Guidance note[1]: Agricultural typologies for Bangladesh

Improved understanding on designing spatially differentiated strategies: Typologies of territories based on poverty, agricultural potential, and efficiency to target investments and interventions in the framework of the Hand-in-Hand Initiative

Abstract

Agricultural development depends on identifying and investing on opportunities, which increase productivity, competitiveness and bring economic growth, but also create employment, increase incomes, and alleviate poverty. In addition, in cases where opportunities are just not present, policies need to provide alternative solutions and deploy interventions that bring inclusive social development. Finding these opportunities depends on interactions of many actors that take place in a complex physical and socioeconomic environment.

Considering and accommodating for the physical and economic dimensions of the environment in which farmers and the poor in agriculture and food systems operate, requires an approach that combines economic, statistical, and spatial data and analysis. The approach needs to consider, in any environment, the capacities of farmers to efficiently generate profit from their farms in the markets they sell their produce.

The present note describes such a tool using GIS and socioeconomic data analysis. The output of the tool is a standard classification of territories in a country which integrates agriculture and food systems potential in relation with farmers' efficiency to generate profit in locations where poverty is pervasive. This classification, or typology, serves thereafter as a broad guide for investments and policy interventions.

Ultimately the guide contributes to the efforts of the Hand in Hand initiative, the flagship FAO corporate programme launched in 2020. The HiH initiative's key objective is to contribute in making progress in SDG1 and SDG2 targets by informing governments, donors and investors on opportunities that bring inclusive agriculture and social development through an evidence-based territorial development approach.

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Content

1. Background

When deciding to invest resources in agri-food systems or implement social policy interventions, governments, development partners and private actors, are confronted with difficult decisions. Difficulties emerge from the need to prioritize across alternative options in terms of their returns like profits, incomes, production, productivity, poverty and hunger reduction. Reality and plenty of research suggest that not all interventions are equal and benefits per dollar spent in different sectors or subsectors and locations vary widely (see Mogues et al. 2012 for a summary).

Returns to investments and other policies are not the same across space since local conditions, available infrastructure (transportation, energy or other), climate, land, soil and water characteristics make some options dominate over others in different territories. When social objectives in terms of poverty or hunger alleviation are key driving forces for policy and investment decisions, targeting areas that host most of poverty and hunger, needs to be integrated in the policy analysis.

These types of challenges are similar for all stakeholders engaging in agri-food systems. Economic performance, social inclusion, but also environmental objectives, may carry different weights across types of stakeholders depending on what is their priority.

Intergovernmental and international development cooperation agencies may give higher priority to social returns and improvements in the livelihoods of the poor. On the other hand, private sector companies engaging in the sector assign different weights when they are to decide among multiple options relating with where and how to invest. Finally, the physical environment and local agroecological characteristics, naturally condition the options and possibilities for policy and investments in any territory.

2. Objectives and output

Identifying opportunities that succeed accommodating diverse incentives and multiple objectives, social and economic but also environmental, would be ideal in the challenging situations that developing regions are facing. For inclusive agricultural development, drivers of investment and resource allocation decisions need to consider local conditions and be based on the best possible outcomes. These outcomes refer to improved agricultural production and productivity, profits and competitiveness while reducing poverty, hunger and malnutrition and promote inclusiveness for vulnerable groups of the population.

The present note describes an analytical tool that in broad terms can guide investment decisions and policy interventions in agriculture and food systems. The tool's objective is to inform about options and priority areas in any given country, where policies and investments can enhance economic performance and at the same time improve the livelihoods of poor people dependent in the agri-food system. At the same time, they need to consider and respect the local physical environment and natural resources. Such interventions bring improvements in the livelihoods of producers, casual workers and many actors engaging in agri-food systems. By improving efficiency in the system, net food consumers are able to benefit too from lower food prices and more diverse diets.

The output of the tool is a standard classification, or a typology of territories in a country. The typology integrates information on agriculture and food systems' potential with farmers' efficiency to generate incomes, revenues, or profit in locations that poverty is pervasive. To succeed in this effort, the typologies classify territories by their agricultural potential and farmers capacities to make profits in conjunction with the level of poverty.

Box 1: The Hand in Hand initiative

The Hand in Hand initiative is an evidence-based, country-led and country-owned initiative launched by FAO with the aim to contribute at eliminating extreme poverty (SDG1) hunger and all forms of malnutrition (SDG2) by accelerating agricultural and food systems transformation and promoting sustainable rural development.

The HiH framework is a tool targeting the poorest (SDG1) and those with higher rates of hunger and malnutrition (SDG2) through spatially differentiated strategies while all dimensions of food and agriculture systems are brought together. The initiative maps donor interventions in order to identify partnering opportunities. The initiative utilizes GIS data in order to overlay multiple information layers to prioritize interventions.

The initiative adopts a market-oriented food systems approach to increase the quantity, quality, diversity, and accessibility of nutritious foods available in local, regional and national food markets and to improve food system capacities to deliver nutrition and healthy diets for everyone.

The initiative focuses on well-recognized, but under-supported potential areas of agriculture and agri-food value chains to lift large numbers of the rural poor out of poverty through integrated approaches by achieving greater collaboration and partnership between the UN agencies, development partners, private sectors including civil society organizations.

The initiative focuses not only on increasing producer productivity but more importantly, on improving realized incomes in the short run along with sustainability for the longer-term. Besides, the initiative promotes the sustainable use of biodiversity, natural resources, and ecosystem services, and supports climate change adaptation, mitigation, and resilience.

The initiative provides data and analysis to evaluate interactions and trade-offs among objectives and actions, helping to pinpoint key bottlenecks and focus policy dialogue, and the key configurations needed in terms of local partnerships. This is in line with the UN's priority commitment to "leave no one behind" and Bangladesh has been selected as one of the pilot countries to roll out the HiH initiative.

This classification aims at serving as a broad guide for setting spatially differentiated policies, programmes, and investments. It does that by informing governments, donors, development agencies, large scale private investors, the civil society but also the farmers themselves where to target investments and/or social policy interventions that improve efficiency, generate profits and incomes, and increase competitiveness.

The guide is a crucial component of the framework guiding the flagship FAO corporate programme of the Hand in Hand initiative. The HiH initiative's ultimate objective is to contribute to making progress in achieving SDG1 and SDG2 targets by promoting inclusive agriculture and social development through an evidence-based territorial development approach. The results from the analysis of the typologies, inform governments, investors and donors about priority areas and opportunities that bring benefits to all.

The next sections describe the steps of the analytical methodology that generate these key layers. Finally, an example is used to indicate how the different data and layers of information are analysed and brought together to create the typologies in a country.

3. Conceptual framework

The tool integrates information layers that are clustered together to generate a classification of typologies of territories as mentioned already. These layers integrate local physical conditions and infrastructure and at the same time approximate socioeconomic aspects about farmers and agri-food system's economic potential and poverty status. They thus create a comprehensive and informative context to base investment and policy decisions across space and territories for the HiH initiative.

a. Biophysical and agroecological conditions

In first information on specific agroecological and biophysical conditions is integrated in the analysis. This refers to key data that characterize agriculture as predominantly land, water, and climate dependent sector in developing countries. In many cases in the past, agroecological zones (AEZs) (FAO, 1978; Fischer et al., 2002), land cover and land use (Anderson et al., 1976, Loveland et al., 2000) supported prioritizing investments in agri-food systems. This information points at the heterogeneity of the biophysical and agroecological dimensions that condition the performance of farmers and agriculture and food system activities.

From this perspective the analysis behind the typologies tool accommodates environmental sustainability aspects. This because in territories that the physical environment does not allow, the regions are identified of low potential for intensive agricultural development. In addition, information on the state of specific natural resources like water, carbon emissions and other, is integrated depending on the context.

Typically, spatial information used in the preparation of the typologies refers to the Normalized Difference Vegetation Index, rainfall patterns, types of land cover and travel time to the nearest market (usually a city). The information is sourced at the FAO-GIS platform or other sources assessed as more accurate by the analyst. The data are aggregated at the lowest available administrative unit in a country, and they feed into the analysis to indicate how conducive is the physical environment to agriculture and farming. Example of map with biophysical information is presented in Figure 1.

Additional information is integrated as needed to reflect specific country contexts as well as entry points that Hand in Hand programmes are leveraging during country operations. This can be information on water availability and efficiency of use, soil types and quality, electricity and energy availability, access to financial services, access to internet and broadband signal, livestock density, production, productivity and yield gaps by crop or groups of crops and many other.

Access to available infrastructure in terms of primary and secondary roads, ports and transportation hubs is used as an extra layer in order to inform about the travel time needed to connect supply with demand areas (Figure 2). This information supports estimates of transportation costs that need to be integrated in relevant investment and business plans.

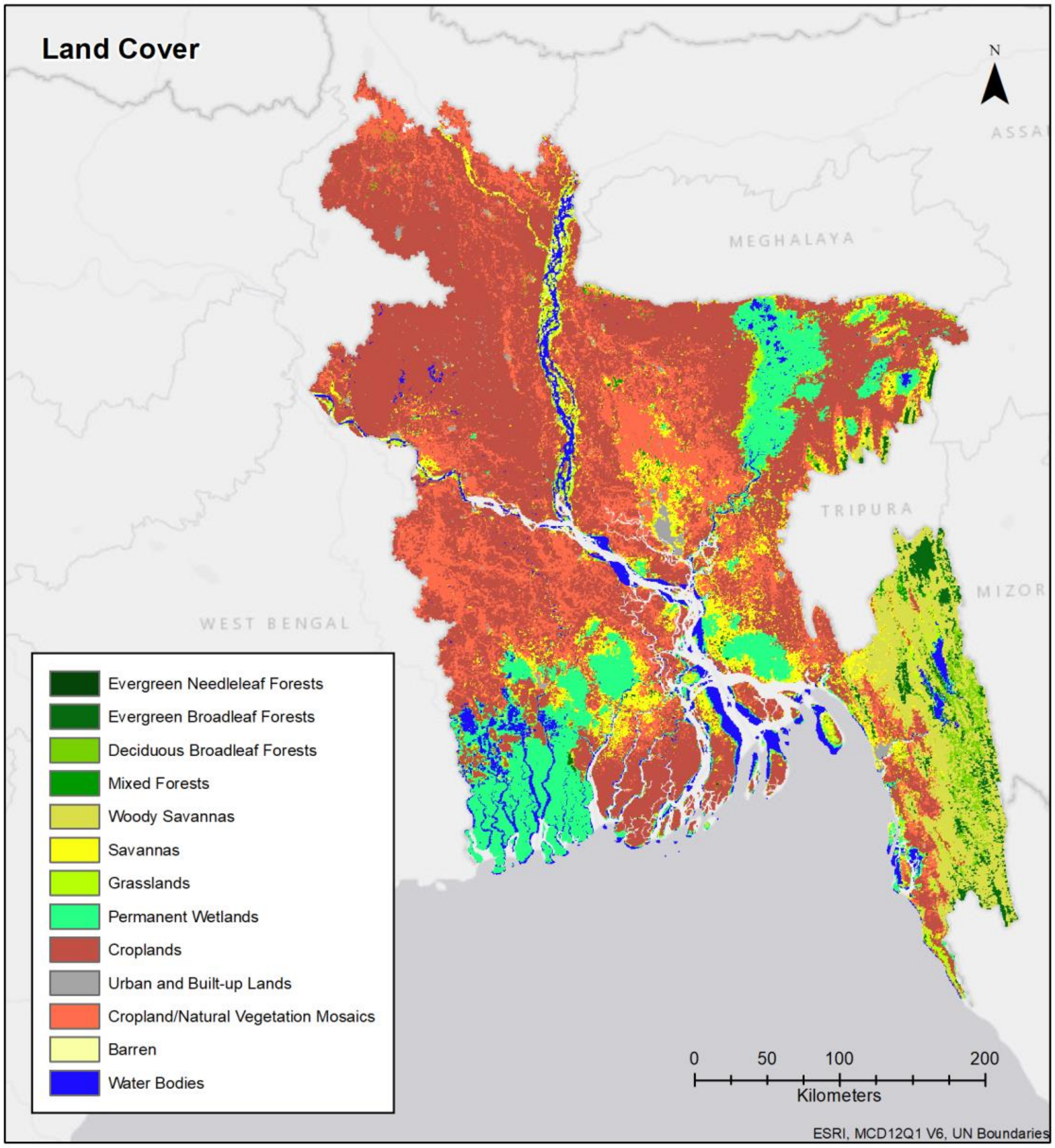
Box 2: The HiH GIS platform

The GIS platform that FAO launched as part of the HiH initiative contains millions of information layers on crops and vegetation, land, soil water and many more. Climate but also other information incorporated in the platform provide real time data on current conditions that allow interventions responding to emergencies.

The platform includes and continuously adds extensive, reliable, detailed, historical as well as contemporaneous, state of the art information and data including from satellite imagery. This improves understanding on gaps and challenges in agrifood systems and allows assessing the feasibility and potential to undertake development projects and investments to provide solutions and fill such gaps.

For example, analysis of the data, contributes to building the evidence base in order to identify if soil types and water availability in a territory are adequate to invest and develop specific commodity value chains. Incorporating additional information layers like electricity availability, transportation and internet connectivity and others, indicates possible locations to install processing or cold storage units that can be integrated with electronic commerce platforms. Data on transportation infrastructure provide extensive information on challenges and opportunities to link rural agricultural areas with markets locally but also internationally.

Figure 1: Land cover map[2]



Source: Stochastic frontier analysis FAO-HiH task force (2022)

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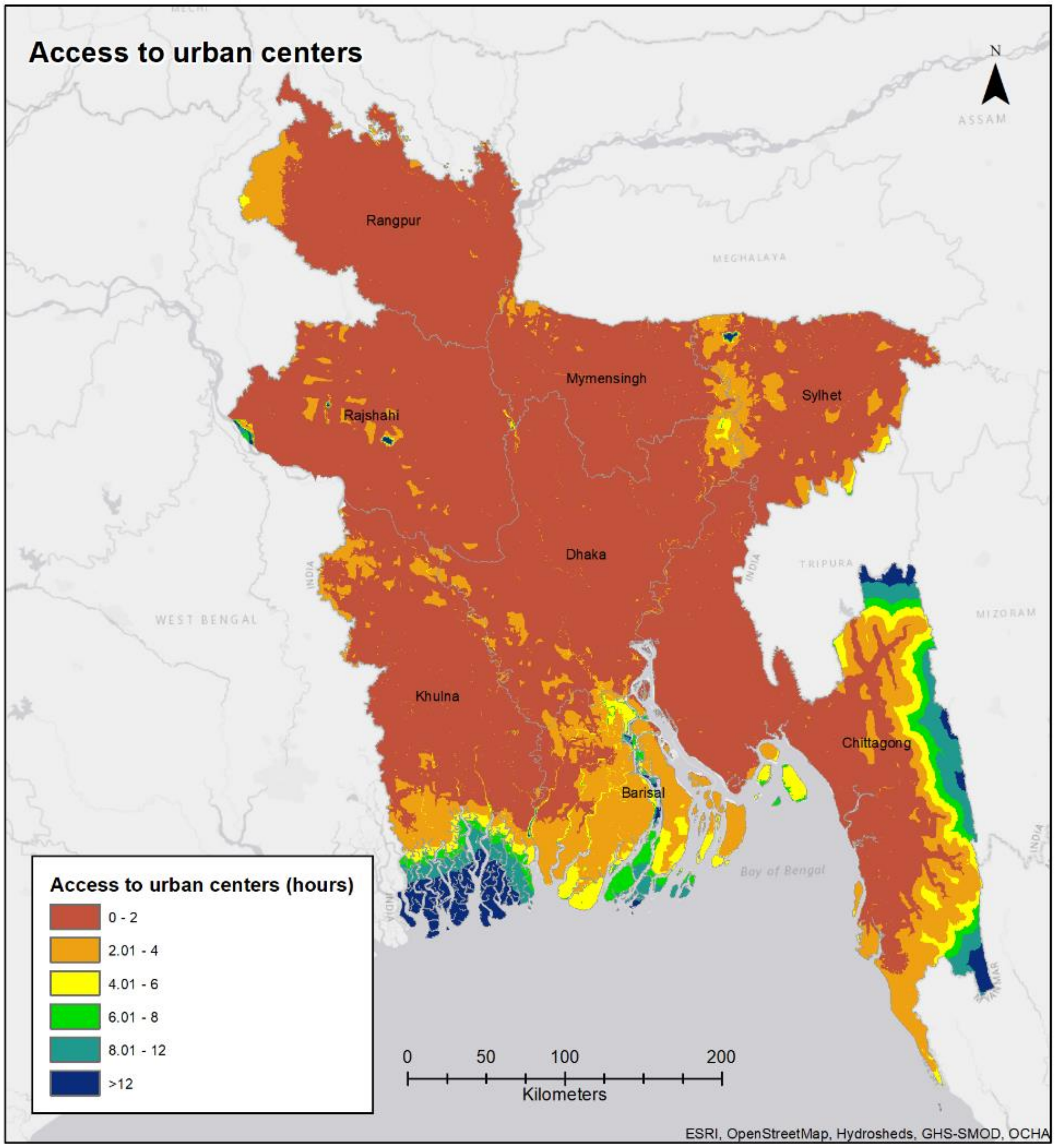
[2] The boundaries and names shown and the designations used on these map(s) do not imply the expression of any opinion whatsoever on the part of FAO concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers and boundaries. Dashed lines on maps represent approximate border lines for which there may not yet be full agreement.

Figure 2: Accessibility map



Source: Stochastic frontier analysis FAO-HiH task force (2022)

b. Agricultural potential and efficiency

Two key information layers in this framework are the calculation of agricultural profit or revenue potential and efficiency. The first layer assesses how much revenues or profits can be realized if all farmers could be able to perform as the most profitable or those with highest incomes among them. The efficiency layer measures the extent to which farmers are able to exploit existing market opportunities while considering their heterogeneity in the context in which they operate.

These layers help identifying the regions or territories with high profit or revenue potential and low efficiency, which are likely to be suitable for agricultural investments or other interventions.

The challenge associated with these variables, however, is that they are not directly observed, and need to be estimated. As such, the agricultural typology tool integrates outputs from a stochastic frontier analysis (methodology, steps and variables used are described in Appendix A) to estimate these dimensions.

The information layer aims to indicate not only where profit or revenue potential is highest, but also those areas where farmers are furthest away from their potential. By adopting differentiated interventions based on the typology classification (discussed later), the methodology also sheds some light into what are some of the possible policies that could be put forward to alleviate existing constraints and increasing competitiveness by taking advantage of market opportunities which exist but are not exploited at their full potential. It does that by using and analysing information on farmers' livelihoods coming from household-level data and combining this information with the GIS data described above.

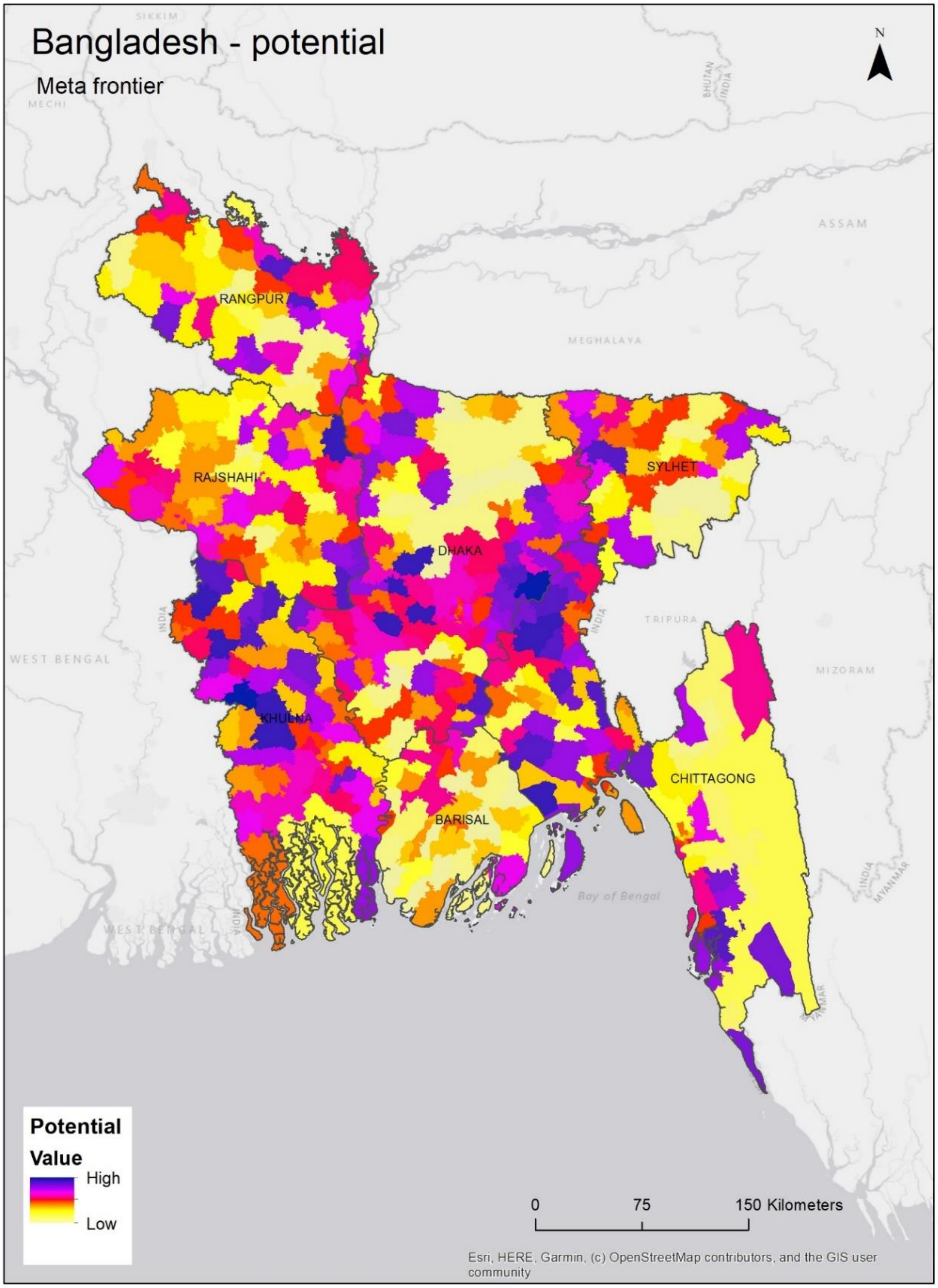
The stochastic frontier analysis uses survey data (i.e. revenues/profits, farm practices, input and output prices) for all farmers selling at least part of their produce and combines this with GIS data which captures aspects such as agro-ecological conditions, climatic conditions and market access. Based on the household-sample, the analysis then specifies a statistical relationship that estimates a maximum attainable revenues or profits (henceforth, the frontier), based on prevailing prices, market conditions agroecological context in which farmers. All producers are then compared to the estimated frontier, with deviations from this frontier also known as unrealized potential.

This part of the analysis provides valuable information that contributes to building the typologies of territories. In first, the distance from the benchmark farmers, defines the size of the unexploited potential in terms of revenues or profits for each farmer. This potential for a number of reasons and constraints is not materialized. The benchmark is also called the frontier in terms of maximum profits or revenues that all things considered is available for grasp.

The maximum attainable income or profits define the **agricultural potential** in broad terms for the average farmer in a given administrative area (Figure 3). The analysis on the preparation of typologies aims at identifying and measuring this potential across space in all countries the HiH initiative operates. Investments or other policies aim at alleviating the constraints that are responsible for this potential left unexploited or not realized.

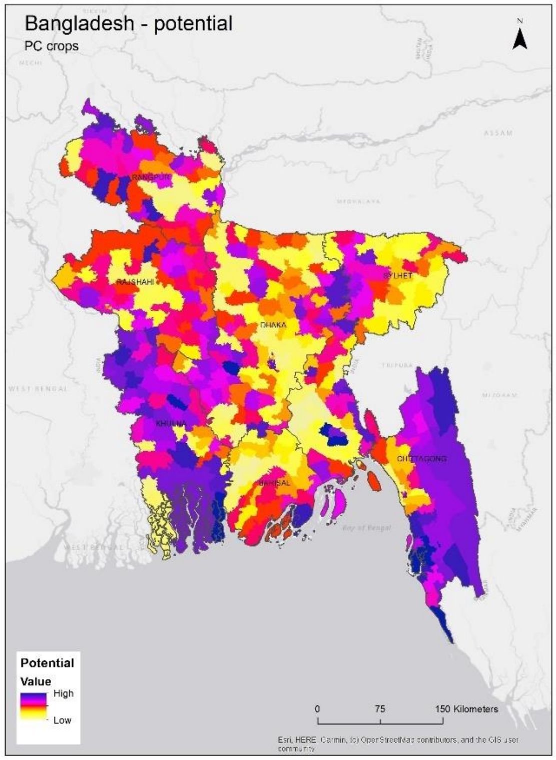
As can be seen in Figure 3, agriculture potential is not confined to one specific region and is distributed across different parts of the country. However, as highlighted by Figure 4, the overall agricultural potential in Figure 3 depends a lot on the analyzed sub-sector and high potential areas hinge on the analyzed subsector.

Figure 3: Agricultural potential map



Source: Stochastic frontier analysis FAO-HiH task force (2021)

Figure 4: Potential map by subsector



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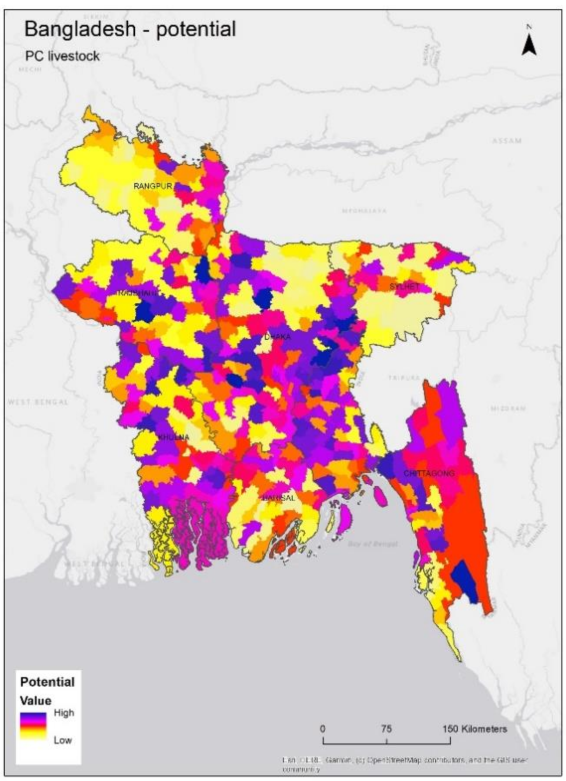
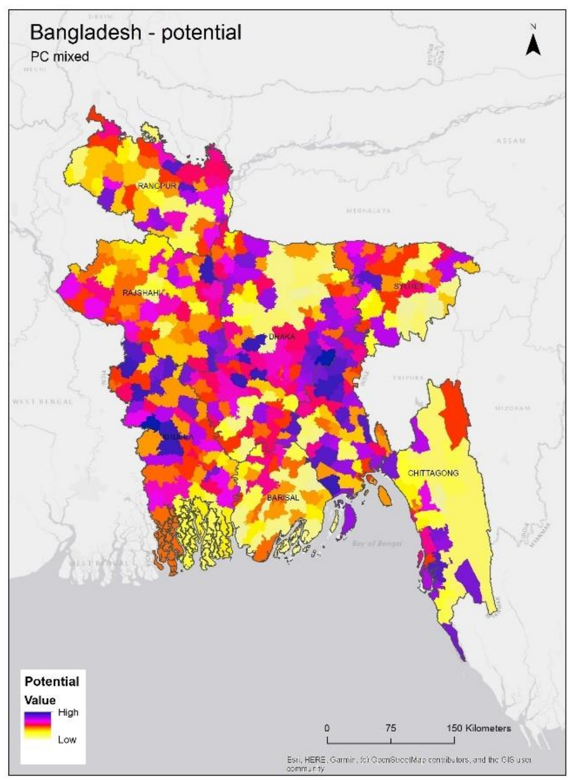




(b) Livestock	(c) Mixed

Stochastic frontier analysis FAO-HiH task force (2022)

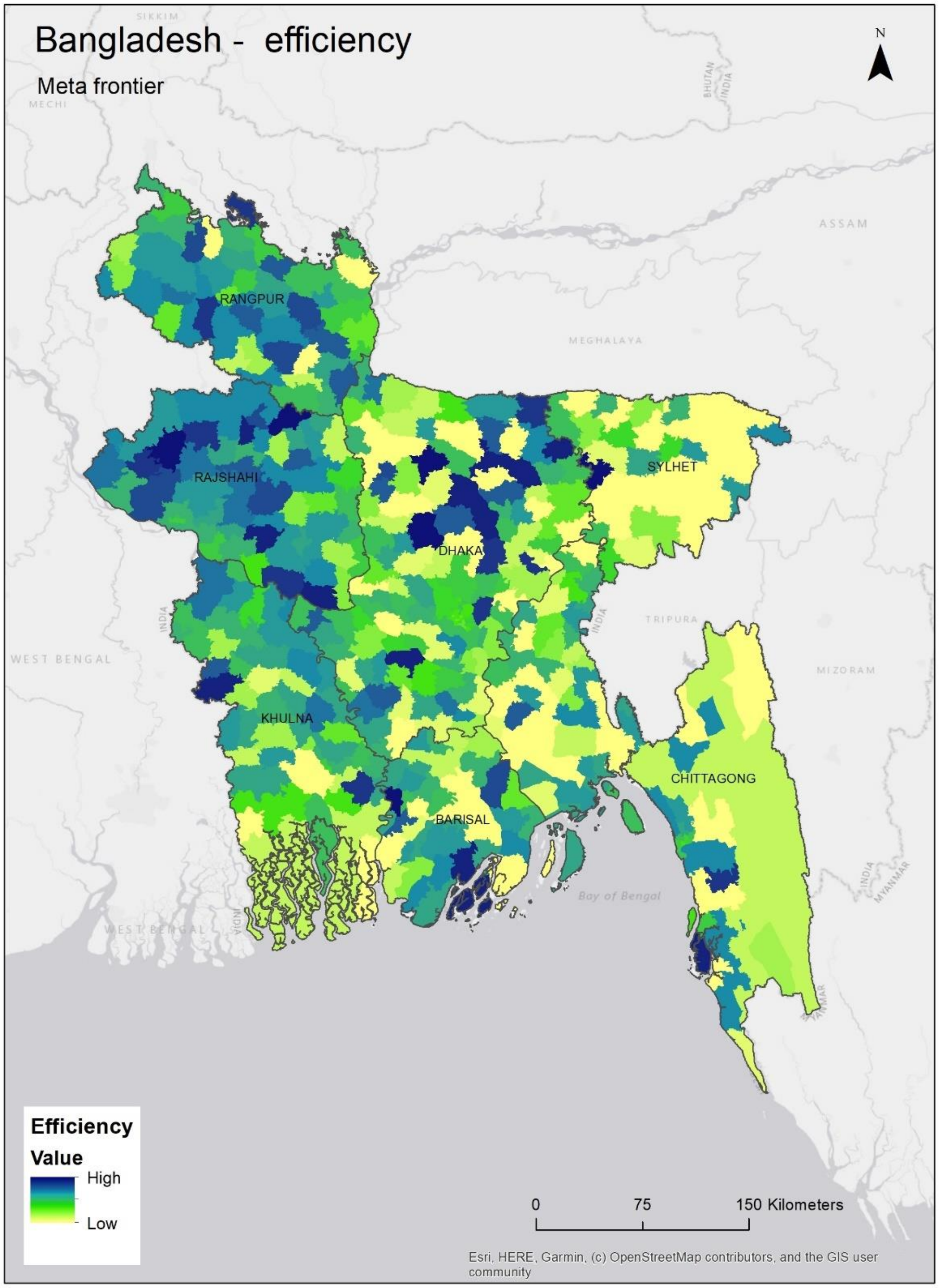
Farmers are not the same with each other even when operating on similar plots of land or when facing similar agroecological conditions within a region, or when they face similar market conditions. They perform the same activities in different ways in view of their knowledge, skills, experiences and other available resources and assets.

Moreover, most of them are small in size and scale in their operations, which means that in the markets they participate to purchase inputs or sell their produce usually face given prices that they cannot easily negotiate. There may be areas where, despite the existence of medium-to-high levels of potential, farmers may not be able to fully exploit this for a number of different reasons, including high transaction costs (due to poor infrastructure), market failures or lack of access to basic services (e.g. extension). Still however, some of the farmers are more efficient than others in taking advantage of market prices whether by choosing the right time to buy or sell, or by using less inputs for a given level of output or by producing more for a given level of inputs relative to their peers. In cases their entrepreneurial spirit and business orientation makes the difference.

A measure of efficiency indicating this diversity in the skill of farmers to take advantage of market opportunities and enjoy higher profits and revenues or lower costs, is estimated through the analysis. This **efficiency score** measures the extent to which farmers are able to exploit market opportunities while considering their heterogeneity in skills and capacities in the context they operate. Figure 5 shows the results for the full sample using the Metafrontier, while Figure 6 shows the results for each of the individual subsectors.

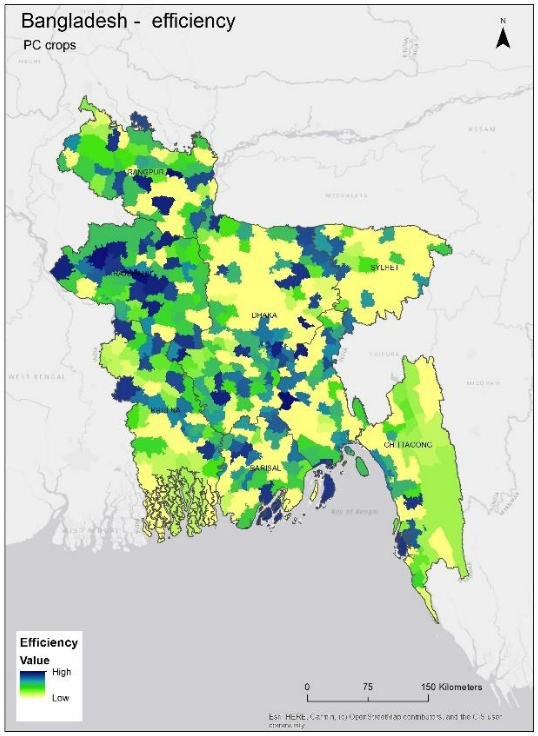
Again, farmers making the most in terms of revenues or profits given their skills, experiences and education and the market prices they face, set the benchmark and all others are ranked under the most efficient ones. The score takes values from unity (most efficient) to zero (least efficient). Averaging across regions and territories provides information on the level of farmers' efficiency to engaging and making the most from their market integration. This information is displayed on the map.

Figure 5: Agricultural efficiency map



Source: Stochastic frontier analysis FAO-HiH task force (2021)

Figure 6: Efficiency by subsector



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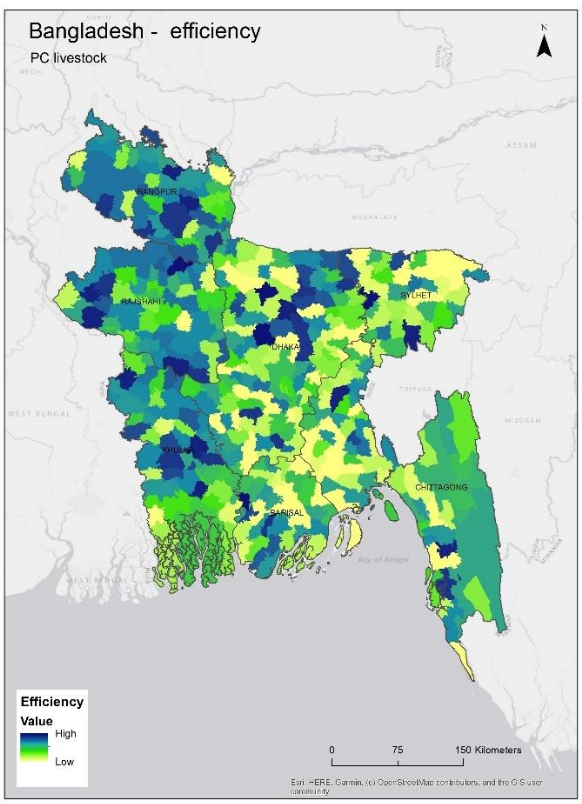
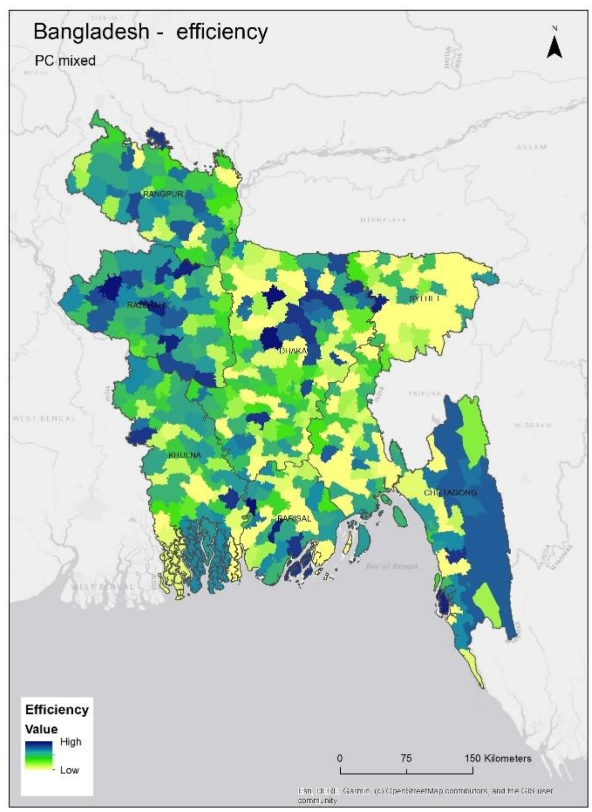




(b) Livestock	(c) Mixed

Stochastic frontier analysis FAO-HiH task force (2021)

c. Poverty maps

Finally, the tool employs data that map poverty across space in order to weigh in, objectives that will support identifying opportunities or other policy options that will lift people out of the state of poverty. Poverty maps are frequently used to guide and target investments and development policies since they provide a method to locate the poor (Lanjouw, 1998; Hentschel et al., 2000; Elbers et al., 2001; Deichmann, 1999).

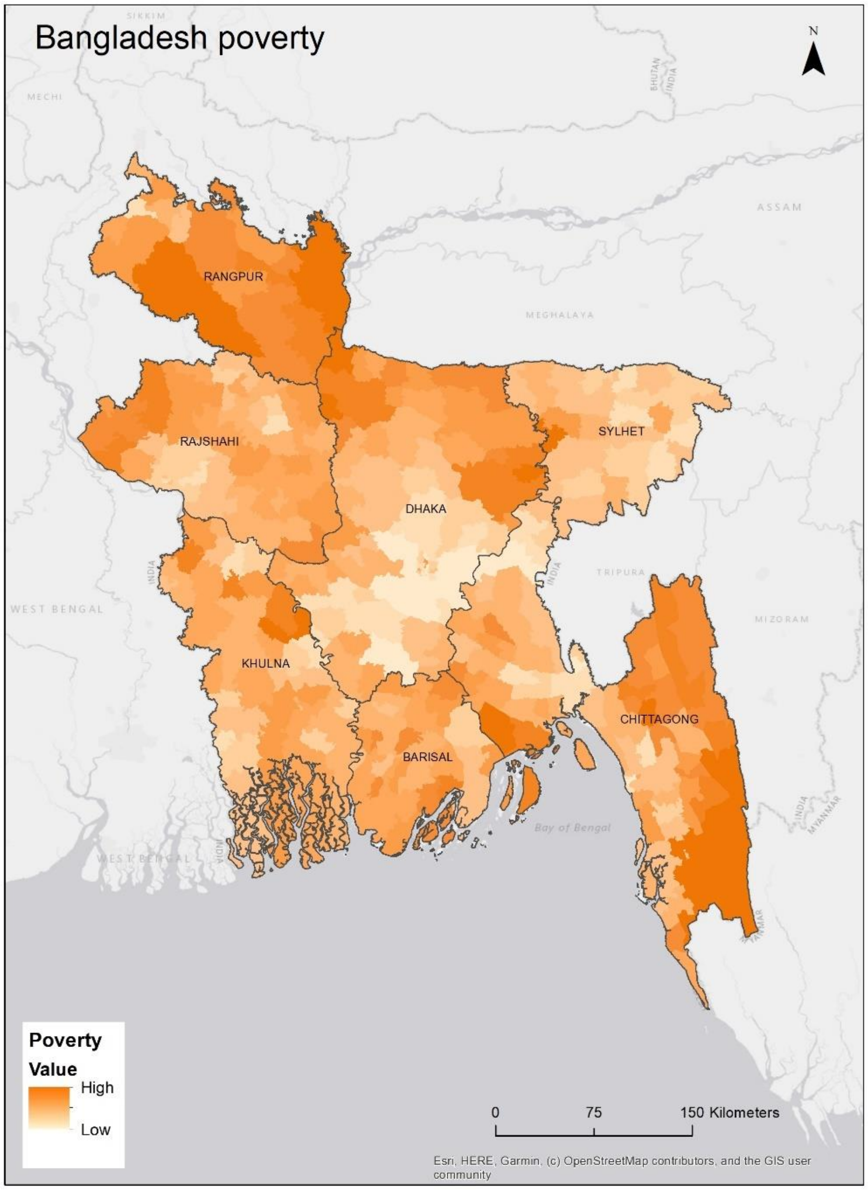
This layer integrates information that supports efforts to make progress in the key objective of the HiH initiative; that is contributing in eradicating extreme poverty which is measured through SDG 1. The poverty map is presented on Figure 5.

Data that map food insecurity in terms of hunger and malnutrition are to be integrated in order to identify territories and improve targeting for interventions food insecure groups. In this way the HiH initiative contributes to making progress in eradicating hunger and malnutrition which is measured through SDG 2.

In addition, and depending on the context in countries under emergencies, crisis or conflict, maps on the severity of hunger and malnutrition are integrated to identify priority regions and territories for interventions. Relevant information from the Integrated Phase Classification (IPC) mapping tool, rapid vulnerability assessments, but also non-conventional sources of information are employed to fill the data gaps. Moreover, other tools based on text mining and artificial intelligence are employed to provide the necessary evidence that will support identifying territories where urgent attention is needed.

Especially in country cases where data scarcity is a critical challenge other layers of information can be integrated in order to identify extreme poverty and food insecurity hotspots. Relevant information from the Integrated Phase Classification (IPC) mapping tool is overlayed with population density, availability, and access to infrastructure (transportation, electricity, communications etc.), is utilized to approximate as close and feasible the welfare situation of the populations across regions and territories. In these cases, welfare (in contrast to poverty maps) maps are developed on a case-by-case basis.

Figure 7: Poverty map



Source: Stochastic frontier analysis FAO-HiH task force (2021)

4. Typologies of territories

The conceptual framework guiding the tool developed by Maruyama et al. (2018), integrates the layers of information described earlier into a single map that identifies different types of territories considering poverty, agricultural potential, and efficiency. Based on these three key layers, the **typologies** provide informative but only broad indications to policymakers in order to focus geographically, decide across types of interventions, prioritize policies, and allocate resources and implement investments in a spatially differentiated way.

At its core, the idea is that different regions should not only be given different degrees of priority, but that the type of policies and investment should be tailored to the physical and socioeconomic dimensions and the needs of each specific region and territory.

In order to do this, the framework puts forward the idea of constructing the **typologies** of territories and regions in a country based on the three key layers presented earlier. The layers reflect:

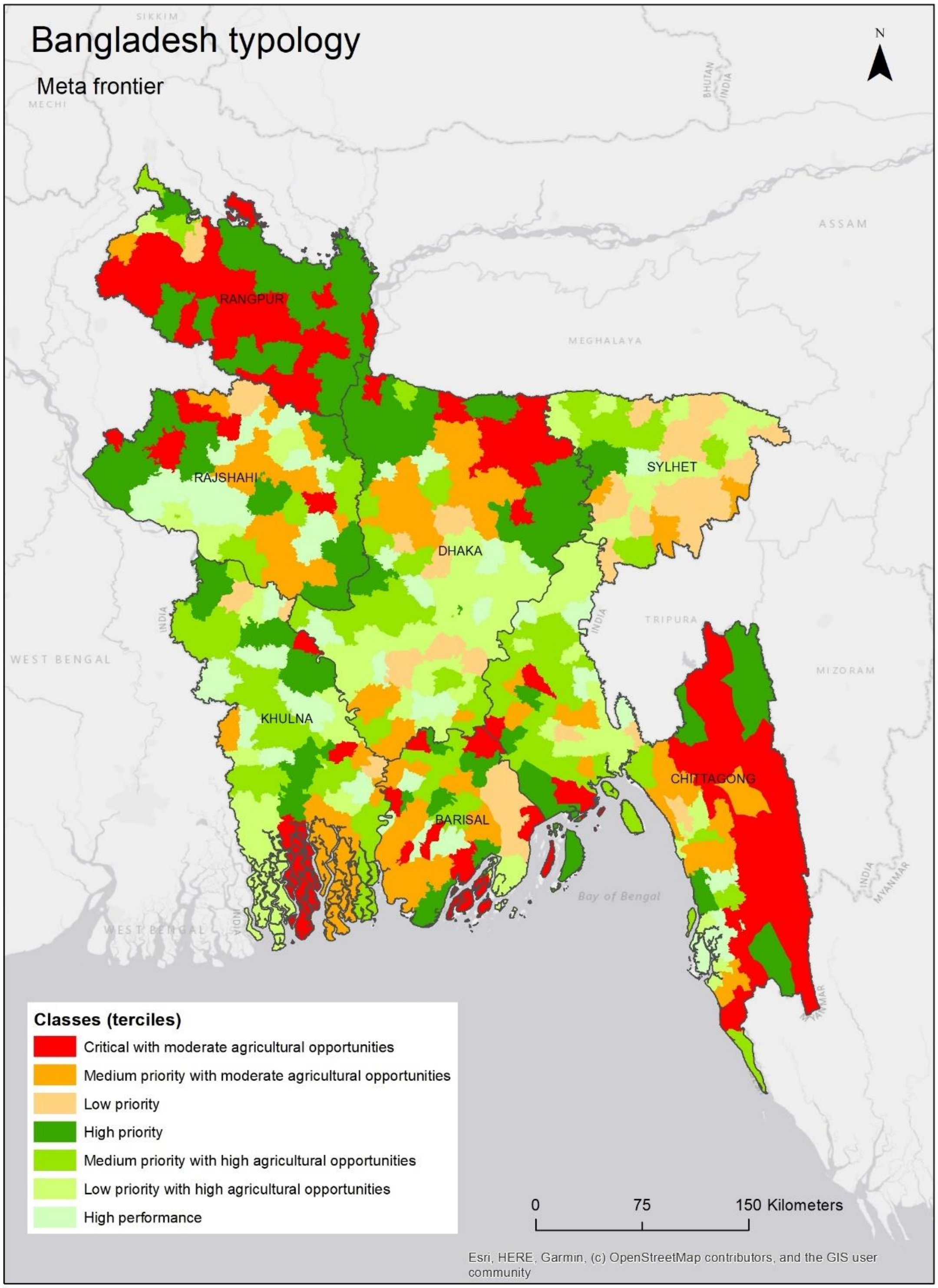
1. The urgency of intervening as approximated by the poverty, hunger and/or malnutrition (and/or their severity) maps.
2. The agricultural potential of the territories in terms of possibilities to leverage unexploited revenues or profits.
3. The efficiency of farmers and producers to make the best in terms of revenues or profits given the market conditions they face but also their practices, skills, knowledge, and experiences in farming and engaging with markets.

The output of this overlaying exercise is presented in Figure 8 and the typologies by subsector are shown in figure 9. Figure 10 provides guidance on how the different colors of the map are interpreted.

Intuitively, the conceptual framework relies on the assumption that regions with medium to high agricultural potential and characterized by high poverty should be prioritized for agricultural interventions. On the other hand, in regions with moderate agricultural potential and/or moderate levels of poverty, agricultural investments are not necessarily and absolute less urgent and it may be best to target these regions with investment in other sectors.

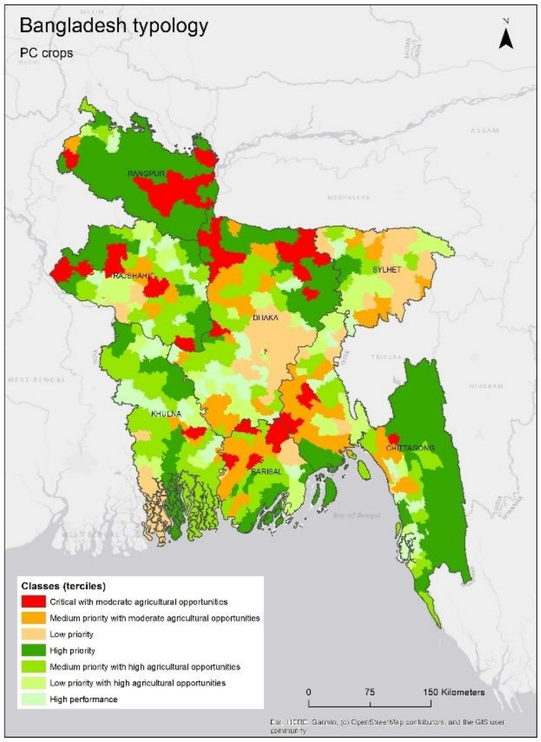
The following section elaborates on the possible or candidate policy bundles that are to be considered in supporting the design and development of HiH supported programmes in different regions and territories.

Figure 8: Agricultural typologies map



Source: Stochastic frontier analysis FAO-HiH task force (2021)

Figure 9: Agricultural typologies map by subsector



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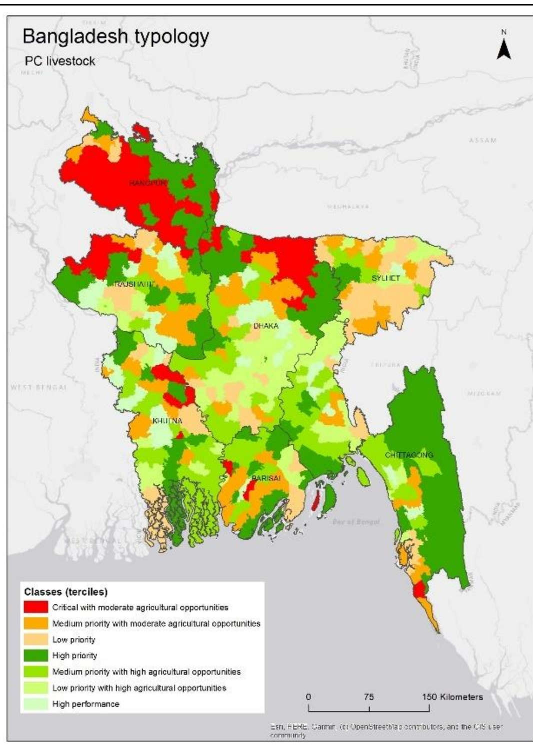
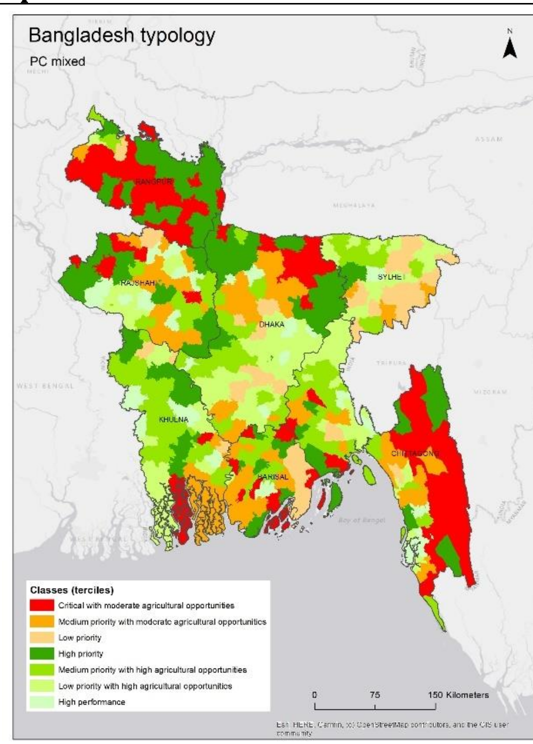




(b) Livestock	(c) Mixed

Stochastic frontier analysis FAO-HiH task force (2021)

Figure 10: List of typologies

	Poverty	Potential	Efficiency
Critical with moderate agricultural opportunities	High	Moderate	Any
Medium priority with moderate agricultural opportunities	Medium	Moderate	Any
Low priority	Moderate	Moderate	Any
High priority	High	Medium / High	Medium / Moderate
Medium priority with high agricultural opportunities	Medium	Medium / High	Medium / Moderate
Low priority with high agricultural opportunities	Moderate	Medium / High	Medium / Moderate
High performance	Moderate	Medium / High	High

Source: Maruyama et al. (2018)

5. Linking the typologies to the design HiH programme supported interventions

The typology of regions and territories indicate bundles of policy interventions to consider and support the design of Hand in Hand supported programmes. Different policy bundles are to be suggested depending on the typology classification, and aim to address needs and challenges facing each region or territory.

Before moving into the description of the suggested policy bundles, a number of points are made to facilitate interpretation.

In first, regions and territories that concentrate poverty, hunger and malnutrition and display high inequality and exclusion for vulnerable population groups, remain the key target locations for Hand in Hand programmes.

Secondly, all regions and territories within the country are of priority. The typologies indicate policies to consider that will support:

i) Exploiting agricultural potential if it is not fully exploited;
ii) Enhancing further or expand the potential even if it is currently fully exploited with interventions that will bring additional value added;

iii) Creating potential in regions or territories where current agroecological or other conditions may indicate that there no potential;
iv) Applying policy bundles that address emergencies or critical conditions in regions in crises or conflict.

Finally, complementary assessment using national and local expertise is necessary in order to validate and contextualize the resulting typologies. Despite the fact that the most advanced and sophisticated techniques and data are used to develop the typologies, the need to cross-reference with expertise at country and local levels is indispensable to complement and guide the design of programmes, policies, projects, interventions and investments. In this aspect focus group discussions with national experts, government officials, key players in the agriculture and food systems and the value chains, regional and local experts and authorities, including field missions have to be integrated in the effort to identify interventions and policies.

After the above points, we continue with a more elaborate presentation of suggested policy bundles by typology of regions or territories. In the approach, interventions in regions and territories are broadly classified as follows:

1) Interventions for areas with moderate agricultural opportunities;
2) Interventions on areas of high agricultural opportunities; and
3) Interventions on high performance areas.

Below each set of interventions is described further. Along with examples of how interventions could be adjusted to reflect and consider prevailing conditions in each territory in terms of poverty agricultural potential and efficiency. For a general summary please refer to Figure 11.

It is important to note that just as the maps presented in the previous section, the different policy bundles described in this one are for guidance only. They should be corroborated, validated, enhance, adapted, and tailored to the country's context at subnational level.

a. Interventions for areas with moderate agricultural opportunities

The set of interventions in areas with moderate agricultural opportunities should be differentiated between short-term and long-term investments. Short-term interventions must be prioritized where poverty levels are high but agricultural potential is moderate. Long-term ones must be considered for all areas with moderate potential regardless of their poverty and efficiency levels.

The purpose of the short-term interventions is to alleviate poverty not necessarily relying on agricultural-based policies. Instead, investments must be focused on protecting the poorest of the poorest covering the areas that had been proven to be more effective: social assistance, labour market, and social insurance.

For social assistance, conditional or unconditional cash transfers have proven to alleviate poverty and vulnerability in the short-term very effectively by raising and smoothing incomes. Also, social pensions provided by the state can help to reduce vulnerability of the elderly. In addition, economic and livelihood asset transfers known as in-kind transfers to households facilitate income generation. Also, they can support nutrition with programs such as school feeding. Finally, public work programs that provide jobs in infrastructure in exchange of cash or food are effective in generating income.

Active and passive labour market interventions are also valuable tools to alleviate poverty in the short-term. Active interventions such as job centres, specific training and policies aimed at the unemployed and most vulnerable, can facilitate and incentivize them to find jobs and generate skills different from agriculture. Passive interventions are aimed to workers and employers. They include changes in labour legislation, maternity benefits, injury compensation, and sickness benefits.

Finally, social insurance includes formal insurance schemes, such as contributory pensions, health, unemployment or disaster insurance, and funeral assistance.

As mentioned earlier, regardless of their technical efficiency and poverty levels, areas with lower levels of potential require investments to increase their agricultural opportunities in the medium and long-term. This is particularly important as Hand in Hand countries are characterized by having a significant agricultural sector, with large portions of the population living in rural areas and being employed in agricultural activities. Therefore, investing in agriculture is a valuable opportunity for increasing returns in the agricultural sector in the long term.

Public spending on agricultural research and development (R&D) has proven to generate high rates of return in developing and developed countries. Recent studies suggest that per USD 1 invested in agricultural R&D, society gains approximately USD 10 in benefits (Alston et al., 2020). Not only R&D have improved factor productivity by increasing yields, but with the climatic challenges ahead, R&D must focus on easing the challenges of climate change. Therefore, R&D in agriculture becomes crucial to increase the agricultural opportunities of regions inside the country. Also, it is important to consider that investments in R&D payoff in the long-term. Accounting for results may take a significant period of time, therefore investments in this area should be steady and sustained (Alston et al., 2020).

Agriculture R&D involves a set of broad and numerous interventions, activities, and innovations. Specific interventions that can be considered for areas with limited agricultural potential can be (but not limited to): developing hybrid and inbred seeds with improved yield potential and higher drought resistance, biofortifying crops to improve vitamin and mineral deficiencies in the population, breeding programs and distribution, adoption of natural resource management and climate smart agriculture, improving water-use efficiency, promoting genetic resource management, improving market information systems, development of animal vaccines, environmentally beneficial cattle, among others (Von Braun et al., 2008).

Finally, investments in infrastructure are crucial to increase agricultural potential. Inadequate infrastructure can significantly hinder productivity and development of the rural sector. While different types of infrastructure support development of the rural sector, such as electricity and roads, the scope of the program focuses on the creation of irrigation infrastructure. Developing irrigation at a small scale is key to generate improvements and increase potential in the medium-term.

b. interventions on areas of high agricultural opportunities

Conversely, the areas where the agricultural potential is medium-to-high, but efficiency levels (i.e. how close to your potential you are) are low, should be targeted with more specific agricultural interventions in order to allow these regions to reach their full potential. There are different policy interventions that could allow agricultural transformation in the short and the long-term: efficient supply chains, sustainability standard and practices, and innovation and technology.

Efficient supply chain policies are targeted to include rural and small households into the supply chain with commercial smallholders, and SMEs. Also, policies can be targeted on improving the supply chains by enhancing efficiency of processing, storage, transportation, and logistics of food, with a special emphasis on reducing food loss. Finally, improving existing policies can reduce distortion and increase incentives for private sector participation.

For sustainability standards and practices, climate smart agriculture practices can increase productivity, ease the pressure on natural resources, adapt and build resilience to climate change, and reduce greenhouse emissions. In addition, implementing global standards can ensure efficient use of land, water, and labour.

Innovation and technology rely on the same principles as the ones discussed in the lower potential regions regarding R&D development. As mentioned, innovations and technology not only increase productivity, but they are becoming crucial to face the challenges all regions will face due to climate change. In this case, innovation and technology can help in improving traceability, disease control, and nutrition. Also, innovations in business and financial models will help provide better services not only to farmers and smallholders but to all value chain actors.

c. High performance areas

Finally, in those regions that are already doing well (compared to the other regions inside the country), the focus should be on policies that promote higher-value products and ensure higher prices to farmers for their output. This includes orientation to international markets for export increase, certifications and organic production for higher premiums, and financial inclusion. This last one should be focused on providing return on profits savings, access to credit to expand access to inputs, land, and non-farm related businesses.

In addition, the high-performance areas represent cases to evaluate, learn and if possible, replicate in other regions and even countries. Therefore, evaluating the best practices of these regions becomes a priority in the public agenda. First it is essential to identify the contributions agriculture has made to reduce poverty. It can be done by designing and implementing impact evaluations and assessments to gather rigorous evidence. Then processes and implementation of successful practices should be documented along with bottlenecks and points for improvement. Finally, the learning process must be a valuable resource that enables south-south cooperation. The development of a web-based knowledge platform for within country and south-south learning, as well as an e-learning centre to share best practices can be considered.

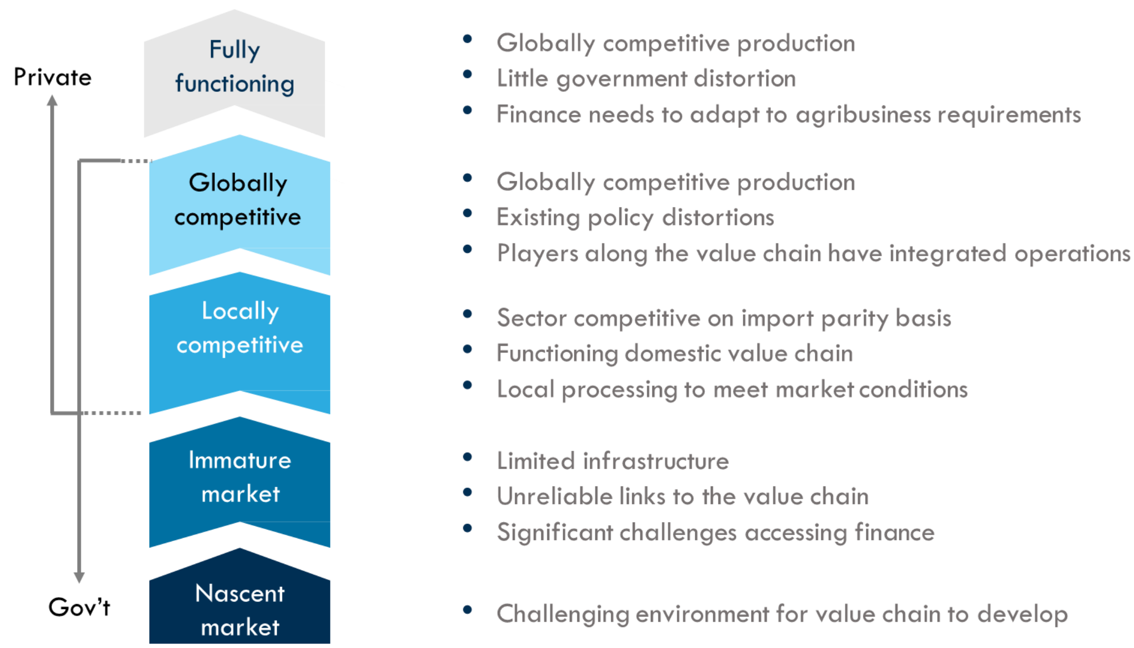
Figure 11: Typologies and example interventions

<table>
<tr><th>Typology class</th><th>Description</th><th>Examples of recommended innovations</th></tr>
<tr><td>Critical</td><td>High poverty, moderate potential</td><td>Long-term investments in agriculture such as funding R&D activities to generate technological changes and major investments in infrastructure.
Short-term assistance programs such as conditional cash transfers that incentivize human capital investments are recommended.</td></tr>
<tr><td>High priority</td><td>High poverty, medium/high potential, medium/moderate efficiency</td><td rowspan="3">Reduction in market access costs through road improvements and price information systems (ICTs).
Innovations that allow for improved access to inputs and extension services.
Innovative inclusive financial instruments to allow for savings of harvest income towards investments in next season's production, credit for working capital, and insurance to mitigate risk of adopting new technologies
Strengthening of horizontal and vertical integration institutions that provide better access to markets to smallholders such as farmer groups and contract farming arrangements
Medium and small-scale productive infrastructure investments such as mini-irrigation projects and land management projects.</td></tr>
<tr><td>Medium priority with high agricultural opportunities</td><td>Medium poverty, medium/high potential, medium/moderate efficiency</td></tr>
<tr><td>Low priority with high agricultural opportunities</td><td>Moderate poverty, medium/high potential, medium/moderate efficiency</td></tr>
<tr><td>High performance</td><td>Moderate poverty, medium/high potential, high efficiency</td><td>Orientation to high values and export markets.
Certification and organic production to obtain higher premiums from agricultural production.
Increased financial inclusion to allow for higher returns on profit savings, credit to purchase additional land and expand farm and non-farm businesses.</td></tr>
</table>

Source: Maruyama et al. (2018)

Finally, the suggested interventions mentioned above can be implemented by private actors, as well as public ones. A continuous collaboration between both parts is illustrated along the continuous market model shown in Figure 12. This is a useful guide to identify which type of interventions (public or private) are more appropriate, depending on the stage of national and subnational markets. As stages of market development are identified before the interventions are designed, public interventions should be aimed at markets with challenging conditions for value chain development. On the contrary, once markets and value chains are more competitive, the private support is crucial for its expansion and full development.

Figure 12. Market segmentation model for identifying interventions



Stochastic frontier analysis FAO-HiH task force (2021)

6. Recommended suitable locations for storage or processing units[3]

Identifying where supply links with demand along the length of food supply chains indicates where interventions and investments can support agricultural transformation and rural development while bringing income growth and contributing to poverty alleviation.

In every country, links of actors in food systems with national but also intra- and inter-regional markets, are identified through the input side (seasonal hired labour and purchases of fertilizers, seeds and other chemical inputs) and in the output side (trade, processing, storage and distribution of food, crops, livestock and dairy products).

This section documents a raster-based Geographical Information Systems - Multicriteria Decision Analysis (GIS-MCDA) proposal, for the calculation of optimal scores (Ribeiro 2021a,b,c) that support the identification of recommended locations for storage (warehouses, mobile warehouses or cold storage), or processing units (agro-industries).

The proposed modelling variables/criteria are the main transportation network infrastructure, human population density and production (livestock, crops or groups of

[3] Section based on Ribeiro (2021a,b,c)

crops varying by country). A raster-based travel time cost analysis was developed using transportation infrastructure data and relevant services like access to financial services (bank locations) or access to IT (internet access) are also incorporated.

GIS multicriteria decision analysis GIS-MCDA consists of a method to convert and combine spatial data/geographical information and decision-makers' criteria to attain evidence for a decision-making process. GIS capabilities are enhanced by MCDA procedures, techniques and algorithms for structuring decision problems, design, evaluate and prioritize alternatives.

The general data dimensions specified were the following:

1. Infrastructure:
   a. ports
   b. electricity grid or average lights
   c. railways, primary and secondary road network
   d. waterways

2. Access to IT:
3. Access to finance:
   a. bank locations
4. Market access:
   a. cities and travelling time to cities
5. Population and other socioeconomic information:
   a. Population density
   b. Socioeconomic information.
6. Production dimension (commodity or groups of commodities).

The analysis is developed for each product, commodity, or groups of commodities, by integrating the maps (layers of information). The layers support assessing suitable locations for storage and processing units in relation with prompt timing to transport food to downstream links of the chain and markets, and so must be:

- Connected with transportation infrastructure (roads, railways, airports, seaports, waterways)
- With access to:
  - energy (electric grid)
  - communications (mobile broadband coverage)
  - finance (banking locations).
- In production areas or regions.
- In regions with high poverty incidence.

Data on energy, communications or finance access might not be available for all Hand-in-Hand countries.

Two major processing steps lead to the final recommended locations or sites:

Step 1: Location Score - Overlaying the diverse layers (factors or criteria) a score is estimated, theoretically varying from 0 minimum, to 100 maximum.

The score is obtained by means of a simple weighted sum of layers (factors, criteria), e.g.:

*("Crop Production" * 0.4) + ("Human Population Density" * 0.2) + (“Major Cities Accessibility” * 0.1) + (“Regional Cities Accessibility” * 0.1) + (“Ports Accessibility” * 0.1) + ("Asset Wealth Index" * 0.1)*

Different weighting and criteria might be used for distinct value chains and agroecological zones, but also according to country data availability.

An example of the weighting for each of the criteria for livestock and dairy products can be as follows:

*("Crop Production" * 0.3) + ("Human Population Density" * 0.1) + (“Major Cities Accessibility” *0.2) + (“Livestock Intensification” * 0.4)*

The livestock intensification layer is created using animal density and livestock production systems (Robinson et al., 2011).[4] The selected livestock production systems vary from country to country, depending on existing agroecological zones.

All data layers are normalized, ranging from 0 to 100. A higher number indicates higher production or population density, but accessibility layers are inversely normalized, higher numbers indicate higher accessibility, lower travel time or cost.

The location score map output is a raster grid covering the country with a value for each cell (pixel).

Step 2: Final Recommended Locations - Top score areas are selected using a high percentile threshold, and then final locations selected overlaying financial services (bank buffer distance), mobile broadband internet coverage and maximum distance to a major road. It is noted that, some highly productive areas might not be recommended locations lacking good cellular coverage, being distant to banks or major roads, but in some cases by a very short distance.

A full adoption of the multi-criteria decision analysis methodology can lead to re-running and recalculating both the location score and final location, the modelling can be used as a what-if scenario tool, generating as many different outputs as the defined thresholds, helping to refine areas and enhancing the location decision-process communication. The analysis results and further links to all metadata, data and methodology are presented in the Appendix B.

[4] Example of selected Livestock Production System (Country_LPS) = (7: MR Mixed Rainfed Humid) + (8: MR Mixed Rainfed Temperate) + (9: MI Mixed Irrigated Hyperarid) + (10 = MI Mixed Irrigated Arid) + (11: MI Mixed Irrigated Humid) + (12: MI Mixed Irrigated Temperate) + (13: Urban).

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7. Appendix A – Description of the methodology

A.1 Introduction

Intuitively, this conceptual framework relies on the assumption that regions with medium to high agricultural potential, medium/high inefficiency and characterized by high poverty levels should be prioritized for agricultural interventions. However, from a practical perspective, there are four important methodological aspects challenges, associated with this approach, namely:

1. **Defining potential and inefficiency.** Conceptually, potential can be measured in a number of different ways, and it is important to be clear in the definition of potential used, as this can have an effect on the ultimate result of the mapping.

2. **How to estimate potential and inefficiency.** As highlighted in the main document, potential and inefficiency are two key variables driving the maps. However, these variables are not observed and therefore need to be estimated. This is where we need to use stochastic frontier analysis to do this.

3. **Mapping the whole country.** Not all regions will be part of a sample and therefore, in order to obtain estimates of potential and inefficiency, there is a need to use the statistical relationship identified at the household-level and extrapolate this relationship using small area estimation

4. **Defining "High", "Medium" and "Low".** In order to implement the methodology, it is important to be able to split each variable into "High", "Medium" and "Low". Methodologically speaking, there are a number of ways in which we can create these three groups and we need to use either clustering algorithms or pre-determined quantiles to create these three categories

This appendix section will thus start by describing the stochastic frontier method. Then it will briefly explain the Maruyama et al. (2018) approach and focus how it deals with the four challenges highlighted above.

A.2 A brief description of stochastic frontier method

The two most commonly used methods to estimate the efficiency of production units are data envelopment analysis (DEA) (Charnes et al., 1978; 1981) and Stochastic Fronteir (SF) analysis (Aigner et al., 1977; Meeusen and van den Broeck, 1977; Khumbakar and Lovell, 2000). DEA is a non-parametric approach that uses linear programming to identify the efficient frontier, while SF analysis is a parametric approach that hypothesizes a functional form and uses the data to econometrically estimate the parameters of that function. Both methods measure efficiency as the distance between observed and maximum possible (frontier) outcomes, but the key advantage of SF analysis for our purposes is that it allows to separate random noise in the error term from the actual efficiency score. This is an important feature when analysing agricultural activities, which are constantly exposed and extremely sensitive to (negative and positive) random shocks, including but not limited to droughts and variation in prices.

In the SF approach, inefficiency is defined as the loss incurred by operating away from the frontier given the current prices and fixed factors faced by the household. By estimating where the frontier lies, and how far each producer is from it, the stochastic frontier approach helps to identify local potential and efficiency levels to construct the typology.

Using the basic model proposed by Aigner et al. (1977) and Meeusen & van den Broeck (1977), the single output stochastic frontier production function is defined as:

$$\mathrm{y_i} = \mathrm{f}(\mathbf{x}_\mathrm{i}, \boldsymbol{\beta})\exp(\mathrm{v_i} - \mathrm{u_i}) \tag{1}$$

Where $\mathrm{y_i}$ is the production for farmer *i*, $\mathbf{x}_\mathrm{i}$ is a vector of inputs for farmer *i*, such as land, labour, etc., $\boldsymbol{\beta}$ is the vector of technology parameters associated to the inputs of production, $\mathrm{v_i}$ is an iid random error distributed as a $N(0, \sigma^2)$, representing random factors that are not under the farmer's control, and $\mathrm{u_i}$ is a non-negative random variable associated with factors that prevent farmer i from being efficient. Aigner et al. (1977) assumed a half-normal distribution, that is, $\mathrm{u_i} \sim N^+(0, \sigma_u^2)$, while Meeusen and van den Broeck (1977) opted for an exponential one, $\mathrm{u_i} \sim \mathrm{E}xp(\sigma_u)$. Other commonly adopted distributions are the truncated normal (Stevenson, 1980) and the gamma distributions (Greene 1980a,b, 2003).

Given the frontier production of farmer i is $y_i^* = \mathrm{f}(\mathbf{x}_\mathrm{i}, \boldsymbol{\beta})\exp(\mathrm{v_i})$, their technical efficiency can be defined as:

$$\mathrm{TE_i} = \frac{y_i}{y_i^*} = \frac{\mathrm{f}(\mathbf{x}_\mathrm{i}, \boldsymbol{\beta})\exp(\mathrm{v_i} - \mathrm{u_i})}{\mathrm{f}(\mathbf{x}_\mathrm{i}, \boldsymbol{\beta})\exp(\mathrm{v_i})} = \exp(\mathrm{u_i}) \tag{2}$$

A very important issue in SF analysis is the inclusion in the model of exogenous variables that are supposed to affect the distribution of inefficiency. These variables, which usually are neither the inputs nor the outputs of the production process but nonetheless affect the productive unit performance, could be incorporated in a variety of ways: i) they may shift the frontier function and the inefficiency distribution; ii) they may scale the frontier function and the inefficiency distribution; and iii) they may shift and scale the frontier function and the inefficiency distribution. Kumbhakar and Lovell (2000) stress that the presence of unobservable heterogeneity in $\mathrm{u_i}$ and $\mathrm{v_i}$ may affect the inference in SF models. Indeed, while neglected heteroskedasticity in $\mathrm{v_i}$ does not produce any bias for the frontier's parameter estimates, it leads to biased inefficiency estimates.

A natural starting point for introducing exogenous variables in the model is in the location of the inefficiency distribution. The most well-known approaches are those suggested by

Kumbhakar, Ghosh, and McGuckin (1991) and Huang and Liu (1994). They proposed to parameterize the mean of the pre-truncated inefficiency distribution:

$$\mathrm{u_i} \sim N^{+}(\mu_i, \sigma_u^2) \tag{3}$$

$$\mu_i = \boldsymbol{z_i}\varphi \tag{4}$$

Where $\boldsymbol{z_i}$ is a vector of farmer-specific factors affecting their performance.

Similarly, Caudill & Ford (1993) and Caudill et al. (1995) showed that in presence of heteroskedasticity in $\mathrm{u_i}$, its distribution will not be the same for all the observations in the sample and a correction for heteroskedasticity needs to be made by parameterizing the variance of the pre-truncated inefficiency distribution in the following way:

$$\mathrm{u_i} \sim N^{+}\left(0, \sigma_{u_i}^2\right) \tag{5}$$

$$\sigma_{u_i}^2 = exp(\boldsymbol{z_i}\varphi) \tag{6}$$

To estimate the model expressed by equations (1)-(6) it is necessary to address the fact that farms are multi-output production units, making it necessary to move from a single output production function to a profit function approach. The SF profit function can be expressed as:

$$\pi_\mathrm{i} = \mathrm{f}(\mathbf{p}_\mathrm{i}, \boldsymbol{w}_i; \boldsymbol{\beta})\exp(\mathrm{v_i} - \mathrm{u_i}) \tag{7}$$

where □□ and □□ are output and input price vectors, respectively. When adequate data on farming costs and/or input prices ($\boldsymbol{w}_i$) are not available, the dependent variable of equation 7 will be replaced by the farmer's revenues and not profit. In this case, the estimation will return a revenue frontier.

Beyond the data on input and output prices, in the agricultural context, it is also necessary to consider other production factors, such as climatic conditions and land cover, that affect the farm's potential, but cannot be easily modified in the short or medium term. For this reason, the farm's frontier is adjusted using GIS data on agroecological zones (or agricultural land cover types) and weather conditions. These variables are introduced as shifters of the deterministic portion of the frontier so that equation (7) becomes:

$$\pi_\mathrm{i} = \mathrm{f}(\mathbf{p}_\mathrm{i}, \boldsymbol{w}_i, LU_i, WS_i; \boldsymbol{\beta})\exp(\mathrm{v_i} - \mathrm{u_i}) \tag{8}$$

Where LU_i and WS_i represent – respectively – the different land cover types (shown in Figure 1 in the main document) and weather conditions (or value of vegetation indices) faced by the farmers.

A.3 A brief description of Maruyama et al. method

In the original Maruyama et al. (2018) model, equation (8) is estimated at the household level with cross-sectional data (i.e. one wave) and limiting the analysis to the sub-sample of farmers that participate in the market (i.e. farmers who do not sell to the market are excluded from the estimation).

A.3.1 Defining potential

Importantly, this means that the potential is defined in terms of **market revenues or market profits.** The key benefit of using a monetary metric is that it allows the aggregation of different products and sub-sectors, which enables the computation of an overall agricultural potential. However, it is very important to highlight that the focus on revenues/profits also means that, due to market conditions, the agronomic potential, while related, may not be fully aligned to the agronomic potential. This becomes very important when interpreting the maps.

A.3.2 Estimating potential

Given the use of profits/revenues as the main outcome variable, the authors then estimate following equation:

$$\ln\frac{\mathrm{\pi_i}}{\mathrm{p}} = \delta_o + \sum_n \delta_n \ln\frac{w_n}{p} + \sum_q \delta_q AEZ_q + v_i - u_i \tag{9}$$

We can break down equation (9) above in different components, namely:

1. Dependent variable ($\frac{\mathrm{\pi_i}}{\mathrm{p}}$) is the log of normalized profits[5] (i.e. divided by the price of one output).

2. Determinants of the frontier (or agricultural potential):
    a. A constant δ_o
    b. Normalized unit prices of outputs and inputs ($\frac{w_n}{p}$). In principle, higher input prices will lead to lower profits whereas the opposite holds true for output prices. In practice, since only revenue frontiers are estimated in the Maruyama et al. (2018) paper, only output unit prices are used. In the case of a profit frontier, however, it is important to also include input costs.
    c. Proportion of land in given administrative unit covered by a given land cover (AEZ_q) – We expect different land cover (e.g. crop land, forest, barren land, water bodies, shrublands and savannah) to affect the frontier in different ways.

[5] In practice, Maruyama et al. 2018 only estimate revenue frontiers due to the challenges of estimating profit frontiers (e.g. log of 0 not being defined).

3. Inefficiency term u_i – In the inefficiency term, the original methodology the authors included a number of determinants of inefficiency which are expected to affect how distant from their frontier a given household will be. These typically included the market accessibility, ownership of agricultural equipment, labour availability (proxied by household size), education and the gender of the head of the household.

4. The random error term v_i

A.3.3 Mapping the whole country: Going from the household-level to an administrative area

For this part of the method, a methodology known as Small Area Estimation (SAE) is used. The starting point for the mapping exercise is the estimated statistical relationship in equation (9), which is estimated at the household-level.

We then use the same variables at a higher-up administrative level (either zonal averages or medians, depending on the variable) and then use the estimated coefficients to generate a prediction of potential an inefficiency by administrative area. GIS variables are observed and representative. For household-level variables, ideally, these would come from census data which is generally representative at a low administrative level. However, the absence of comprehensive recent census data often forces analysts to use averages from the samples used to estimate the statistical relationship instead.

A.3.4 Defining "Low", "Medium" and "High"

As highlighted in Figure 10, the typology methodology requires us to define, for each variable, what can be considered as "Low" (moderate), "Medium", and "High". Here we rely on clustering algorithms or on breaks based on pre-defined quantiles of the data.

Specifically, after the potential and inefficiency has been predicted for every administrative level, the approach essentially creates three separate clusters for each variable, either based on a k-cluster means algorithm or using the tercile method. In simple terms, the k-cluster means algorithm is an algorithm that seeks to minimize the within-cluster differences while maximizing the across cluster differences. The main difference between the k-mean cluster algorithm and the tercile method is that while the latter always implies that the "low", "medium" and "high" groups have the same number of observations, the same is not always the case for the k-means algorithm.

A.4 Introducing the concept of a stochastic Metafrontier

One of the weaknesses of stochastic frontier in the original Maruyama et al. (2018) is that it is unable to distinguish between sector-specific inefficiency and lack of sectoral potential because the same frontier applies to all farmers, irrespective of the subsector they are engaged in (crops, livestock, and mixed systems). One way to address this concern is to use a stochastic meta-frontier approach.

This approach effectively consists of two steps:

In the first step, instead of estimating equation (9) for the full sample directly, we estimate equation (9) by sub-sample (i.e. crops, livestock and mixed systems). We then obtain a predicted frontier for each farmer and re-estimate equation (9) for the full sample. This step gives us a sector-specific frontier and a farmer-sector-specific inefficiency term (i.e. how far a farmer is from his peers in his subsector)

In the second step, we use the predicted frontier values for the farmer specific frontier and re-estimate equation using predicted farmer-specific frontier for the full sample. Since we use the predicted frontiers that take into account the sub-sector the farmers work in, the predicted inefficiency from this equation, also known as the technical gap ratio (TGR), provides a measure of how far the sector-specific frontier is from the overall frontier.

This approach has two main benefits. First, it allows maps to be derived for different sub-sectors, which may have very different potentials in different regions. Second, the computation of the TGR, to a certain extent, also allows us to have an idea of how much of the overall inefficiency is driven by farmer-specific inefficiency versus sectoral inefficiencies.

The main challenge when applying the Metafrontier in this context is the extrapolation of potential. In our case, for the potential variable, we use the potential from the highest-performing sub-sector as the potential variable for the meta-frontier and for the technical efficiency we use the Meta technical efficiency (MTE) score which, in the case of the maps, is defined as the inefficiency of the sector with the highest potential multiplied by the predicted TGR for this sub-sector.

A.5 – Applying the methodology to Bangladesh

A.5.1 – Data sources

In Bangladesh, we used three data sources to produce the maps, namely:

1. **Household-level and crop and livestock data –** All household variables, crop and livestock prices were obtained from Bangladesh Integrated Household Survey: Round 3 2018-2019, developed by the International Food Policy Research Institute (IPFRI).
2. **Geospatial data –** Geospatial data was obtained from MODIS for land-use data. NDVI was sourced from Terra, while elevation was sourced from NASA. Precipitation data was obtained from CHIRPS.
3. **Poverty data –** Poverty Maps Bangladesh 2016 - Bangladesh Bureau of Statistics (BBS)

A.5.2 – Estimation procedure used in Bangladesh

In Bangladesh we used the Stochastic Metafrontier Approach to produce the maps using market profits as the main outcome variable.

In terms of the variables used, as explained in equation (9) we use four sets of variables in the frontier (prices, inputs, land uses and climatic conditions). In the inefficiency term, we assume an exponential distribution and we focus on market access variables, household characteristics and climatic shocks (proxied by the NDVI). The full set of variables and associated coefficients can be seen below:

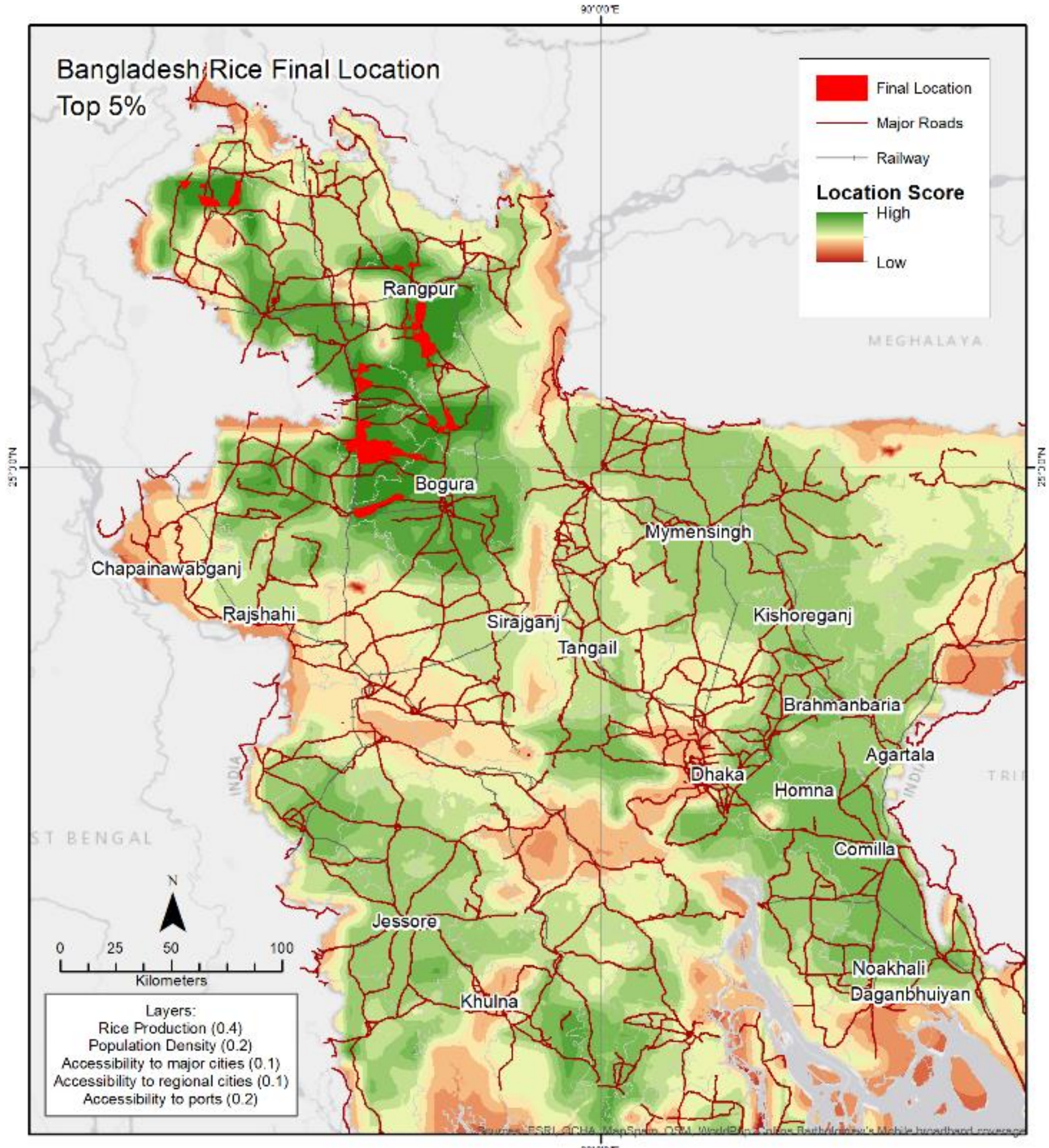
	Crops Frontier	Livestock Frontier	Mixed Frontier	Meta Frontier
	Frontier			
Outputs				
iprice_paddy_use_n	-0.937		0.493	0.330***
	(0.847)		(0.488)	(0.0366)
iprice_jute_use_n	-0.305		-0.938**	-0.996***
	(0.525)		(0.439)	(0.0417)
iprice_mustard_use_n	4.936***		1.360**	1.637***
	(1.323)		(0.571)	(0.107)
iprice_chilli_use_n	-0.287		-0.171	-0.139***
	(0.208)		(0.126)	(0.0134)
iprice_onion_use_n	-0.262		-0.230	-0.276***
	(0.808)		(0.535)	(0.0525)
price_potato_use	-0.0288		0.0282*	0.0155***
	(0.0203)		(0.0167)	(0.00162)
iprice_straw_use_n	0.0931		0.333	0.374***
	(0.601)		(0.451)	(0.0419)
ilvuprice_cow_sell_use_n		0.885***	0.813***	0.813***
		(0.165)	(0.153)	(0.00931)
ilvuprice_goat_sell_use_n		0.303	0.0725	0.0745***
		(0.197)	(0.121)	(0.00900)
lvuprice_chicken_sell_use		8.49e-05	-0.00354***	-0.00341***
		(0.00132)	(0.00103)	(6.02e-05)
ilvuprice_opoultry_sell_use_n		-0.349	-0.139	-0.130***
		(0.296)	(0.202)	(0.0233)
lvuprice_milk_sell_use		-0.00279	-0.00368	-0.00431***
		(0.00630)	(0.00624)	(0.000483)
lvuprice_eggch_sell_use		-0.141	0.0227	0.0182***
		(0.0935)	(0.0755)	(0.00487)
ilvuprice_manure_sell_use_n		2.055	2.952	2.243***
		(3.361)	(3.873)	(0.329)
Inputs				
iucost_urea_kg_use_n	-3.093**		-1.518*	-1.811***
	(1.348)		(0.913)	(0.0966)
iucost_mp_kg_use_n	0.261		-0.564	-0.382**
	(1.387)		(0.506)	(0.158)
iucost_tsp_kg_use_n	-1.131		-0.0832	-0.189***
	(0.813)		(0.643)	(0.0506)
iucost_dap_kg_use_n	-1.641*		0.426	0.274***
	(0.990)		(0.678)	(0.0896)
iucost_hirlab_use_n	0.639		-0.700***	-0.537***
	(0.408)		(0.222)	(0.0204)
iucost_lvstck_feed_use_n		0.179***	0.0874*	0.0764***
		(0.0664)	(0.0451)	(0.00381)
iucost_lvstck_medicine_use_n		-0.000206	0.00591	0.00437
		(0.0601)	(0.0519)	(0.00369)
Constant	11.38***	4.696**	10.06***	10.14***

	(2.446)	(2.194)	(1.466)	(0.165)
Land uses				
% land covered by Savannas	-0.0408***	-0.00130	0.00635	-0.00226***
	(0.00724)	(0.00786)	(0.00741)	(0.000836)
% land covered by Croplands	-0.00695*	-0.00330	0.00127	-0.00257***
	(0.00385)	(0.00328)	(0.00359)	(0.000524)
% land covered by Cropland/Natural vegetation mosaic	0.00413	-0.00153	0.00527	0.00182***
	(0.00527)	(0.00392)	(0.00406)	(0.000564)
ihs_ndvi_cseason_LRm	-0.453	-0.770	-1.824*	-1.075***
	(1.457)	(1.218)	(1.095)	(0.183)
U-sigma				
ihs_hhsize	0.439***	0.121	0.553***	
	(0.124)	(0.237)	(0.206)	
ihs_edu_head	-0.180***	0.0471	-0.0689	
	(0.0365)	(0.0720)	(0.0562)	
Female headed household	-0.151	0.522**	-0.118	
	(0.135)	(0.225)	(0.228)	
ihs_irrigated_land	-0.787***		-0.301	
	(0.224)		(0.301)	
HH received visit from agricultural extension agent	0.0462		0.241	
	(0.197)		(0.230)	
HH uses HYV/Hybrid seed	1.838***		1.060***	
	(0.124)		(0.208)	
ihs_altitude	-0.246***	-0.155		
	(0.0794)	(0.153)		
ihs_time_cities_hr	-0.108	-0.306*	-0.00200	
	(0.0848)	(0.163)	(0.143)	
ihs_ndvi_cseason_dev	0.177	0.165	-0.151	
	(0.295)	(0.594)	(0.441)	
ihs_asset_index		-0.251**	-0.501***	
		(0.124)	(0.0907)	
HH uses improved breeding through artificial insemination		0.635**	-0.231	
		(0.254)	(0.177)	
HH received visit from lvstck/fish extension agent		-0.414	0.120	
		(0.385)	(0.265)	
ihs_cash_assistance			0.0279	
			(0.0720)	
Average monthly ndvi value during the cropping season				-0.0732
				(0.514)
ADM1_PCODE==BD10				-0.198
				(0.149)
ADM1_PCODE==BD20				0.865***
				(0.103)
ADM1_PCODE==BD30				0.145
				(0.0959)
ADM1_PCODE==BD40				0.0485
				(0.104)
ADM1_PCODE==BD45				-0.606***
				(0.125)
ADM1_PCODE==BD50				-0.631***
				(0.126)
ADM1_PCODE==BD55				-0.330***
				(0.125)
Constant	3.844***	3.168***	2.400***	-0.813***
	(0.401)	(0.786)	(0.554)	(0.298)
V-sigma				
ihs_cultivated_land	0.727*		0.917***	
	(0.414)		(0.297)	
ihs_TLU_main		0.614*		
		(0.335)		
Constant	-1.124***	-1.653***	-2.016***	-4.867***
	(0.284)	(0.597)	(0.254)	(0.214)
Observations	1,493	746	1,373	3,612

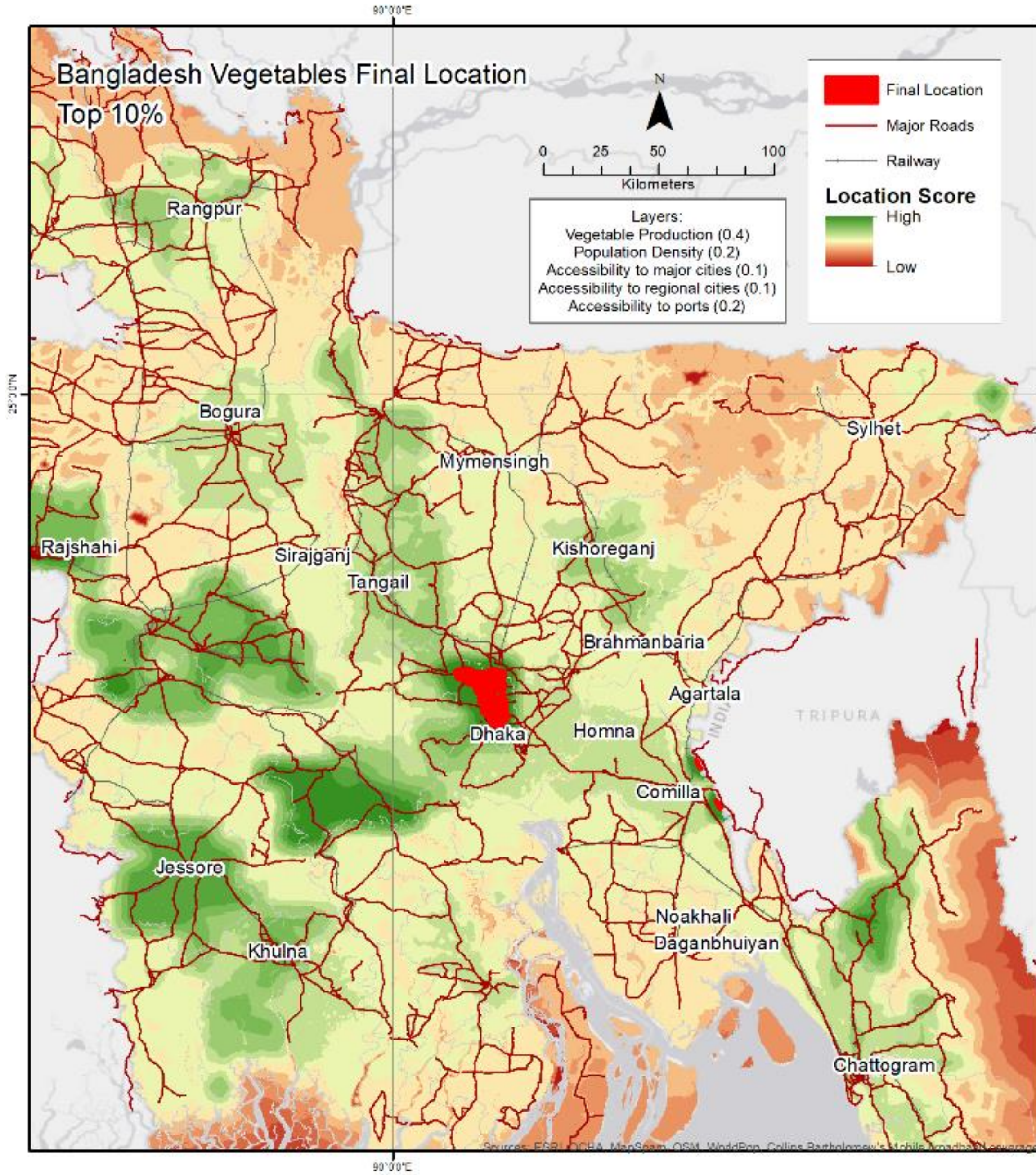
Robust standard errors in parentheses

8. Appendix B – GIS-MCDA Final Location Mapping outputs

Figure 13: Crop Storage Final Locations.

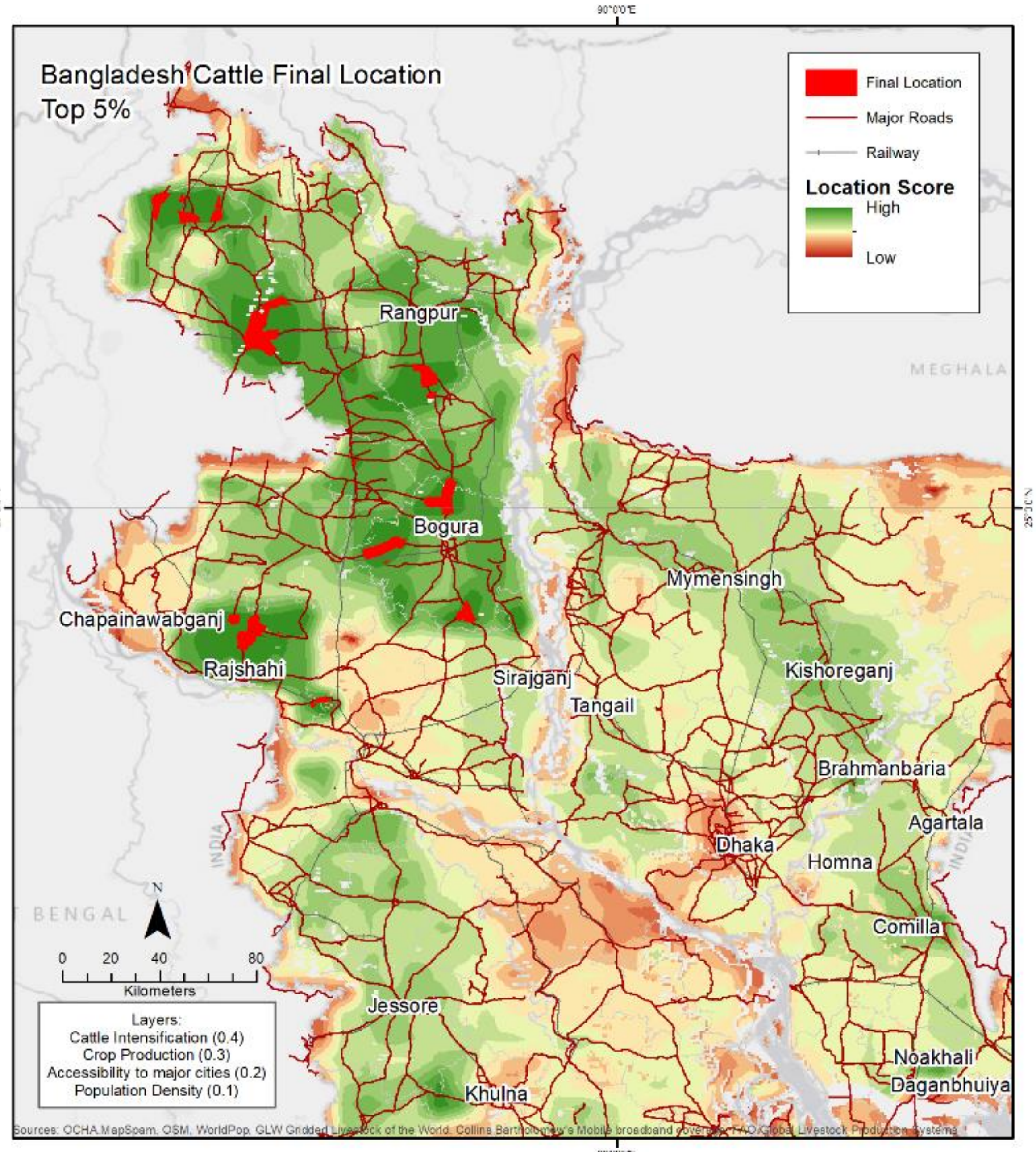


Metadata, data and resources: https://data.apps.fao.org/catalog/iso/816710d9-5262-432c-9064-4ab68256a8b2

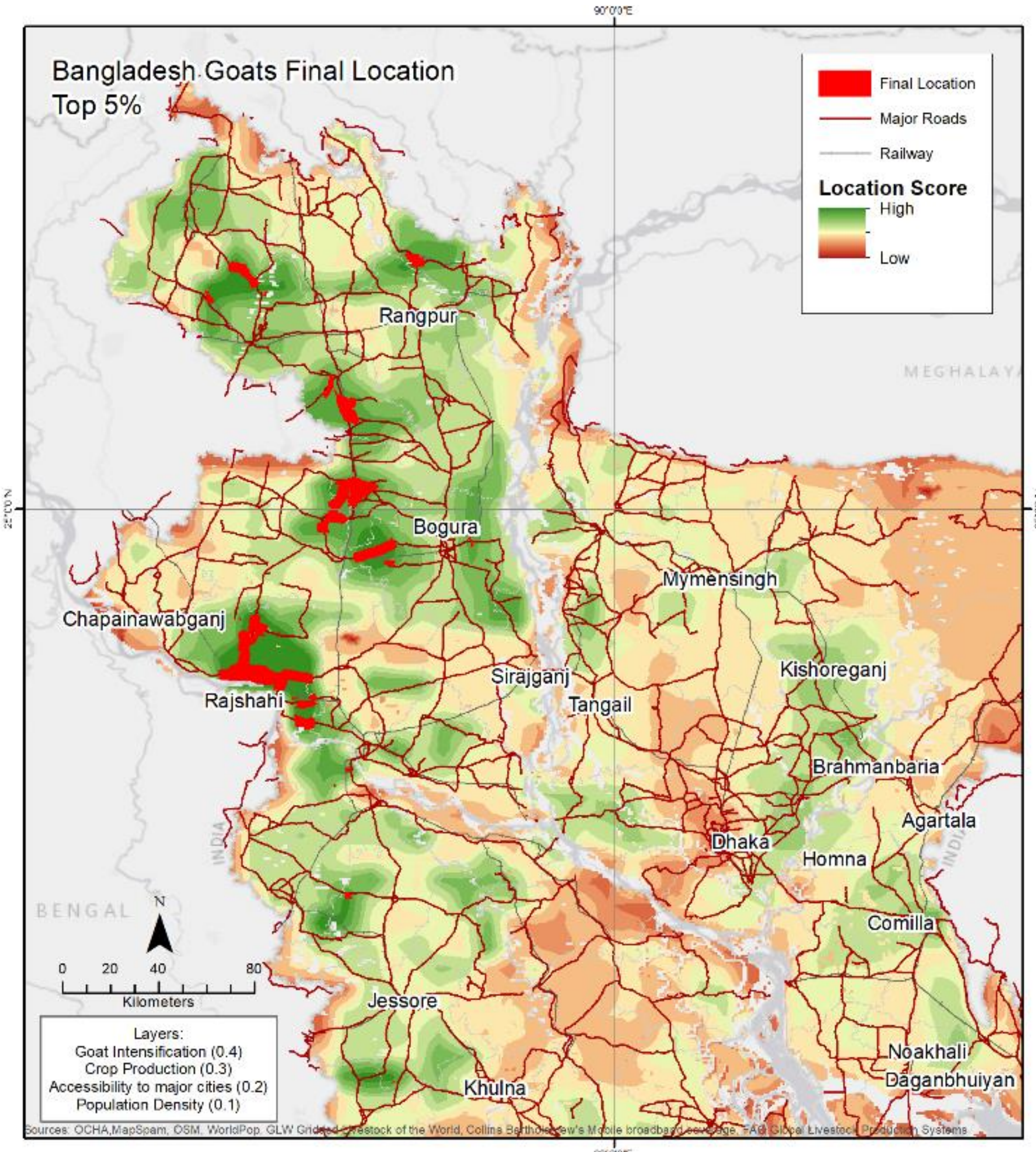


Metadata, data and resources: https://data.apps.fao.org/catalog/iso/1551e261-5cfa-4b9d-8b06-2d19489cbdf6

Figure 14: Dairy Processing Final Locations.



Metadata, data and resources: https://data.apps.fao.org/catalog/iso/16f42fe1-2499-45bc-a932-4d52a2b84287



Metadata, data and resources: https://data.apps.fao.org/catalog/iso/0e833cd5-029e-449a-868f-b57264a5f795