequently, residuals e_{ch} are modelled using the group of comparable variables (not already included in Beta model) and the interaction of comparable variables with interacted variables such as $\hat{y}_{ch}$ and $\hat{y}^2_{ch}$. Subsequently, the best model is selected to predict residuals and highly collinear variables are dropped using Variance Inflation Factor (VIF) test. Finally, the variables are selected through model adjustment and backward selection based on BIC.

Similarly, after Beta and Alpha estimations, GLS model is estimated. The OLS regression coefficient estimates are based on the assumption of identical error distribution for all households. Conversely, GLS assumes different error distributions across households or areas, which supports the assumption of our study. In addition, GLS estimators are efficient as compared to OLS estimators and GLS provides the distribution estimates as well as errors of the estimated coefficients. The GLS model is estimated using the following equation:

$$C = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \tilde{\eta} + \tilde{e} \qquad (5)$$

Here, x_1 and x_2 are the selected variables from Beta model. The insignificant variables are dropped until all the included variables are significant for the model with a high value of adjusted-R^2.

Subsequently, the parameters β_1 and β_2 estimated from equation (5) are utilized for calculating the probability of each household in PSLM data experiencing the food insecurity. Finally, the household level probabilities are aggregated at district level through averaging the household level probabilities for geographical units concerned. Expression (5a) indicates the predicted value of lnC for each household in the concerned area based on the parameters estimated from equation (5):

$$\beta_1 \cdot X. \qquad (5a)$$

Additionally, the estimated value of the benchmark indicator is compared with threshold level to determine the probability of food insecure household as:

$$\begin{Bmatrix} F_{ij} = 1 \; if \; lnC_{ij} < lnZ \\ F_{ij} = 0 \;\; if \; otherwise \end{Bmatrix}. \qquad (5b)$$

The expected food security status of household i (Fi) is:

$$F_i = E(F_i \therefore \; X_i, \beta, \sigma) = \varphi \left[\frac{\ln Z - \acute{X}_i \beta}{\sigma} \right], \qquad (5c)$$

where φ – cumulative standard normal distribution.

Expression (5c) gives the probability of a food insecure household.

The Regional Food Insecurity (F) is given as:

$$F = \frac{1}{N}\sum_{i=1}^{N} F_i, \qquad (5d)$$

where N represents number of household in a district.

Finally, the food insecurity incidence is estimated as the average probability of a household being food insecure given as:

$$F^* = E(F \therefore X, \beta^{\wedge}, \sigma^{\wedge}) = \frac{1}{N}\sum\nolimits_{i=1}^{N} \varphi\left[\frac{lnZ - \acute{X}_\iota\sigma^{\wedge}}{\sigma^{\wedge}}\right]. \qquad (5e)$$

The value of $F*$ in expression (5e) can be computed based on different food insecurity levels.

Step-3. Next, after the consumption is modelled using HIES data, the consumption simulation is performed using PSLM data. The simulation process involves parametric and bootstrap simulation techniques. It has been identified that Monte Carlo simulation can derive multiple vectors of welfare estimates through the estimated model from the survey data [79]. In addition, food security and welfare are non-linearly related, therefore, linear characteristics-based SAE methods are not suitable [81]. This study uses Monte Carlo simulation to obtain the number of simulations sufficient for obtaining the reliable levels of welfare from the PSLM data. Typical simulation follows the sampling of estimates from the posterior distribution of the model parameters.

OLS assumptions and normality of the model are relied upon as:

$$\hat{\beta}_{GLS}^{HIES} \sim N(\beta^{HIES}, var(\beta^{HIES})), \qquad (6)$$

$$\tilde{\varepsilon} \sim N(0, \hat{\sigma}^2), \qquad (7)$$

$$\hat{\sigma}^2 \sim \frac{\hat{\sigma}(T-K)}{\chi^2{}_{T-K}}. \qquad (8)$$

The regression estimates of food consumption expenditures as defined in equation (9) are obtained with the normality assumption defined above.

$$ln\tilde{y}_{ch} = X_{ch}^{PSLM}\tilde{\beta}_{GLS} + \tilde{\eta}_c + \tilde{e}_{ch}\,. \qquad (9)$$

The parameters, randomly drawn from the estimated distributions are applied to estimate each household's food consumption expenditure in PSLM and simulation is 100 times repeated. Consequently, based on simulated food expenditures of household, for all rounds the food insecurity headcount rates are calculated. Next, average food insecurity rates at district level are computed.

Alternatively, for simulating consumption, the bootstrap technique [82] can be applied. The Bootstrap technique uses the survey data bootstrapped samples, to get the required parameters for PSLM vector simulation. Each simulation provides the HIES data bootstrapped samples. Then, a GLS model is run and a set of beta coefficients along with error terms is acquired for each simulation. The simulation is 100 times repeated. Food insecurity headcount rates are computed on the basis of simulated household food expenditures, for each round. Finally, the district level averages of food insecurity rates are found.

Step-4. Subsequently, in validation process best simulation results are selected from the comparison of simulated results with estimates of HIES data and later, these estimates are aggregated at the provincial and the district level. Next, a comparison of food insecurity rates is performed at a relevant aggregation level. Subsequently, absolute, and squared differences between computed rates from HIES data and simulated food insecurity rates are observed and the simulation with minimum squared difference is selected.

Step-5. Final step involves map visualization of national, provincial and district level of food insecurity incidence and density estimates. Map visualization is performed by combining result files with shapefiles including the coordinates of Pakistan. The study used the available Stata packages[1] for converting shapefiles in the required format and food insecurity mapping.

Results and discussion. In this section, the map visualization of SAE based results of food insecurity incidence, food insecurity density estimates are made and the results are analyzed in detail. In addition, the main findings of the study are compared with the results of existing literature. Also, the contribution of this study is highlighted.

Food insecurity incidence. This study indicates that Pakistan has not experienced improvement in food security situation. As, the estimated food insecurity incidence in Pakistan is 67.84 %, a figure very close to the food insecurity estimates presented by the National Nutrition Survey of Pakistan [83; 84]. The estimated figure indicates that about two-third of the Pakistani households are experiencing food insecurity as they fail to avail the subsistence food expenditures.

The estimated provincial food insecurity incidence in Pakistan is represented in Table A. Balochistan is at the top with about 89 % food insecure households, followed by Sindh (71.72 %) and Punjab (65.35 %) whereas KP is found to be the least food insecure having 63.43 % food insecure households. As compared with the result of SDPI [29] report, the food insecurity situation has deteriorated in all the provinces. Balochistan is still the most food insecure and KP is the least food insecure province. This result is supported by the existing literature [15; 16; 23] on food insecurity situation in Pakistan

Similarly, Figure 2 presents the provincial level food insecurity incidence in Pakistan, which shows that Balochistan has the maximum food insecure households highlighted in red, whereas blue zones represent areas with comparatively lower food insecurity levels comprising KP and Punjab. Finally, grey zones represent areas with no available data, such as FATA.

[1] 'shp2dta' for converting shapefile into data file and 'spmap' for creating maps.

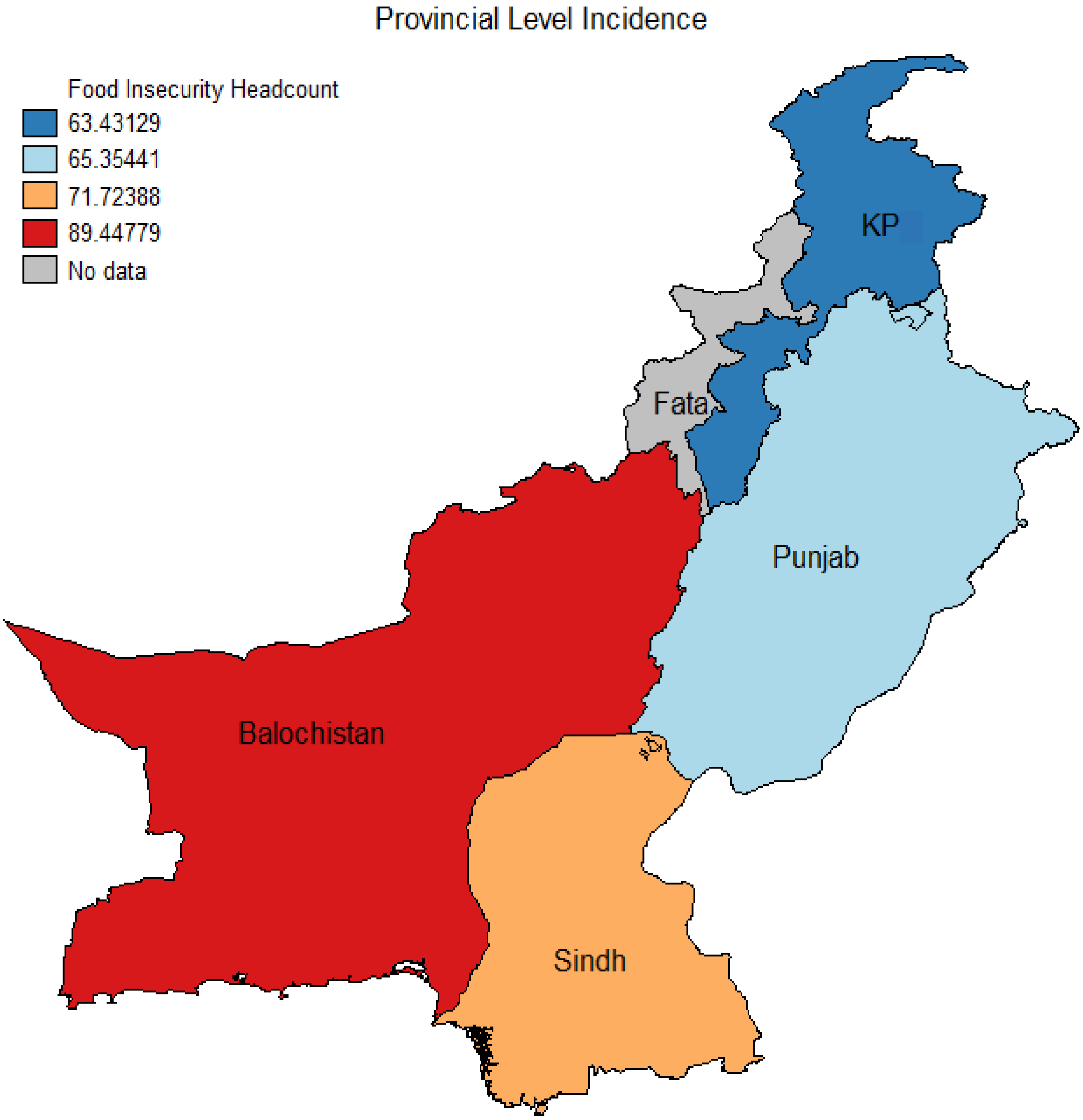

Figure 2. Provincial food insecurity incidence in Pakistan, 2015

Source: authors' own work.

As mentioned earlier, this study aims to estimate geographically disaggregated food insecurity incidence at district level. Table B shows district level food insecurity incidence where districts are ranked from the most food insecure to the least food insecure. Washuk district from Balochistan is identified as the most food insecure district having approximately 93 % households with less than subsistence monthly per adult equivalent food expenditures. In addition, results from Table B shows that 20 of the most food insecure districts are from the province of Balochistan having food insecurity incidence between 85 to 93 %, a figure double as compared with SDPI report [29].

The districts include Killa Abdullah, Khuzdar, Awaran, Ziarat, Jhal Magsi, Nasirabad, Gwadar, Jaffarabad, Dera Bugti, Kharan, Harnai, Kohlu, Chagai, Kachhi, Mastung, Nushki, Sibi and Barkhan.

All of these 20 districts from Balochistan come under the category of high vulnerability to food insecurity [30]. On the other hand, there were only 10 districts with the worst food insecurity situation from Balochistan according to SDPI [29]. Conversely, Abbottabad district from KP is the least food insecure with 44.27 % households being food insecure, a figure similar to SDPI report [29].

Moreover, five of the least food insecure districts with food insecurity incidence ranging from 53 to 44 % are Haripur, Mansehra, Chitral, Karachi City and Abbottabad. Out of these 5 districts, 4 belong to KP and fall under the category of low vulnerability to food insecurity according to ICA [30]. Similarly, Figure 3 depicts the map of district level of food insecurity incidence where red zones represent the food insecure districts having more than 90 % food insecure households. All six red zone districts are from Balochistan province. Subsequently, the orange zones represent the districts having food insecurity headcount ranging between 80–89 %. In total, 29 districts fall in this zone. Most of the orange zone districts are found in Balochistan followed by Sindh province. None of the districts from KP and Punjab fall under this category, except for the Rajanpur district from Punjab.

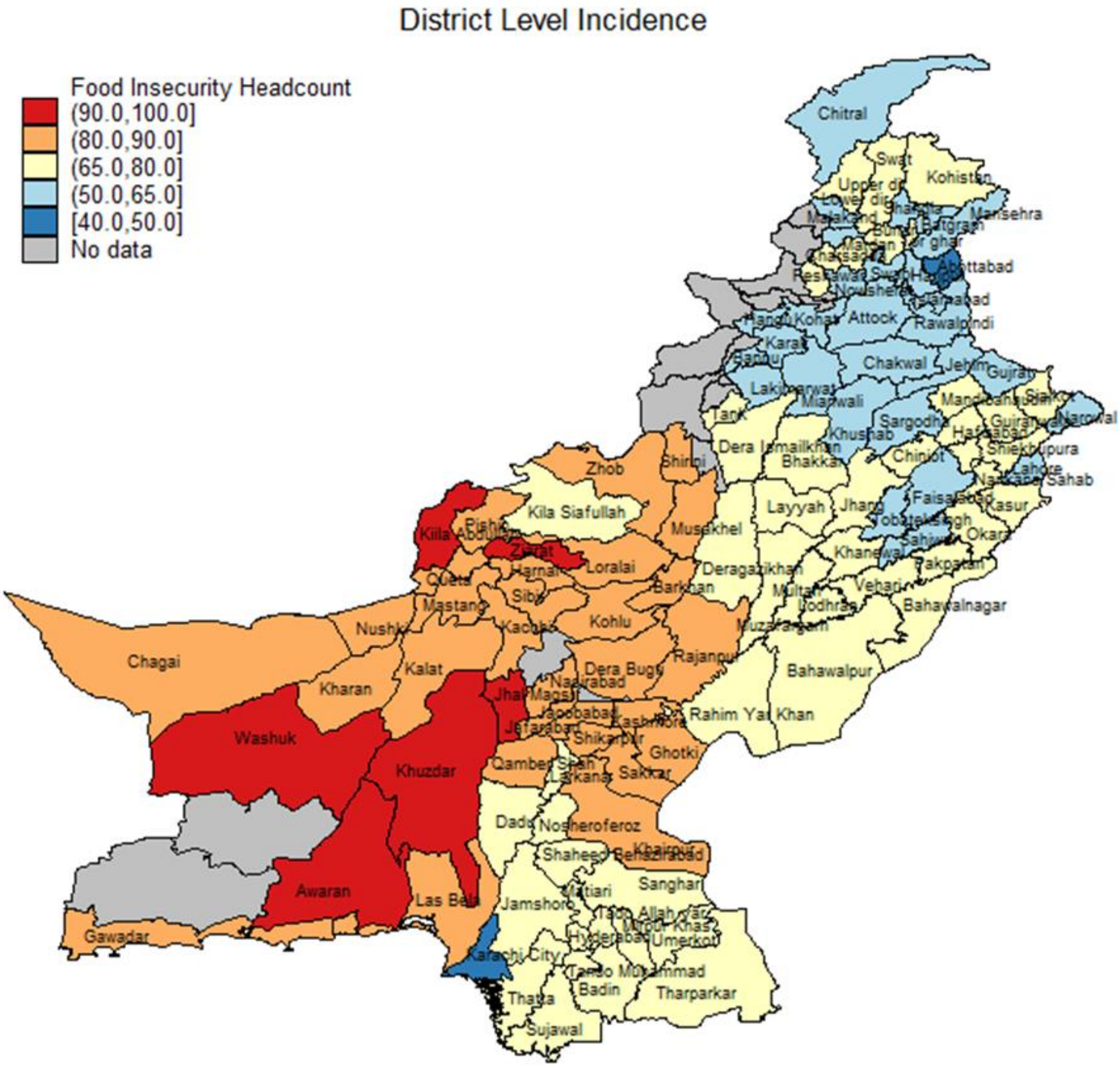

Figure 3. District food insecurity incidence in Pakistan, 2015

Source: authors’ own work.

Food insecurity density at the district level. This section presents a detailed analysis of specific food insecurity density in the district as well as comparison with the food insecurity incidence analysis of the districts under consideration.

The estimates of food insecurity density at the district level are shown in Table C. It has been identified that the situation regarding food insecurity status in Karachi has turned upside down mainly because Karachi is the second least food insecure one in terms of food insecurity incidence. Therefore, Karachi has been characterized with the highest figure of food insecure people (6.4 million) based district level food insecurity density estimates. ICA [30] indicated Karachi under the category of low vulnerability to food insecurity. Contrarily, top-20 districts with most food insecure people are from the province of Punjab except Peshawar and Karachi which belong to KP and Sindh. Similarly, it has been identified that 20 of the most food insecure districts were from Balochistan according to the food insecurity incidence analysis. Some of the districts, including Karachi City, Lahore, Rahim Yar Khan, Faisalabad, Muzaffargarh, Multan, Gujranwala, Bahawalpur, Rawalpindi, and Sheikhupura have a food insecurity density ranging from 6.43 to 2.24 million.

Similarly, Washuk district from Balochistan is the most food insecure district in terms of food insecurity incidence. In addition, Washuk is reported as highly vulnerable to food insecurity in ICA [30]. However, Washuk is found to be the 13th least food insecure district having only 0.17 million food insecure people. In addition, other districts in Balochistan namely Zhob, Dera Bugti, Kachhi, Jhal Magsi, Chagai, Mastung, Nushki, Sibi, Kharan, Harnai, Ziarat, Kohlu and Barkhan, were included in top-20 districts with more than 80 % households being food insecure. All of these 20 districts from Balochistan come under the category of high vulnerability to food insecurity [30]. These districts are now among the 20 least food insecure districts having food insecure people less than 0.20 million.

On the other hand, there were only 10 districts with the worst food insecurity situation from Balochistan according to SDPI [29]. Furthermore, district of Sheerani has been identified as the least food insecure having 0.05 million food insecure people. Earlier, Sheerani district was the 35th most food insecure with more than 80 % households being food insecure according to the food insecurity incidence analysis. According to the ICA [30] Sheerani fall under the category of highly vulnerable areas to food insecurity in Pakistan.

The map analysis in Figure 4 highlights food insecurity at the district level. Karachi is the only district in the province of Sindh that is the most food insecure with more than 6.0 million food insecure people. Therefore, Karachi is located in the red zone, whereas Lahore is the second most food insecure district from the province of Punjab with approximately 5.50 million food insecure people. Therefore, Lahore district is represented by orange whereas yellow region indicates that Rahim Yar Khan is the third most food insecure district from the province of Punjab with more than four million food insecure people. On the other hand, green regions represent the districts with food insecure people ranging from 2.0 to 3.78 million mainly from the provinces of Sindh and Punjab. Finally, dark blue regions represent the districts, mostly from the provinces of Balochistan and KP having number of food insecure people below one million.

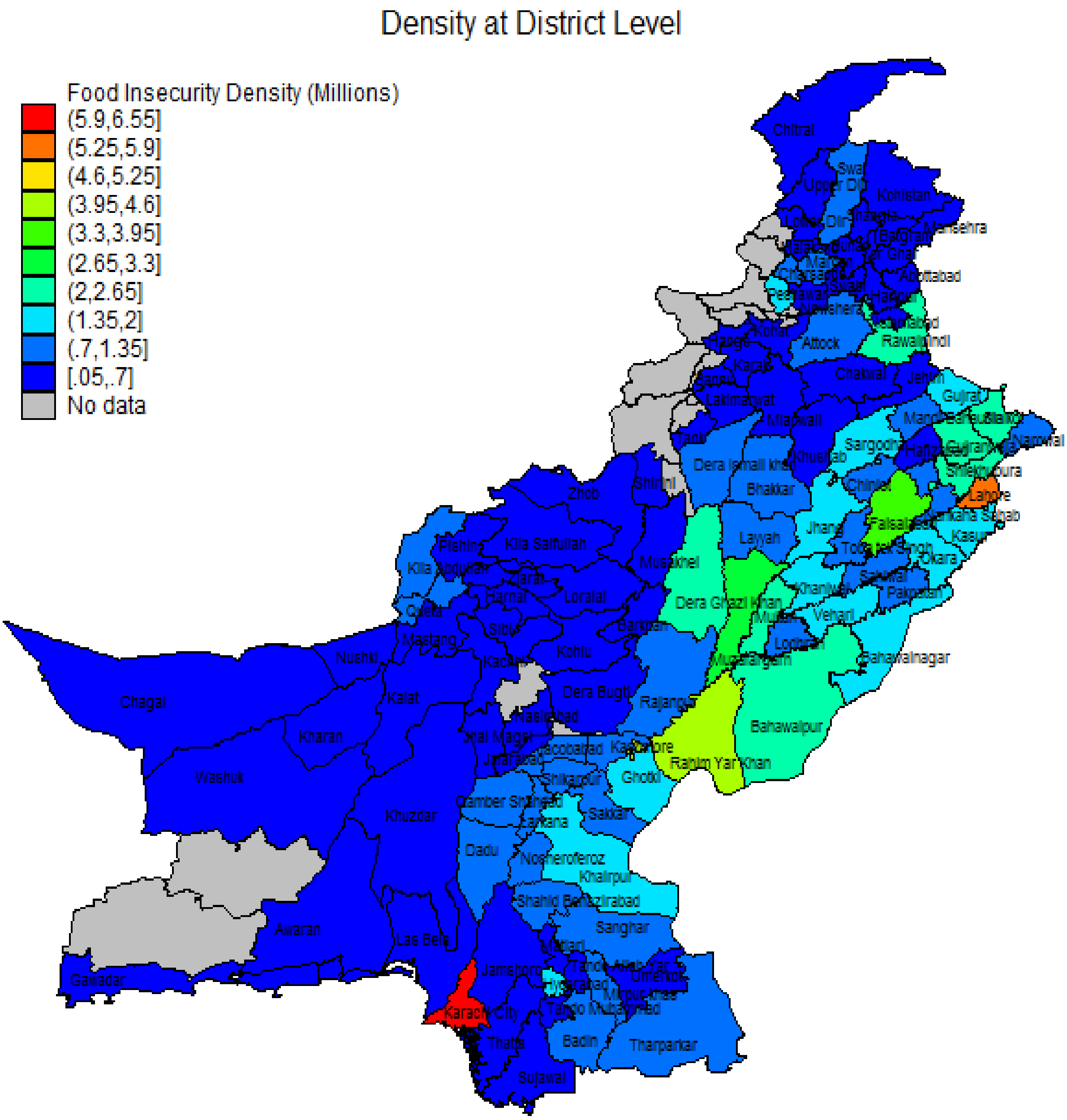

Figure 4. Food insecurity density at the district level in Pakistan, 2015

Source: authors' own estimation.

Overall, food insecurity density at the district level according to each province reveals that the districts of Balochistan, except Killa Abdullah, have less than 0.7 million food insecure people. Similarly, districts of KP have less than one million food insecure people except Peshawar where food insecurity is higher reaching a total of 1.81 million. In addition, districts of Sindh, except Karachi, have less than two million food insecure people. Karachi has maximum number of food insecure people reaching almost 6.0 million. Interestingly, some districts in Punjab have lower levels of food insecurity with less than one million food insecure people, whereas others have higher numbers of food insecure people ranging from 2 to 6 million. For instance, the district of Chakwal has 0.52 million food insecure people, whereas the districts of Kasur, Rahim Yar Khan, Faisalabad, and Lahore have 2.00, 3.78, 4.12, and 5.50 million food insecure people, respectively. Finally, grey regions represent FATA and districts of Punjgur and Kach from Balochistan with no available data.

The analysis of food insecurity density estimates at the district level has pointed to the fact that there are many districts with high food insecurity incidence level and relatively small number of food insecure people. On the other hand, there are many districts with low food insecurity incidence and a large number of food insecure people as expected.

Finally, the Table 1 presents the comparison of different study's results. This study shows that Pakistan has not achieved improvement in food security situation.

Table 1

Comparison of results with district food insecurity assessments conducted by FSA Pakistan 2009 and ICA Pakistan 2017

District	Food Insecurity Incidence, %	Food Insecurity Incidence (FSA 2009), %	Food Insecurity Vulnerability Incidence* (ICA 2017)	District	Food Insecurity Incidence, %	Food Insecurity Incidence (FSA 2009)	Food Insecurity Vulnerability Incidence* (ICA 2017)	District	Food Insecurity Incidence	Food Insecurity Incidence (FSA 2009)	Food Insecurity Vulnerability Incidence* (ICA 2017)
1	2	3	4	5	6	7	8	9	10	11	12
1. Washuk (B)	93.44	NE	41.70	39. Naushahro Feroze (S)	78.05	39.30	27.22	77. Swat (KP)	66.38	54.20	25.60
2. Killa Abdullah (B)	92.19	64.30	43.70	40. Tando Muhammad Khan (S)	77.82	34.30	39.76	78. Gujranwala (P)	66.28	37.00	8.35
3. Khuzdar (B)	91.50	63.90	35.21	41. Dadu (S)	77.72	49.20	28.92	79. Dera Ismail Khan (KP)	65.80	56.00	33.14
4. Awaran (B)	90.92	67.20	45.43	42. Badin (S)	77.13	40.00	39.29	80. Mandi Bahauddin (P)	65.75	31.60	16.15
5. Ziarat (B)	90.92	57.90	42.79	43. Rahim Yar Khan (P)	77.10	39.00	30.68	81. Peshawar (KP)	65.63	49.30	15.02
6. Jhal Magsi (B)	90.91	52.10	44.78	44. Muzaffargarh (P)	76.79	49.90	34.99	82. Nankana Sahib (P)	65.49	NE	15.58
7. Nasirabad (B)	89.81	41.40	41.09	45. Matiari (S)	76.59	33.50	30.67	83. Kohistan (KP)	65.16	73.50	61.40
8. Gwadar (B)	89.75	53.60	29.70	46. Sanghar (S)	76.27	25.00	31.21	84. Sialkot (P)	65.11	29.20	11.08
9. Jaffarabad (B)	89.51	41.60	37.22	47. Shaheed Benazirabad (S)	76.08	57.50	33.61	85. Sahiwal (P)	64.94	33.80	20.06
10. Dera Bugti (B)	89.45	82.40	52.21	48. Sujawal (S)	76.01	NE	43.69	86. Shangla (KP)	64.92	60.90	NE
11. Kharan (B)	89.28	60.60	50.10	49. Larkana (S)	75.48	37.30	25.23	87. Sargodha (P)	64.82	39.90	20.24
12. Harnai (B)	89.22	NE	46.52	50. Jamshoro (S)	75.16	36.00	32.94	88. Nowshera (KP)	64.42	47.50	17.33
13. Kohlu (B)	89.18	NE	53.56	51. Umerkot (S)	74.22	59.40	41.82	89. Faisalabad (P)	64.16	31.90	10.68
14. Chagai (B)	87.69	NE	21.62	52. Thatta (S)	74.00	39.10	39.67	90. Lower Dir (KP)	64.10	64.50	24.79
15. Kachhi (B)	87.58	NE	45.80	53. Kasur (P)	73.92	40.20	16.49	91. Bannu (KP)	64.07	52.10	29.31
16. Mastung (B)	87.27	65.00	31.00	54. Buner (KP)	73.64	60.60	31.03	92. Toba Tek Singh (P)	63.61	29.90	16.27
17. Nushki (B)	87.00	69.60	33.79	55. Mirpur Khas (S)	73.48	38.60	35.17	93. Narowal (P)	63.40	43.50	19.32
18. Sibi (B)	86.46	56.00	36.38	56. Tank (KP)	73.26	60.00	35.00	94. Khushab (P)	63.25	48.30	21.35
19. Barkhan (B)	85.90	62.20	47.50	57. Bahawalpur (P)	73.21	43.60	27.86	95. Mianwali (P)	63.18	44.00	24.75
20. Zhob (B)	85.46	67.00	50 94	58. Bhakkar (P)	72.74	40.80	30.54	96. Lahore (P)	62.17	29.10	3.87

Continuation of Table 1

1	2	3	4	5	6	7	8	9	10	11	12
21. Pishin (B)	85.28	58.20	33.94	59. Upper Dir (KP)	72.03	75.60	39.59	97. Lakki Marwat (KP)	61.75	66.30	32.84
22.Kashmore (S)	84.94	NE	35.68	60. Bahawalnagar (P)	71.98	33.30	24.81	98. Batagram (KP)	60.69	50.40	33.32
23. Ghotki (S)	83.89	NE	31.75	61. Layyah (P)	71.60	37.40	24.51	99. Hangu (KP)	60.57	54.20	25.63
24. Kalat (B)	83.82	64.20	38.53	62. Lodhran (P)	70.94	39.00	28.48	100. Kohat (KP)	59.69	52.60	21.60
25. Jacobabad (S)	83.72	38.70	36.54	63. Tharparkar (S)	70.77	53.40	44.17	101. Swabi (KP)	59.60	53.00	20.96
26. Las Bela (B)	83.64	49.80	39.92	64. Chiniot (P)	70.65	NE	19.92	102. Malakand PA (KP)	59.43	61.00	20.41
27. Musakhel (B)	83.59	78.50	47.16	65. Khanewal (P)	70.26	39.20	24.45	103. Gujrat (P)	59.26	38.00	8.58
28. Quetta (B)	82.85	40.90	15.13	66. Multan (P)	69.75	44.60	21.36	104. Karak (KP)	58.62	63.70	27.26
29. Shikarpur (S)	82.63	32.40	30.22	67. Sheikhupura (P)	69.63	35.80	13.62	105. Attock (P)	57.09	41.90	10.52
30. Khairpur (S)	81.55	50.40	26.88	68. Vehari (P)	69.56	35.40	21.96	106. Jhelum (P)	56.13	34.30	6.34
31. Sukkur (S)	81.24	66.90	21.95	69. Charsadda (KP)	69.55	54.70	24.28	107. Rawalpindi (P)	55.28	28.60	5.08
32. Qambar Shahdadkot (S)	81.12	44.10	32.66	70. Okara (P)	69.40	36.10	23.59	108. Islamabad (FCT)	54.07	23.60	0.87
33. Loralai (B)	80.60	68.80	43.60	71. Hyderabad (S)	68.99	46.60	14.87	109. Chakwal (P)	53.66	41.70	7.67
34. Rajanpur (P)	80.34	55.30	39.78	72. Jhang (P)	68.67	38.70	27.63	110. Haripur (KP)	53.45	40.20	15.16
35. Sheerani (B)	80.31	NE	49.57	73. Pakpattan (P)	68.45	29.90	25.91	111. Mansehra (KP)	53.20	46.70	23.83
36. Killa Saifullah (B)	78.82	57.00	47.04	74. Hafizabad (P)	67.62	34.30	17.07	112. Chitral (KP)	51.06	60.70	21.29
37. Dera Ghazi Khan (P)	78.52	55.00	37.20	75. Mardan (KP)	67.03	51.30	19.95	113. Karachi City (S)	49.85	38.00	3.94
38. Tando Allah Yar (S)	78.32	59.50	32.38	76. Tor Ghar (KP)	66.43	NE	NE	114. Abbottabad (KP)	44.27	40.60	16.10

Notes. NE – No Estimates;
*% ages calculated from the estimates reported in ICA Pakistan 2017;
(B) – Balochistan; (S) – Sindh; (P) – Punjab; (KP) – Khyber Pakhtunkhwa.
Source: authors' own estimation comparison with 2009 and 2017 estimates.

The above comparison and generalization showed that this study helped highlight areas affected by food insecurity for which SDPI did not have estimates [29]. Additionally, this study highlighted the districts with greater food insecure population, which were not indicated in ICA [30], rather, those districts were presented as less vulnerable to food insecurity in ICA [30]. Finally, this study indicated the figure of actual food insecure districts in contrast with ICA [30], in which, districts vulnerable to food insecurity have been indicated.

Conclusions. Food insecurity maps play an important role in efficient resource allocation by governments and other international organizations. However, the geographically disaggregated food insecurity estimates based on large integrated datasets in Pakistan are not sufficiently explored. In this study, we have analyzed food insecurity at the district level with special reference to Pakistan by integrating PSLM 2014–2015 and HIES 2015–2016 datasets. The analysis includes estimation and mapping of district specific food insecurity incidence as well as district specific food insecurity density based on SAE approach. The results reveal that the overall food security situation in Pakistan has not improved. For instance, approximately two-third households fail to make even the subsistence food expenditures at national level. Similarly, at provincial level, Balochistan has been identified to be the most food insecure and KP is the least food insecure province. In addition, the results indicate that Washuk is the most food insecure whereas Abbottabad is the least food insecure district in Pakistan.

On the other hand, the SAE based food insecurity density estimates at the district level have provided quite the opposite results. For instance, Karachi is ranked as the most food insecure in terms of food insecurity density whereas Washuk is ranked as the 13th least food insecure district. Similarly, the top-20 districts with most food insecure population, except for Peshawar and Karachi, are from the province of Punjab. Finally, the Sheerani district that was categorized under high food insecurity incidence, has the least food insecure population.

In addition, the district level food insecurity maps based on incidence and density estimates are significant in locating the food insecure districts as well as the districts that are highly concentrated with food insecure population. The analysis also revealed that many districts with a low food insecurity incidence have a lot of food insecure people. Furthermore, the results of this study have strong policy implications in relation with the disaggregated level of food insecurity estimation in Pakistan. The obtained information based on food insecurity maps at the district level can ultimately guide the government and policy makers for targeted allocation of resource and solution oriented planning. However, policy interventions guided only by the results of food insecurity incidence might cause deprivation of the real beneficiaries. Therefore, both, food insecurity intensity and density dimensions should be considered during the formulating of food insecurity alleviation programs and policies as well as allocation of resources. In addition, the policy interventions should consider the district level or household level effects within food insecure districts as socio-economic factors may differ across households in determining the food insecurity intensity.

Finally, it is recommended that the policy makers consider food insecurity density and incidence for targeted interventions at the district level in Pakistan. This study can serve as a guideline for local actions to reduce food insecurity. In addition, efforts at district level for combating food insecurity in Pakistan may bring promising results as compared to an inflexible national approach. Long term targeted food assistance and cash assistance programs in the most food insecure districts of Balochistan such as Washuk, Killa Abdullah, Khuzdar, Awaran and Ziarat may result in improving the economic and physical access to food. Additionally, policy intervention should focus on providing financial assistance to the number of food insecure people in the areas with low food insecurity incidence, such an example is Karachi where the largest number of food insecure people are located.

Future studies could be performed with rural / urban apartheid at district level for highlighting the differences in food insecurity prevalence among the rural and urban segments in Pakistan.

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Appendix

Table A

Provincial food insecurity incidence in Pakistan

Ranking	Province	Food Insecurity Incidence, %
1	Balochistan	89.45
2	Sindh	71.72
3	Punjab	65.35
4	Khyber Pakhtunkhwa	63.43

Source: authors' own estimation.

Table B

Food insecurity incidence at the district level in Pakistan

Ran-king	District	Pro-vince	Food Insecurity Incidence, %	Ran-king	District	Pro-vince	Food Insecurity Incidence, %	Ran-king	District	Pro-vince	Food Insecurity Incidence, %
1	Washuk	B	93.44	39	Naushahro Feroze	S	78.05	77	Swat	KP	66.38
2	Killa Abdullah	B	92.19	40	Tando Muham-mad Khan	S	77.82	78	Gujranwala	P	66.28
3	Khuzdar	B	91.50	41	Dadu	S	77.72	79	Dera Ismail Khan	KP	65.80
4	Awaran	B	90.92	42	Badin	S	77.13	80	Mandi Bahauddin	P	65.75
5	Ziarat	B	90.92	43	Rahim Yar Khan	P	77.10	81	Peshawar	KP	65.63
6	Jhal Magsi	B	90.91	44	Muzaffargarh	P	76.79	82	Nankana Sahib	P	65.49
7	Nasirabad	B	89.81	45	Matiari	S	76.59	83	Kohistan	KP	65.16
8	Gwadar	B	89.75	46	Sanghar	S	76.27	84	Sialkot	P	65.11
9	Jaffarabad	B	89.51	47	Shaheed Benazirabad	S	76.08	85	Sahiwal	P	64.94
10	Dera Bugti	B	89.45	48	Sujawal	S	76.01	86	Shangla	KP	64.92
11	Kharan	B	89.28	49	Larkana	S	75.48	87	Sargodha	P	64.82
12	Harnai	B	89.22	50	Jamshoro	S	75.16	88	Nowshera	KP	64.42
13	Kohlu	B	89.18	51	Umerkot	S	74.22	89	Faisalabad	P	64.16
14	Chagai	B	87.69	52	Thatta	S	74.00	90	Lower Dir	KP	64.10
15	Kachhi	B	87.58	53	Kasur	P	73.92	91	Bannu	KP	64.07
16	Mastung	B	87.27	54	Buner	KP	73.64	92	Toba Tek Singh	P	63.61
17	Nushki	B	87.00	55	Mirpur Khas	S	73.48	93	Narowal	P	63.40
18	Sibi	B	86.46	56	Tank	KP	73.26	94	Khushab	P	63.25
19	Barkhan	B	85.90	57	Bahawalpur	P	73.21	95	Mianwali	P	63.18
20	Zhob	B	85.46	58	Bhakkar	P	72.74	96	Lahore	P	62.17
21	Pishin	B	85.28	59	Upper Dir	KP	72.03	97	Lakki Marwat	KP	61.75
22	Kashmore	S	84.94	60	Bahawalnagar	P	71.98	98	Batagram	KP	60.69
23	Ghotki	S	83.89	61	Layyah	P	71.60	99	Hangu	KP	60.57
24	Kalat	B	83.82	62	Lodhran	P	70.94	100	Kohat	KP	59.69
25	Jacobabad	S	83.72	63	Tharparkar	S	70.77	101	Swabi	KP	59.60
26	Las Bela	B	83.64	64	Chiniot	P	70.65	102	Malakand PA	KP	59.43
27	Musakhel	B	83.59	65	Khanewal	P	70.26	103	Gujrat	P	59.26
28	Quetta	B	82.85	66	Multan	P	69.75	104	Karak	KP	58.62
29	Shikarpur	S	82.63	67	Sheikhupura	P	69.63	105	Attock	P	57.09
30	Khairpur	S	81.55	68	Vehari	P	69.56	106	Jhelum	P	56.13
31	Sukkur	S	81.24	69	Charsadda	KP	69.55	107	Rawalpindi	P	55.28
32	Qambar Shahdadkot	S	81.12	70	Okara	P	69.40	108	Islamabad	FCT	54.07
33	Loralai	B	80.60	71	Hyderabad	S	68.99	109	Chakwal	P	53.66
34	Rajanpur	P	80.34	72	Jhang	P	68.67	110	Haripur	KP	53.45
35	Sheerani	B	80.31	73	Pakpattan	P	68.45	111	Mansehra	KP	53.20
36	Killa Saifullah	B	78.82	74	Hafizabad	P	67.62	112	Chitral	KP	51.06
37	Dera Ghazi Khan	P	78.52	75	Mardan	KP	67.03	113	Karachi City	S	49.85
38	Tando Allah Yar	S	78.32	76	Tor Ghar	KP	66.43	114	Abbottabad	KP	44.27

Note. B – Balochistan; S – Sindh; P – Punjab; KP – Khyber Pakhtunkhwa.
Source: authors' own estimation.

Table C

Food insecurity density at the district level in Pakistan

Ran-king	District	Population	Food Insecurity Density	Food Insecurity Density (In Million)	Ran-king	District	Population	Food Insecurity Density	Food Insecurity Density (In Million)
1	2	3	4	5	6	7	8	9	10
1	Karachi City	12906861	6433680	6.43	58	Swabi	1114258	664146	0.66
2	Lahore	8843249	5498182	5.50	59	Khushab	1028518	650506	0.65
3	Rahim Yar Khan	5348066	4123502	4.12	60	Islamabad	1193019	645086	0.65
4	Faisalabad	5889614	3778838	3.78	61	Umerkot	864589	641715	0.64
5	Muzaffargarh	3887101	2985013	2.99	62	Nowshera	971351	625709	0.63
6	Multan	3754034	2618497	2.62	63	Hafizabad	918667	621222	0.62
7	Gujranwala	3929469	2604291	2.60	64	Upper Dir	857602	617731	0.62
8	Bahawalpur	3319128	2429825	2.43	65	Bannu	929833	595731	0.60
9	Rawalpindi	4361061	2410982	2.41	66	Mansehra	1056086	561787	0.56
10	Sheikhupura	3212433	2236909	2.24	67	Tando Allah Yar	716487	561188	0.56
11	Sialkot	3355016	2184294	2.18	68	Jhelum	978516	549257	0.55
12	Dera Ghazi Khan	2564761	2013945	2.01	69	Buner	724949	533834	0.53
13	Kasur	2701741	1997085	2.00	70	Jamshoro	709168	532978	0.53
14	Khairpur	2279620	1858990	1.86	71	Jaffarabad	593865	531593	0.53
15	Peshawar	2765210	1814715	1.81	72	Matiari	690761	529044	0.53
16	Bahawalnagar	2518799	1812968	1.81	73	Chakwal	966607	518650	0.52
17	Vehari	2571864	1789098	1.79	74	Khuzdar	559213	511657	0.51
18	Okara	2540204	1762955	1.76	75	Tando M. Khan	643086	500448	0.50
19	Sargodha	2663323	1726443	1.73	76	Kohat	814850	486392	0.49
20	Khanewal	2421789	1701495	1.70	77	Thatta	648226	479713	0.48
21	Hyderabad	2400748	1656183	1.66	78	Abbottabad	998542	442028	0.44
22	Jhang	2231870	1532541	1.53	79	Sujawal	532241	404568	0.40
23	Gujrat	2402434	1423574	1.42	80	Haripur	732266	391374	0.39
24	Ghotki	1685820	1414198	1.41	81	Lakki Marwat	616959	380996	0.38
25	Dadu	1690461	1313818	1.31	82	Kohistan	575178	374808	0.37
26	Mardan	1918591	1286074	1.29	83	Karak	596761	349838	0.35
27	Quetta	1514926	1255116	1.26	84	Shangla	498621	323728	0.32
28	Swat	1821357	1209028	1.21	85	Malakand PA	525037	312050	0.31
29	Rajanpur	1501935	1206728	1.21	86	Pishin	359049	306195	0.31
30	Sanghar	1541806	1175994	1.18	87	Nasirabad	318533	286075	0.29
31	Sahiwal	1802312	1170454	1.17	88	Awaran	304883	277202	0.28
32	Layyah	1595306	1142308	1.14	89	Las Bela	327661	274069	0.27
33	Larkana	1461160	1102877	1.10	90	Batagram	444162	269557	0.27
34	Badin	1364759	1052703	1.05	91	Tank	356403	261095	0.26
35	Qambar Shahdadkot	1288521	1045238	1.05	92	Gwadar	288714	259125	0.26
36	Toba Tek Singh	1624319	1033310	1.03	93	Loralai	300845	242481	0.24
37	Lodhran	1444935	1025010	1.03	94	Chitral	414672	211728	0.21
38	Tharparkar	1420785	1005471	1.01	95	Kalat	248541	208338	0.21
39	Pakpattan	1466192	1003585	1.00	96	Killa Saifullah	251189	197978	0.20
40	Bhakkar	1369981	996559	1.00	97	Tor Ghar	293427	194934	0.19
41	Narowal	1569602	995061	1.00	98	Zhob	227634	194539	0.19
42	Sukkur	1218131	989569	0.99	99	Dera Bugti	212289	189894	0.19
43	Shikarpur	1194674	987170	0.99	100	Hangu	285553	172949	0.17
44	Naushahro Feroze	1260697	983933	0.98	101	Kachhi	196555	172149	0.17

Continuation Table C

1	2	3	4	5	6	7	8	9	10
45	Shaheed Benazirabad	1287249	979342	0.98	102	Washuk	178031	166347	0.17
46	Mirpur Khas	1275710	937335	0.94	103	Jhal Magsi	172028	156392	0.16
47	Kashmore	1052990	894390	0.89	104	Chagai	135244	118593	0.12
48	Jacobabad	1050980	879888	0.88	105	Mastung	133200	116240	0.12
49	Charsadda	1178430	819543	0.82	106	Nushki	132152	114978	0.11
50	Mandi Bahauddin	1213458	797902	0.80	107	Sibi	124664	107789	0.11
51	Dera Ismail Khan	1158701	762444	0.76	108	Kharan	116378	103900	0.10
52	Chiniot	1059590	748623	0.75	109	Harnai	114534	102190	0.10
53	Killa Abdullah	794245	732203	0.73	110	Ziarat	107710	97929	0.10
54	Attock	1260429	719579	0.72	111	Kohlu	96315	85895	0.09
55	Nankana Sahib	1086237	711405	0.71	112	Barkhan	88261	75820	0.08
56	Lower Dir	1091554	699695	0.70	113	Musakhel	73948	61815	0.06
57	Mianwali	1068581	675104	0.68	114	Sheerani	64647	51918	0.05

Source: authors' own estimation.

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