# Spatial organization of food supply in four West African cities

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**Abstract**

As global urbanization accelerates, food security and the resilience of urban supply chains have become critical issues, particularly in West Africa, where the urban population is projected to reach 65.7% by 2050. This study, based on food flow data collected from 2013 to 2017 by Karg et al. (2023), analyzes the spatial organization of supply inflows in four West African cities: Bamenda, Bamako, Ouagadougou, and Tamale. A constraint-based model was developed to assess both the efficiency and resilience of supply chains in response to various shock scenarios, such as climate disruptions or fuel price increases. The results show that several factors—including product type, perishability, geographic origin, seasonal variations, and the specific characteristics of each city—shape the organization of food supplies. These dynamics play a central role in the cities' capacity to maintain stable supplies and adapt to crises, thereby enhancing the resilience of urban food systems. The model calibration will further enable a detailed interpretation of future results through the lens of supply dynamics and resilience.

**Keywords :** Urbanization, Food Security, West Africa, Spatial Organization, Supply Flows (inflows), Constraint-Based Model, Resilience, Supply Chains.

## Introduction

With the acceleration of urbanization, the challenges related to food security and the resilience of urban supply chains are becoming increasingly pressing, particularly in developing countries (Lemeilleur et al. 2019). In West Africa, one of the most urbanized regions on the continent, the urban population has risen from 44.9% in 2011 to a projected 65.7% by 2050 (Karg et al. 2016). This rapid growth poses both quantitative and qualitative challenges for food supply (Moustier et al. 2023), exacerbated by inadequate transport infrastructure, high operational costs, and the vulnerability of food systems to external shocks, such as climate change and economic disruptions. While urbanization is altering consumption patterns, it mainly affects production and distribution systems, increasing the risks of inefficiency, waste, and rising costs.

The growing pressure on urban land, combined with economies of agglomeration and improvements in logistical infrastructure, is pushing supply zones further away from urban consumption centers. This phenomenon, well-illustrated by the Von Thünen model (Huriot 1994), remains relevant in many African countries, where distance plays a crucial role in the organization of agricultural land and the efficiency of supply systems (Moustier 2017).

Although research and policy generally focus on the role of cities as consumption centers receiving food from local, regional, and global hinterlands (Karg et al. 2022), it remains difficult to understand how these cities are actually supplied, where the food comes from, and in what quantities. While FAO food balance sheets provide theoretical estimates at the national level, subnational data remains limited.

In this context, modeling food transport costs has emerged as a promising approach. It stems from the need to ensure adequate food supply for urban populations while minimizing the associated logistical costs.

This study examines the dynamics of food supply flows in four West African cities: Bamenda, Bamako, Ouagadougou, and Tamale. It aims to understand why food comes from varying distances relative to the focal city, by analyzing the role of transportation modes and distance in this process. The supply flows are assumed to be influenced by several factors, including food type, its perishability, origin, seasonal variations, and the size and specific characteristics of each city, while also examining the extent to which these patterns align with or deviate from the Von Thünen theoretical model. Simultaneously, a constraint-based optimization model is developed to assess the efficiency and resilience of supply chains under shock scenarios. The model has been implemented for the city of Tamale, Ghana, with the goal of providing policymakers with analytical tools to enhance the efficiency of food systems and strengthen their resilience to future crises.

This paper is structured as follows: the first section presents a state of the art, focusing on the challenges posed by urbanization, food security, and urban supply in West Africa, as well as relevant economic theories, particularly the spatial organization of agricultural activities and optimization models. The second section introduces the methodology employed. We then present our conceptual model and its mathematical formulation. Finally, we discuss our results and their implications before concluding.

## 1. State of the Art

Rapid urban growth, particularly in West Africa, is profoundly altering food consumption and production patterns, making food systems more vulnerable to disruptions. With rising incomes and evolving dietary habits, supply chains are lengthening and becoming more complex (Karg et al. 2022), thus increasing their exposure to external shocks. At the same time, urban expansion is causing a significant loss of agricultural land due to urban sprawl, which increases pressure on the food supply (Hemerijckx et al. 2023). This reduction in cultivable land, combined with the decreasing number of rural households able to supply cities, presents a major challenge to ensuring adequate food supply for a growing population (Drechsel, Graefe, et Fink 2007).

One of the primary challenges lies in the ability of production systems to keep pace, especially since food policies are often focused on rural areas, while urban authorities prioritize housing and economic development, leaving food management as a secondary concern (Moustier et al. 2023).

The geographic location of economic activities and the phenomena of agglomeration have inspired numerous theories and models, including that of Von Thünen (1826), a pioneer of geographic economics. This model, represented by concentric circles around cities, shows that increasing transportation costs reduce land rent and, consequently, the economic interest of agricultural activities located far from the city center (Huriot 1994). This principle explains why high-value-added activities, such as perishable products, are concentrated in regions close to urban centers, while lower-value-added activities are located in more distant areas (Moustier 2017).

With the development and modernization of logistical infrastructure, distribution systems, and organizational innovations, large cities no longer rely exclusively on their urban and peri-urban agriculture for supply. Supply chains have expanded to local, national, and international levels, becoming broader, more complex, and diversified (Pingali et al. 2019).

The food supply chain is a complex network of interconnected entities, collaborating through various processes and activities to deliver products and services to the market to meet consumer needs (Ahumada et Villalobos 2009). It is divided into two main categories: perishable and non-perishable product chains (Nadal-Roig et Plà-Aragonés 2015). Food supply flows, essential to this network, are influenced by several factors that increase their management complexity, making them harder to control than other types of supply chains (Nguyen et al. 2021). This complexity is particularly heightened for fresh products, where the uncertainties related to limited shelf life impose additional constraints (Soto-Silva et al. 2016).

The evolution of food markets and supply chains highlights the need to improve current management practices (Soto-Silva et al. 2017). A more refined and in-depth assessment of food networks is crucial, as these systems, interconnected between human activities and nature, can have significant environmental repercussions while strengthening food security (Lin et al. 2019). Additionally, a comprehensive analysis of food supply flows on a spatial scale would allow for a better understanding of the vulnerabilities within food systems and enable detailed evaluations to strengthen supply chain resilience in the face of various shocks and disruptions (Lin et al. 2019).

As a result, the adoption of mathematical optimization models is becoming increasingly common to help decision-makers navigate these uncertainties. These models provide tools capable of rationally evaluating and planning for different possible outcomes (Soto-Silva et al. 2016). They allow for the simulation of various scenarios, anticipation of potential problems, and formulation of strategies that maximize efficiency while minimizing risks and costs (Nguyen et al. 2021). Moreover, risk management and vertical coordination between different actors in the supply chain become more manageable through these models, allowing for a more efficient allocation of resources and a more agile response to market fluctuations and potential disruptions (Nadal-Roig et Plà-Aragonés 2015).

Several researchers have developed specific models to optimize food flows. In the fruit industry, Nadal-Roig and Plà (2015) proposed a linear programming model to minimize the transportation costs of fruits between different storage centers and a logistics distribution center. Soto-Silva et al. (2016) presented a model for planning the daily transport of fresh products from different cold storage facilities to a processing plant. Lamsal et al. (2016) proposed an optimization model for collecting perishable products from producers and delivering them to processing plants to optimize transportation use. Bortolini et al. (2016) developed a model for designing a perishable food distribution network to minimize operational costs, carbon footprint, and delivery times. Nakandala et al. (2016) proposed a model to maintain the quality of perishable products during transportation from producers to retailers, aiming to minimize costs while maintaining product quality.

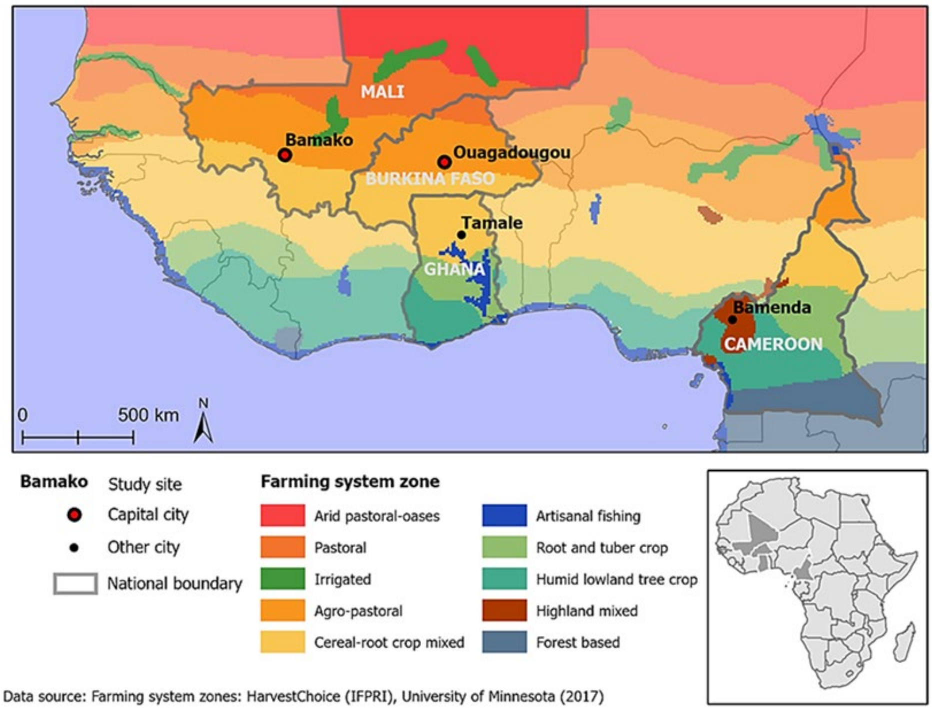
Taking a different approach, Raoui et al. (2020) designed a model for the distribution of perishable foods in urban environments, based on a real road network graph and integrating alternative routes as well as time window constraints. Unlike traditional methods, which optimize routes primarily based on criteria such as distance or travel time, their model uses real spatial data from geographic information systems (GIS) to determine more optimal routes. This approach allows for the creation of more realistic routes, adapted to the transport conditions of perishable products while respecting time windows and vehicle capacity. For their part, Mkondiwa and Apland (2022) developed a mathematical equilibrium model for the food sector in Malawi, aiming to calibrate interdepartmental food flows and analyze the impact of transport cost variations on these flows.

## 2. Methodology

### 2.1 Study sites

The study was conducted in four rapidly growing West African cities, each distinguished by its agricultural systems and socio-economic importance: Tamale (Ghana), Bamenda (Cameroon), Bamako (Mali), and Ouagadougou (Burkina Faso) (Figure 1). Ouagadougou and Bamako, both national capitals, have populations exceeding 2 million, while Tamale and Bamenda, regional capitals, had over 300,000 inhabitants in 2015 (Karg et al. 2022). Except for Bamenda, these cities are part of the Economic Community of West African States (ECOWAS) and are situated along major trade corridors linking landlocked Sahelian countries to coastal nations (De Steenhuijsen Piters et al. 2021).

**Figure 1 :** Location of study sites and agroecological agricultural zones




Source : Karg et al. (2022)

Food supply in these cities is influenced by a variety of biophysical, economic, and cultural factors, including climate, soil, consumer preferences, contemporary and historical trade regimes, and agricultural specialization (Karg et al. 2022).

Bamenda is part of the mixed agricultural zone of the highlands. Its cool, humid climate and volcanic soils give it superior agricultural potential compared to the other cities (Karg et al. 2022). Ouagadougou, with an average annual rainfall of 880 mm, is primarily focused on subsistence crops like maize, sorghum, and millet, in addition to livestock, which plays a significant role in the Burkinabe economy (Karg et al. 2016). Tamale, located in the Guinean savanna, belongs to the mixed cereal-root crop farming system, with an average rainfall of 1 033 mm. Northern Ghana favors staple crops such as maize, rice, and yam, while the south is also a producer of fruits and cocoa (De Steenhuijsen Piters et al. 2021). Bamako, situated in a transition zone between the cereal-root crop and agro-pastoral systems, shares similarities with Ouagadougou, with livelihoods relying on sorghum, maize, millet, and livestock, including cattle, sheep, and goats (De Steenhuijsen Piters et al. 2021).

### 2.2 Data

We utilize the database from Karg et al. (2023), which was collected between 2013 and 2017 with a particular focus on road transport records, and has been analyzed in several studies (Karg et al. 2016; Akoto-Danso et al. 2019; Karg et al. 2019; Amprako et al. 2021; Karg et al. 2022). The data covers different seasons: three in Bamako, Ouagadougou, and Tamale, and two in Bamenda, due to the political crisis that prevented a third survey (Karg et al. 2023).

The covered seasons include the hot/peak season, with the main harvests taking place in November/December, marked by an abundance of food supply; the lean season, from March to

May, characterized by low product availability; and the rainy season, with peak rainfall in August/September (Karg et al. 2019).

A subset of data focusing on common food products, excluding processed foods but including lightly processed items like flour, was selected. Leafy vegetables were excluded due to their limited transport through checkpoints, being primarily produced in intra-urban areas. To enhance the database, we established a classification of transported products based on their perishability (Kumar et al. 2017; Barruga 2022). The classification is as follows:

- Perishable: foods whose quality deteriorates rapidly within days of production or harvest.
- Semi-perishable: foods whose quality deteriorates after several weeks to months.
- Non-perishable: products that retain their quality for several months without significant deterioration.

**Table 1** : Classification of foods based on their degree of perishability

| | |
|---|---|
| **Perishable** | Banana, Mango, Orange, Papaya, Pineapple, Watermelon, Avocado (pear), Cabbage, Carrot, Cucumber, Eggplant, Okra, Hot pepper, Green onion, Sweet pepper, Tomato, Fresh fish, Zucchini, Leek, Green beans, Plantain |
| **Semi-perishable** | Onion, Cassava, Cocoyam, Potato, Sweet potato, Yam, Groundnut (unspecified level of processing), Cassava flour, Ginger, Wheat flour, Cattle, Chicken, Goat, Guinea fowl, Pig, Sheep |
| **Non-perishable** | Maize, Millet, Rice, Sorghum, Wheat, Dried cassava, Gari, Dried yam, Unprocessed groundnuts, Bambara beans, Beans, Cowpea, Groundnuts, Soybean, Dried tomato, Dried okra, Dried fish |

The initial database from Karg et al. (2023) covers food flows from four West African cities, comprising 34 variables and 113,946 observations. These variables, detailed in Karg et al. (2023), include both quantitative and qualitative data.

To develop a more comprehensive optimization model, supplementary data were collected. These include fuel prices, fuel consumption per kilometer, labor wages, average transport speed, maximum travel distance per trip, and the maximum transport duration before food deterioration. These data were sourced from platforms such as World Development Indicators, FAOSTAT, Opendataforafrica, national statistical institutes, the International Energy Agency, and the FAO.

### 2.3 Data preprocessing

The analysis began with the structuring and preparation of the data, with adjustments made according to the type of variables, in line with the specifications of Karg et al. (2023). Similar modes of transport were grouped into homogeneous categories, and certain food product names were standardized to optimize the analysis. New variables were introduced, including the classification of products by perishability and the categorization of food flows by their origin and destination (inflows, outflows, and transit flows). The data cleaning process, which focused on critical variables, reduced the total number of observations from 113 946 to 77 759. The preprocessing steps and the final database are presented in the supplementary materials.

### 2.4 Statistical data analysis

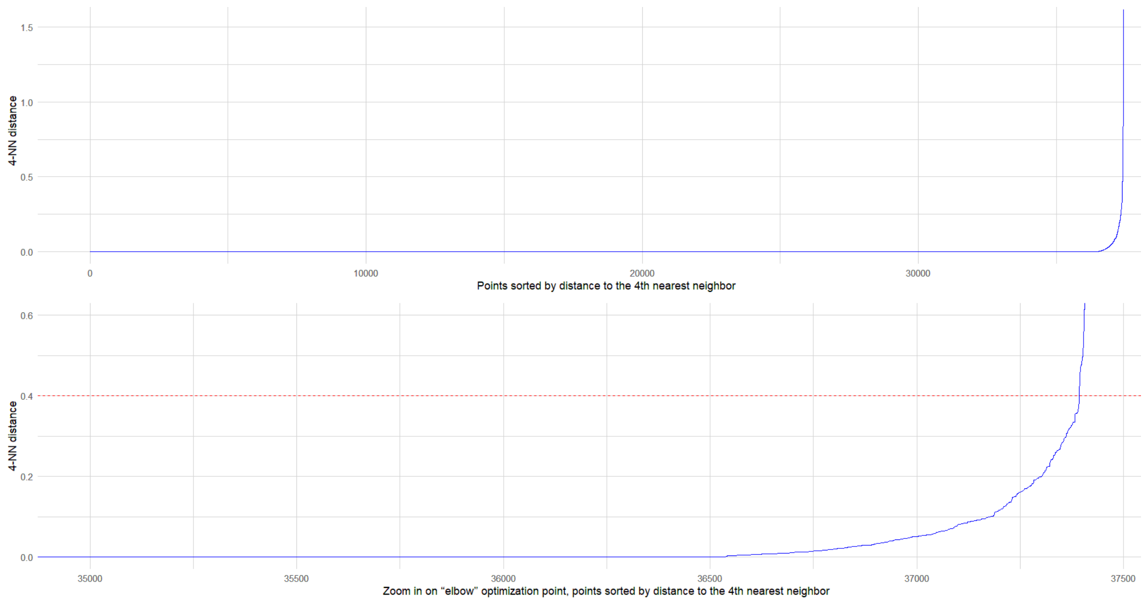
The statistical analysis is based exclusively on the food flow database from Karg et al. (2023), without using supplementary data. One of the key variables for our study is the "source specification" variable, which describes the type of supply source (farm, market, warehouse, etc.). This variable plays a crucial role in understanding the geographical origins of food flows and analyzing supply dynamics. However, it contains a large number of missing values, limiting its full exploitation in the analysis.

To address this issue and avoid significant data loss, we implemented an inference approach based on geographic clustering. Using the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm, we grouped geographically close supply points (Mullin 2020).

This algorithm relies on two key parameters: MinPts, the minimum number of points required to form a cluster, and epsilon (eps), the maximum distance between two points for them to be considered neighbors (Sander et al. 1998). In our case, with two-dimensional geospatial data (latitude and longitude), MinPts was set to 4, following the empirical rule (MinPts = 2 * number of dimensions).

To determine the optimal epsilon value, we used the "k-NN distance graph," which plots the average distance of the k-nearest neighbors (Schubert et al. 2017). The observed elbow point at 0.4 (Figure 2) was chosen as the optimal value for epsilon, marking the balance where adding more clusters no longer significantly improves the model, while minimizing the risk of overfitting (Mullin 2020).

**Figure 2** : Analysis of the 4th nearest neighbor distances for detecting the 'Elbow Point'



Once the clusters were identified, an estimation function was developed to impute missing source types by assigning the most frequent value within each cluster. This method is based on clustering-based imputation (Gao, Khan, et Qu 2022), assuming that geographically close points share similar characteristics.

However, for clusters containing only missing values or points that could not be grouped due to their isolation, estimation could not be performed. In total, 37 434 source points were grouped into 77 clusters, while the "noise" points or outliers, grouped in cluster 0, along with isolated points, were excluded from the analysis. This approach significantly reduced the number of missing observations from 15 620 to just 28. Consequently, the analysis proceeds using the 'estimated_source_specification' variable instead of 'source_specification'.

### 2.5 Pre-modeling analysis

To build the transport cost model, additional data were integrated into the Karg et al. (2023) database. The DBSCAN algorithm was applied to cluster the supply points in each city (e.g., 12 943 for Tamale, 7 913 for Bamako, 8 625 for Bamenda, and 7 953 for Ouagadougou) to reduce data volume and avoid overloading the model. In this paper, we illustrate the process using Tamale, where the MinPts parameter was set to 4, and the elbow point was identified at 0.25 (Figure 3). This allowed the 12 943 supply points to be grouped into 22 clusters. Figure 4 shows an example of a single cluster grouping 766 source points.

**Figure 3**: Analysis of the 4th nearest neighbor distances for detecting the 'Elbow Point' for Tamale

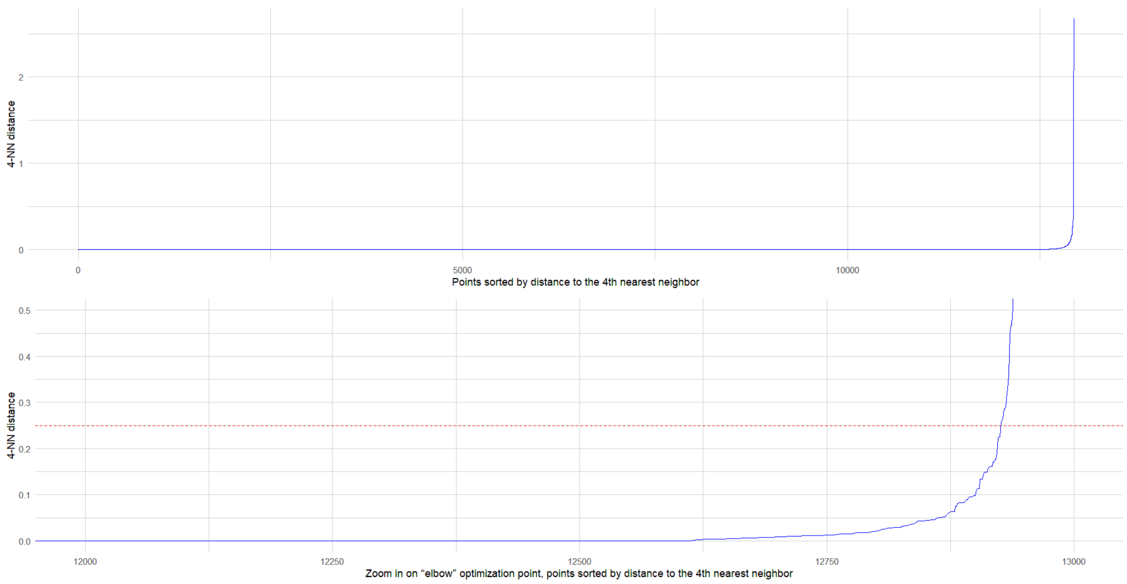


**Figure 4** : Example of a cluster grouping 766 source points in Tamale

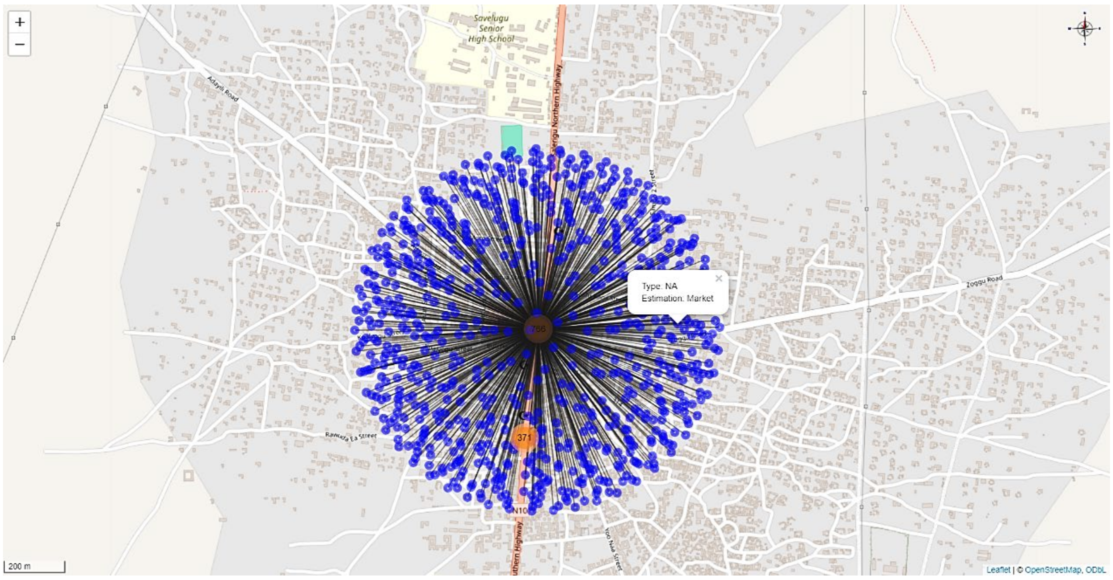
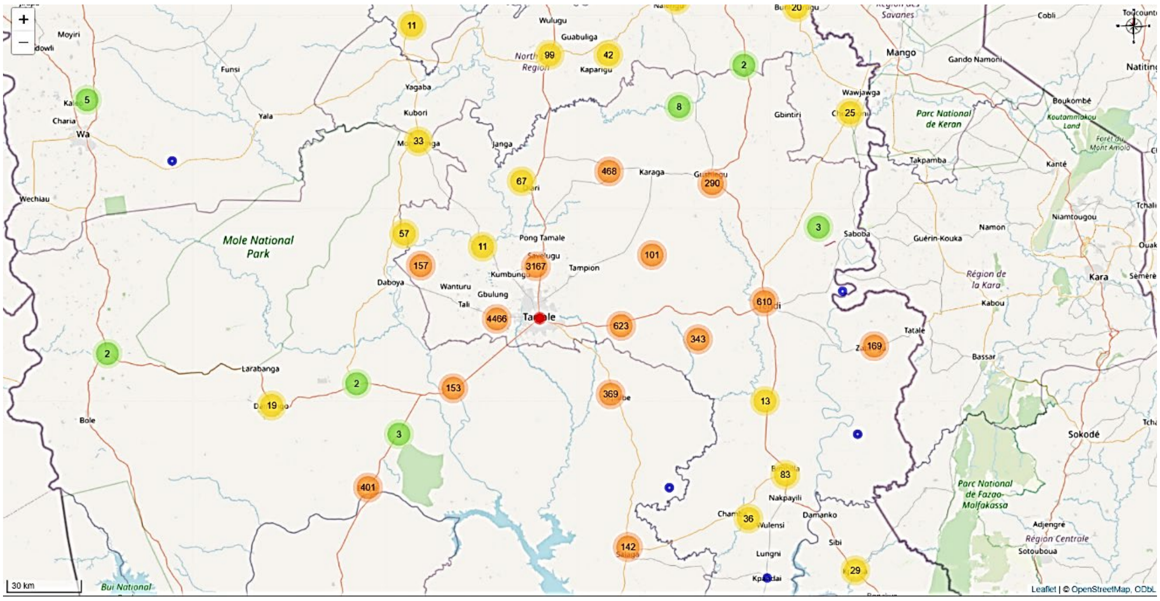



Figure 5 shows the distribution of clusters around Tamale, represented by a red dot. Zooming in reveals the grouped geographic points, with orange clusters containing the most points, followed by yellow and green clusters. The blue points represent individual source points.

**Figure 5** : Spatial distribution of supply source points for Tamale




However, this initial clustering is based solely on geographical proximity, without considering other characteristics of the points, such as the type of supply source. As a result, the same cluster may contain different types of sources. To address this limitation, a post-treatment step subdivided the clusters into homogeneous sub-clusters based on the type of source. Figure 6 illustrates an example of one of these sub-clusters, with each source type represented by a distinct color.

**Figure 6** : Zoom on a cluster comprising three sub-clusters


After identifying these homogeneous sub-clusters, outliers (cluster 0 and isolated points) and points with missing data for "estimated_source_specification" were excluded.

The use of sub-clusters to represent sources in our transport cost model offers several advantages. It reduces the data volume by aggregating points and, unlike clusters that require an additional dimension for the source type, sub-clusters are already homogeneous in this respect. Each sub-cluster represents a specific source type, retaining the necessary information without overloading the model.

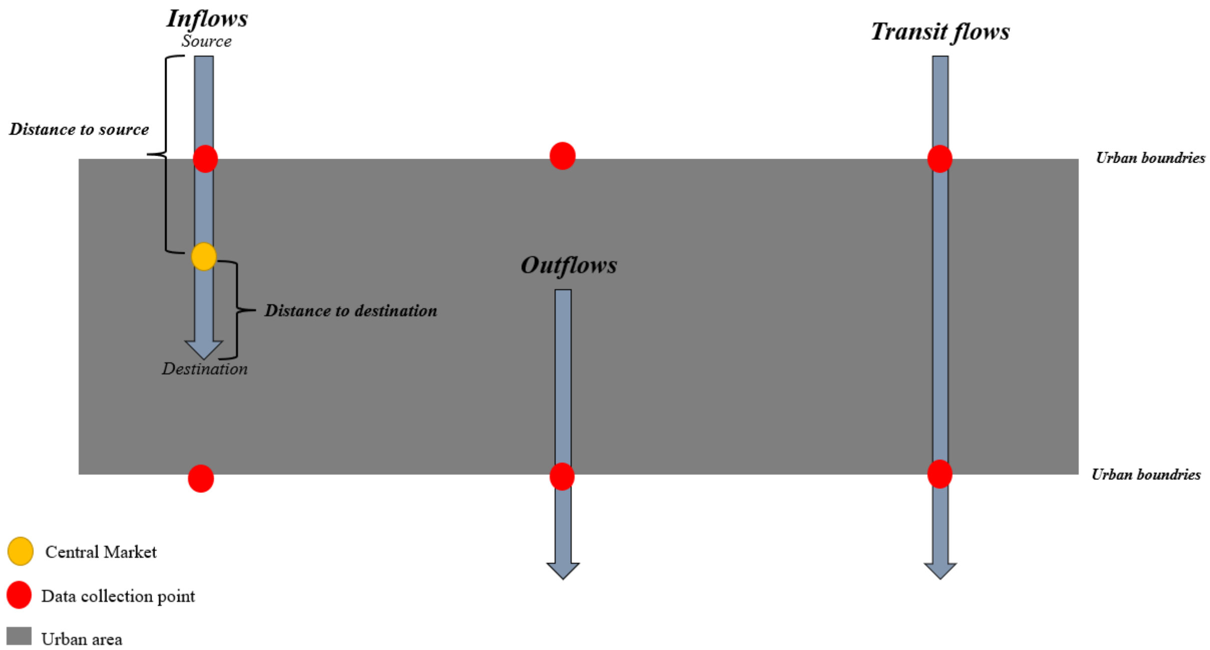
To verify distance accuracy, the "distance_to_source" variable from the Karg et al. (2023) database was examined. It was found that this variable represented straight-line distances calculated from geographic coordinates converted to UTM (e.g., Zone 30 N for Tamale and Ouagadougou). To better reflect real-world conditions, "distance_to_source" was replaced with "distance_real," which measures actual travel distances using the OSRM and the osrmRoute function in R. Alternative routes were also integrated from Google Maps and Bing Maps to enhance route flexibility.

## 3. Modeling

### 3.1 Conceptual Model

We developed a transport cost minimization model, the logic of which is illustrated in Figure 7. This model focuses on inflows, meaning those originating from sources located outside urban areas to supply urban centers.

**Figure 7** : Simplified schema illustrating the logic of the model




In each city, food supply relies on various sources whose capacities vary depending on the season, product types, and specific characteristics of supply zones, to meet the city's demand, which fluctuates according to the seasons, product types, and the specific city. Traditional models often link two nodes via a single optimal route. However, in practice, multiple alternative paths may exist (Raoui, Oudani, et Hilali Alaoui 2020). To account for this, our model proposes at least one route per source-city pair, with up to three alternative routes. This approach enhances resilience by providing alternatives in case of disruptions, such as adverse weather, and optimizes transport efficiency by allowing routes to connect multiple sources, maximizing load capacity. The model also considers product perishability, with transport time constraints to prevent deterioration, and imposes limits on the number of hours per trip.

Shipment planning is organized according to three distinct seasons: the lean season, the rainy season, and the hot season. However, to better manage flow variability, we opted for a more refined approach by using a weekly time scale. This temporal granularity prevents shipment concentration, improving the model's efficiency by accounting for short-term variations that influence logistical decisions.

The main objective of this model is to optimize food supply flows (inflows) to meet the needs of the cities while minimizing logistical costs, encompassing both financial expenses and the time transporters spend on logistical tasks (Raton et Raimbert 2019).

The determination of the quantities of food products to be transported is based on both supply and demand. However, as the database only includes supply data, two approaches were considered. The first involves assuming a balanced market. In this case, the model would not focus on determining the quantities to be sent but rather on logistical aspects, such as the shipment period during a specific week in a given season, food product selection, choice of transport mode, and route, to ensure the most optimal options. The second approach relies on using net flows as a proxy for demand. In this case, the model will determine the optimal quantity of a food product to be transported from a given source to a specific destination, while planning weekly shipments tailored to each season. At the same time, the model will be able to choose the most optimal route and select the most appropriate means of transport for each trip.

### 3.2 Mathematical Formulation of the Transport Cost Model

This model is based on a set of mathematical equations capturing the interactions between supply sources (i) and cities (j) across different periods, represented by seasons (s) and weeks (w), while considering transport modes (m), food product types (c), and possible routes (r). The parameters and variables presented in Table 2 are used to build the model.

**Table 2** : Parameters and variables for the transport cost model

| | |
|---|---|
| ***Parameters*** | |
| distance_real (i, j, r) | Actual distance between sub-cluster i and city j via route r |
| supply (i, s, c) | Supply from source i for season s and product c |
| demand (j, s, c) | Demand from city j for season s and product c |
| price_fuel (s) | Fuel price for season s |
| salary_labor (m) | Labor wage for transport mode m |
| consumption_fuel (m) | Fuel consumption for transport mode m |
| average_speed (m) | Average speed of transport mode m |
| transport_capacity (m) | Maximum load capacity for transport mode m |
| max_hours_transport (m) | Maximum number of hours a transport mode m can travel in a single trip |
| max_time_product (c) | Maximum number of hours a product c can be transported without deteriorating |
| supply_weekly (i, s, w, c) | Weekly calculated supply from source i for product c during week w of season s |
| demand_weekly (j, s, w, c) | Weekly calculated demand from city j for product c during week w of season s |
| ***Decision Variables*** | |
| x(i,j,s,w,m,c,r) | Quantity of product c transported from source i to city j for week w of season s, using transport mode m and route r |
| y(i,j,s,w,m,c,r) | Integer variable representing the number of shipments of product c made from source i to city j for week w of season s, based on transport mode m and route r. This variable calculates the total number of trips required, considering the maximum capacity of each transport mode |
| t(i,j,s,w,m,c,r) | Adjusted version of x(i,j,s,w,m,c,r), incorporating perishability constraints and transport time limitations. This variable represents the actual quantity transported, accounting for both product characteristics and operational constraints of transport modes |

**Objective function:**

$$\boldsymbol{Z} = \sum_{i,j,s,w,m,c,r} \Big[ (\boldsymbol{distance\_real}(\boldsymbol{i},\boldsymbol{j},\boldsymbol{r}) * \boldsymbol{price\_fuel}(\boldsymbol{s}) * \boldsymbol{consumption\_fuel}(\boldsymbol{m})) + ((\boldsymbol{distance\_real}(\boldsymbol{i},\boldsymbol{j},\boldsymbol{r}) \,/\, \boldsymbol{average\_speed}(\boldsymbol{m})) * \boldsymbol{salary\_labor}(\boldsymbol{m}))\Big] * \boldsymbol{y}(\boldsymbol{i},\boldsymbol{j},\boldsymbol{s},\boldsymbol{w},\boldsymbol{m},\boldsymbol{c},\boldsymbol{r})$$

**Constraints:**

1. Shipment constraint:

$$y(i,j,s,w,m,c,r) = \frac{t(i,j,s,w,m,c,r)}{transport\_capacity(m)}$$

For all i, j, s, w, m, c, r

2. Supply constraint:

$$\sum_{j,m,r} t(i,j,s,w,m,c,r) \leq supply\_weekly(i,s,w,c)$$

For all i, s, w, c

3. Demand constraint:

$$\sum_{i,m,r} t(i,j,s,w,m,c,r) \geq demand\_weekly(j,s,w,c)$$

For all j, s, w, c

4. Perishability constraint:

$$\frac{distance\_real(i,j,r)}{average\_speed(m)} \leq max\_time\_product(c) * b\_perish(i,j,m,c,r)$$

For all i, j, m, c, r

5. Maximum transport hours constraint:

$$\frac{distance\_real(i,j,r)}{average\_speed(m)} \leq max\_hours\_transport(m) * b\_time(i,j,m,r)$$

For all i, j, m, r

6. Binding constraint for perishability and transport time:

$$t(i,j,s,w,m,c,r) = x(i,j,s,w,m,c,r) * b\_perish(i,j,m,c,r) * b\_time(i,j,m,r)$$

For all i, j, s, w, m, c, r

The objective function consists of two main components: fuel costs, calculated based on distance, fuel price, and consumption, and labor costs, which depend on travel time and hourly wages. Labor costs are particularly relevant for transport modes that do not consume fuel.

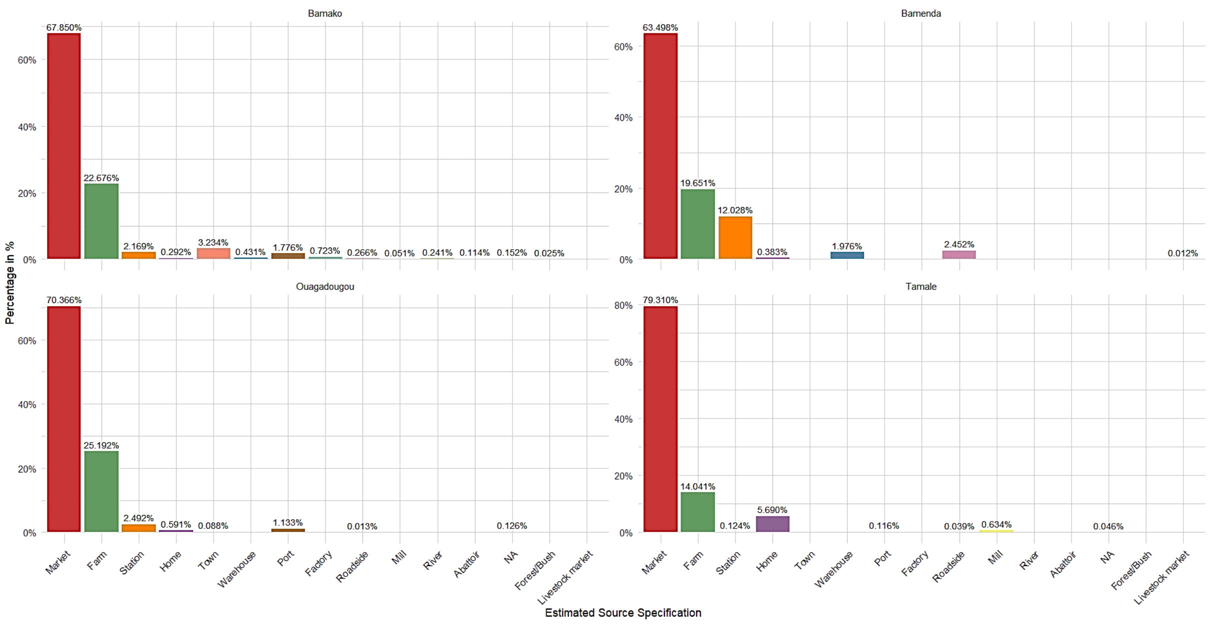
The first constraint links the number of shipments to the total quantity transported and the load capacity of each transport mode, optimizing resource use and preventing overloading. The supply constraint ensures that the quantity sent from each source in a given week does not exceed the available weekly supply, while the demand constraint guarantees that the city's weekly needs are met. The model also incorporates a perishability constraint for sensitive products, ensuring they are transported within time limits that preserve their quality. A binary indicator, *b_perish*, acts as a switch to activate or deactivate this constraint. If the constraint is deactivated, the *b_perish* variable takes the value 0, indicating that the acceptable transport time for this product has been exceeded. In this case, transport is not allowed, and the model does not plan any shipment. Similarly, a time constraint limits the hours spent in transit, with a binary indicator, *b_time*, deactivating transport if the limit is exceeded. The binding constraint ensures that only the quantities of food products that simultaneously meet both constraints are actually transported.

The purpose of this optimization is to assess how it can be used to evaluate the resilience of West African supply chains in the face of various shocks. By simulating different hypothetical scenarios, it becomes possible to observe how these supply chains would react and better anticipate their responses to disruptions. This approach would help identify weaknesses and explore ways to strengthen their resilience.

## 4. Results

Figure 8 shows the distribution of estimated supply sources for each city.

**Figure 8** : Distribution of estimated supply sources for the four cities




Despite the geographical and cultural differences between the cities, markets and farms remain the main sources of food supply. Markets dominate in all cities, serving as key hubs where a large portion of food transactions occur, ensuring access to a variety of products for urban populations. Farms, in second place, highlight the importance of agricultural production in meeting urban food needs, demonstrating the reliance of cities on nearby rural areas.

On the other hand, alternative supply sources, such as stations[1], homes[2], rivers, forests, roadsides[3], warehouses, factories, mills, slaughterhouses, livestock markets, and ports, play a less significant role in overall supply. Although their contribution is limited in terms of volume,

[1] Stations refer to railway or bus stations serving as transit points for goods.
[2] The home category may refer to producers who, despite operating a farm, declared their home during the survey, which led to their classification in this category. It also includes retailers who use their home as a storage facility due to the lack of dedicated infrastructure.
[3] The roadside category represents traders operating directly along the roads.

these sources can still be essential for certain specific product categories or in particular situations, such as seasonal needs.

**Figure 9** : Boxplot for distance to source by estimated source specification

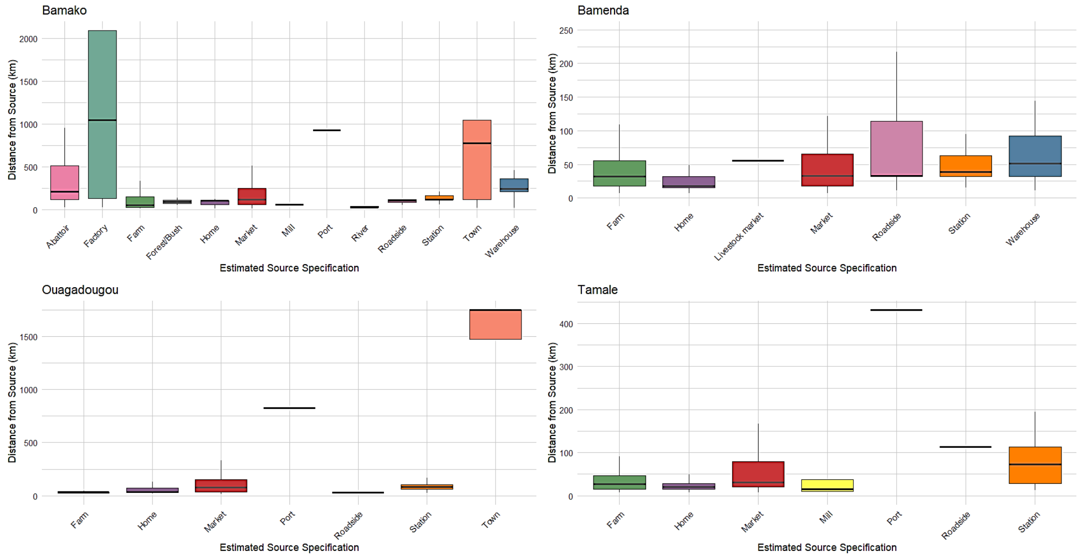



Figure 9 highlights significant variations in supply source distances for each city studied. In Bamako, supply distances are particularly high, with factories and ports located more than 2,000 km and 900 km away, respectively. This reliance on distant sources can be seen as both a strength and a vulnerability. While it diversifies food sources, reducing the risk of shortages in case of local production disruptions, it also introduces potential vulnerabilities to logistical challenges, political instability, or environmental shocks that may affect these distant sources. This reliance on distant sources could also be explained by local constraints in agricultural production or by integration into larger-scale trade networks.

In Ouagadougou, farms are much closer to the city compared to those in the other cities studied, but certain specific products require long-distance sourcing, with villages and ports located over 1,500 km and 800 km away, respectively. This diversification of supply sources offers greater flexibility in meeting the city's diverse food needs, but it also exposes the supply chain to potential interruptions.

Bamenda, thanks to its high agricultural potential, relies primarily on local sources, reflecting strong availability of local resources. The proximity of farms, markets, and other local sources allows Bamenda to meet a large portion of its food needs without relying on distant supplies. However, this reliance on local sources could become a limitation if local production is affected by climate-related disruptions or other challenges.

In Tamale, source distances are moderate, with a primary reliance on nearby sources, although some specific products come from more distant sources, such as ports. This suggests that Tamale relies on local sources for the majority of its food needs and turns to distant sources only for products not locally available.

It is important to note that national capitals, such as Bamako and Ouagadougou, due to their size and more diversified demand, depend more on distant sources, while regional capitals, such as Bamenda and Tamale, rely on local resources. While this diversification enhances the ability of national capitals to meet their diverse food needs, it also increases their vulnerability to disruptions in these distant supply chains. This distinction between national and regional capitals partly explains the observed differences in supply distances, highlighting the influence of city size, demand, and diversity of needs on supply strategies. These observations align with the findings of Karg et al. (2022), which show that Bamako and Ouagadougou receive only 7% and 8% of their supplies from local areas, compared to 29% in Tamale and 44% in Bamenda.

Given that our data did not follow a normal distribution, we used the non-parametric Kruskal-Wallis test to examine the relationship between distance to the source and product perishability. The test statistic follows a chi-square distribution with k−1 degrees of freedom, where k is the number of groups being compared.

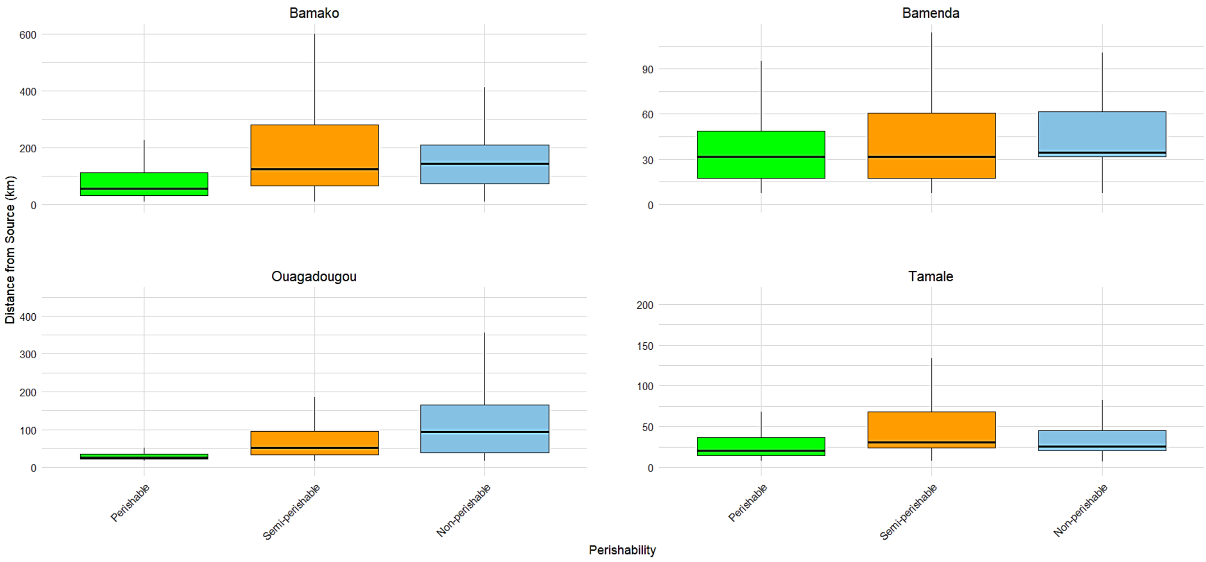
The results, presented in Table 3, show that the distance to supply sources varies significantly according to product perishability in all the cities studied.

**Table 3** : Results of the Kruskal-Wallis chi-squared test for each city

| | City | Chi_squared | Degrees_of_freedom | p_value |
|---|---|---|---|---|
| **Kruskal-Wallis chi-squared** | Tamale | 228.6781 | 2 | 2.203902e-50 |
| **Kruskal-Wallis chi-squared1** | Ouagadougou | 1279.7969 | 2 | 1.246327e-278 |
| **Kruskal-Wallis chi-squared2** | Bamako | 695.0369 | 2 | 1.187545e-151 |
| **Kruskal-Wallis chi-squared3** | Bamenda | 147.0886 | 2 | 1.148488e-32 |

The results reveal a general trend where perishable products mainly come from the closest sources, with a median distance of less than 50 km in all the cities studied (Figure 10). This trend is particularly pronounced in Ouagadougou but less so in the other three cities.

**Figure 10** : Boxplot for distance to source by perishability categories




In Ouagadougou, the median distances for the supply of perishable products are significantly shorter compared to those of semi-perishable and non-perishable products. While sourcing perishable products locally can minimize spoilage and transportation costs, it also creates a dependency on local supply chains. For instance, while Ouagadougou sources most of its perishable products from local farms, it relies heavily on intra-regional or international trade for non-perishable goods like rice, with 90% of rice being imported (Karg et al. 2022). This diversification of non-perishable product sources can enhance resilience by ensuring the availability of essential goods during local disruptions. However, it also introduces vulnerabilities to international supply chain risks, such as trade restrictions or transport delays.

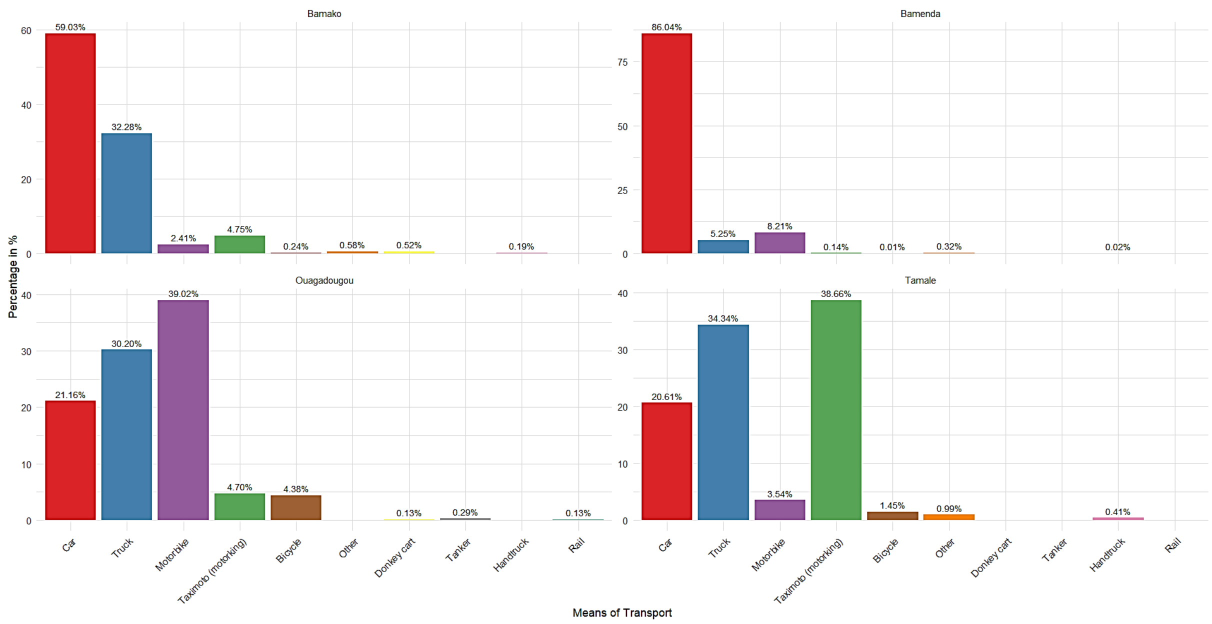
In Bamako, semi-perishable products travel the longest distances compared to the other cities studied. Additionally, according to Karg et al. (2022), certain semi-perishable products, such as onions and potatoes, are often imported or sourced from abroad, which further increases the distances traveled for their supply. This reliance on distant sources for semi-perishable products introduces logistical challenges, particularly in maintaining a consistent supply.

In Tamale and Bamenda, supply primarily relies on nearby sources, giving these cities smaller foodsheds compared to national capitals like Bamako and Ouagadougou (Karg et al. 2022). Although their reliance on local sources may improve resilience to international supply chain disruptions, it could limit their flexibility during local crises. Semi-perishable products in these cities travel longer distances than non-perishable products, which may be due to the fact that some semi-perishable products adopt similar storage and transport characteristics to non-perishable goods, causing them to travel longer distances.

The strong reliance of the four cities on nearby sources for perishable products is explained not only by the perishable nature of these goods, which requires short transport times to avoid spoilage, but also by the higher profit margins associated with high-value crops. By growing perishable products close to the cities, producers can take advantage of higher prices while minimizing the risks of losses due to rapid food spoilage. This observation aligns with Von Thünen's theory (1826), which describes how agricultural products are grown at varying distances from the central market based on their profitability and perishability.

The analysis of transport choices reveals that each city favors specific modes of transportation to ensure their supply (Figure 11). In Bamako and Bamenda, cars are the most commonly used mode, likely due to road networks that are well-suited for light vehicles and the need to transport smaller quantities of goods more frequently. This reliance on cars provides flexibility and efficiency for routine deliveries.

**Figure 11** : Distribution of transport modes by city




In contrast, in Ouagadougou and Tamale, motorcycles and taximotos dominate transportation, driven by local conditions such as narrower roads and the need for greater flexibility in congested urban areas. These vehicles enable quick and frequent deliveries, ensuring continuous mobility even in challenging environments. Their widespread use also suggests a more active informal economy, where smaller, regular deliveries enhance resilience by reducing reliance on large, less frequent shipments. This decentralized transport approach can be an asset during crises, allowing cities to maintain food inflows even when larger-scale logistics are disrupted.

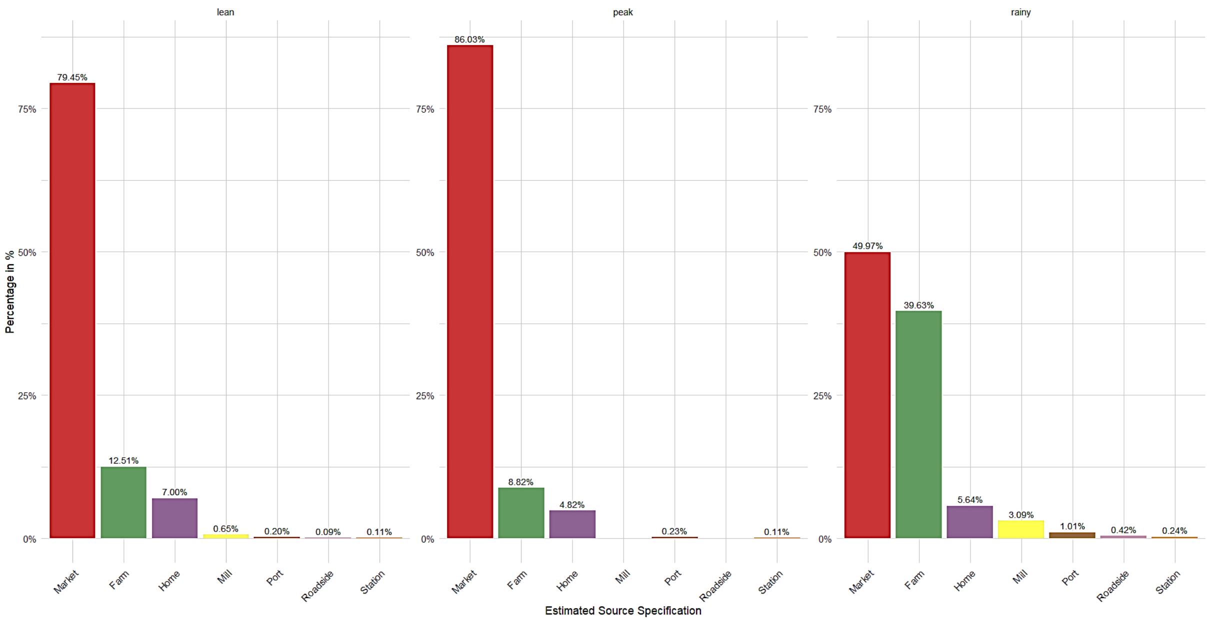
To better understand the factors influencing the variation in food supply flows, we chose to focus on the city of Tamale, which has the largest number of observations in the Karg et al. (2023) database, with 26 463 records. In comparison, Bamako has 18 956, Bamenda 18 757, and Ouagadougou 13 583. This choice allows us to use Tamale as a reference for similar studies in other cities, while accounting for local specificities and available data. Figure 12 presents the distribution of estimated supply sources by season in Tamale: the lean season, the hot/peak season, and the rainy season.

During the lean season, markets dominate supply in Tamale, accounting for 79.45% of sources, due to the reduced farm production (12.51%) caused by unfavorable weather conditions. Homes play a minor role at 7%, while mills, ports, and stations contribute less than 1%.

During the peak or hot season, the dominance of markets increases further, reaching 86.03% of supply sources. This increase can be explained by the high commercial activity and the abundance of products available in the markets during the harvest period. Farms, though contributing less compared to the lean season, still represent 8.82% of the supply, indicating a continued role in food provisioning. Homes contribute 4.82% of supply, while contributions from mills and roadside sources disappear, likely due to economic activities shifting towards central markets and main selling points during this period of high activity.

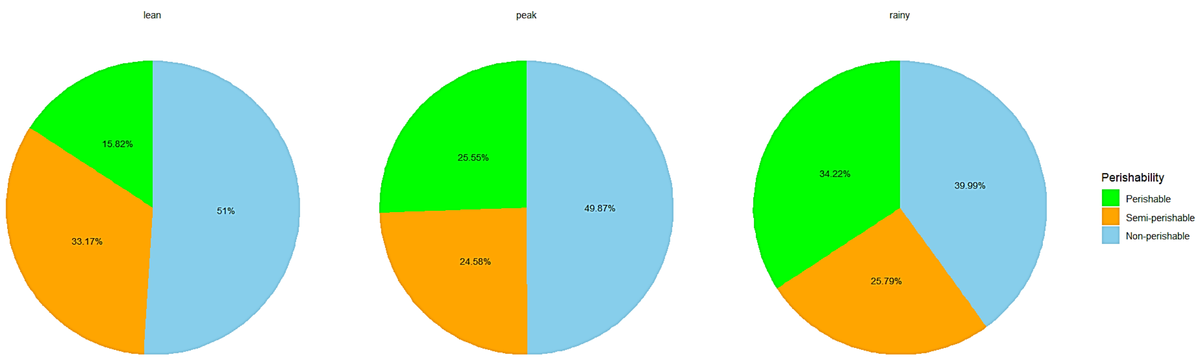
In the rainy season, markets remain important (49.97%), but the contribution from farms increases significantly to 39.63%, supported by favorable weather conditions. Homes maintain a 5.64% share, and the contribution of other sources, while still marginal, increases slightly, possibly reflecting specific adaptations to the rainy season.

**Figure 12** : Distribution of estimated supply zones by season




The distribution of food products therefore varies significantly across seasons, as illustrated by Figure 13.

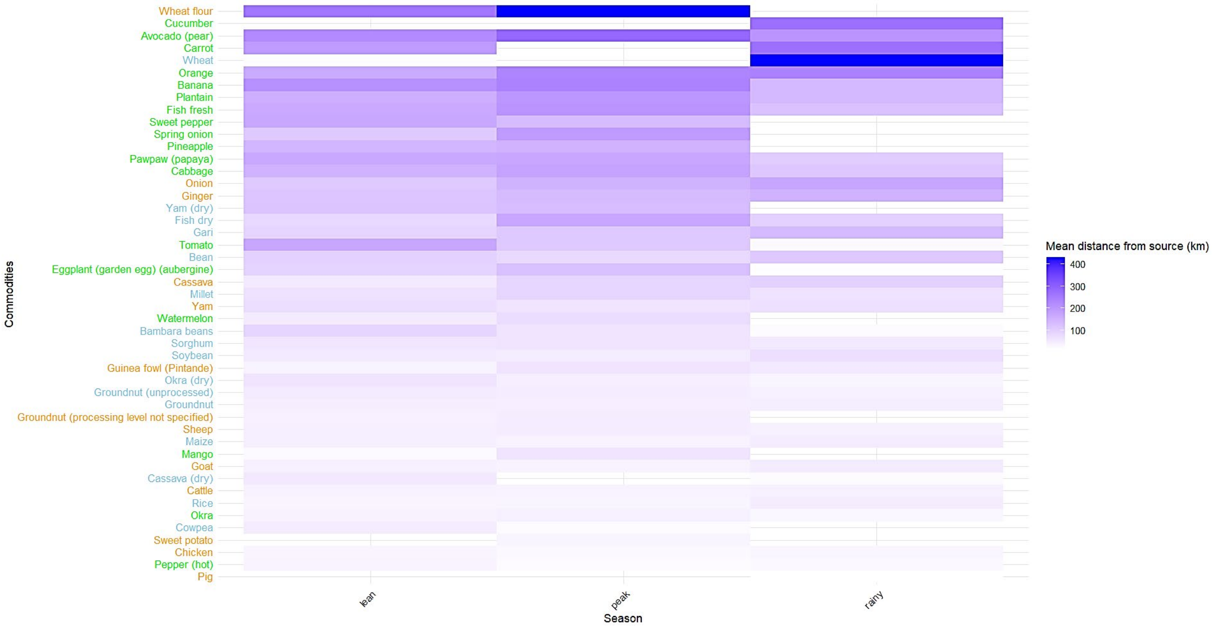
**Figure 13** : Distribution of food products by perishability across seasons




During the lean season, non-perishable products dominate supply at 51%, highlighting their critical role in maintaining food security during periods of scarcity. Semi-perishable products account for 33.17%, while perishable products make up only 15.82%, reflecting the limited availability of fresh goods. During the peak season, non-perishables remain the majority at 49.87%, but perishables increase to 25.55%, driven by the harvest. In the rainy season, perishable products rise to 34.22%, reflecting the city's capacity to adapt to favorable agricultural conditions.

Figure 14 illustrates the seasonal variations in supply distances in Tamale, based on food product types and seasons.

*Figure 14 : Heatmap of food products by season, with the color of product names indicating their perishability category*




During the lean season, products like wheat flour, avocados, and tomatoes are sourced from long distances to compensate for local deficits and prevent shortages. During the peak or hot season, while some supply distances remain significant, a slight decrease is observed due to increased local production, reducing reliance on imports for many products, except for certain ones like wheat flour. In the rainy season, supply distances decrease for many products due to better local availability, driven by favorable weather conditions. However, wheat, which is absent during other seasons, is transported over long distances during this period.

It is also noteworthy that some products, available during the lean and peak seasons, are absent during the rainy season. This seasonal absence highlights the significant impact of weather conditions on food supply and underscores the vulnerability of the food system to seasonal shifts.

## 5. Discussion

The food supply flows in the four West African cities studied are influenced by an interaction of geographical, logistical, and seasonal factors. These elements not only determine the distances traveled to reach the cities but also shape the structure and logistical organization of urban food supply chains. This interaction reveals how cities manage supply flows, balancing local production with external sources to mitigate risks and ensure a steady food supply despite seasonal and logistical challenges.

The study by Karg et al. (2022) provides an overview of food supply flows, emphasizing the role of cities as hubs for aggregation and distribution of food products. Their approach is primarily descriptive, aiming to outline the panorama of food flows and the interactions between cities and their hinterlands, whether local, regional, national, or international. In contrast, our study adopts a more in-depth approach, focusing on the dynamics of supply and the factors influencing these flows, as well as on optimizing the city's food supply by leveraging these factors.

In all the cities studied, markets and farms emerge as the main convergence points for food supply. Markets, as dynamic centers of commerce, meet the daily needs of urban populations, while farms play a crucial role in local supply, highlighting the essential connection between urban and rural areas.

Seasons play a crucial role in shaping supply flows, affecting not only the distances traveled but also the sources of supply and the quantities of products available. During the lean season, marked by local shortages, cities often turn to distant sources to maintain a continuous supply, which increases travel distances and exposes vulnerabilities. Markets play a central role in compensating for the decline in local agricultural production. In contrast, during the peak season, characterized by abundant harvests, supply distances shorten due to the increased availability of local products, reducing dependence on distant sources. The role of markets becomes even more pronounced. The rainy season, with favorable climatic conditions, further boosts local agricultural production. Farms become major sources of supply, significantly contributing to urban food availability and reflecting the adaptation of supply chains to the abundance of fresh products. Although secondary, other sources of supply also see a slight increase in contribution based on seasonal needs.

The results clearly show that perishability is a key factor in managing supply distances. Perishable products, which deteriorate rapidly, are mainly sourced from areas close to urban centers, a trend particularly evident in Ouagadougou. This pattern aligns with Von Thünen's theory. Conversely, semi-perishable and non-perishable products, which are less sensitive to deterioration, can be transported over longer distances without significant quality loss. Our findings confirm this theory: in the four cities studied, perishable products are sourced from a median distance of less than 50 km, whereas semi-perishable and non-perishable products are transported from greater distances, reflecting greater flexibility in the supply chains.

Transport modes vary significantly between cities. In Bamako and Bamenda, cars are the most commonly used mode, likely due to road networks suited for light vehicles and the need to transport smaller quantities of goods more frequently. This reliance on cars provides flexibility and efficiency for routine deliveries. In contrast, Ouagadougou and Tamale rely more on motorcycles and taximotos, which offer greater flexibility for frequent and efficient deliveries in congested urban environments.

Finally, supply distances vary notably depending on the size and status of the cities studied. In national capitals like Bamako and Ouagadougou, more diverse and complex supply needs result in a greater dependence on distant sources, which can introduce vulnerabilities during disruptions. These cities require extensive flows from distant or international regions. In contrast, regional capitals like Bamenda and Tamale benefit from shorter supply distances, reflecting less diversified needs and a greater ability to rely on local resources, thus strengthening their resilience to external shocks. This distinction highlights the influence of city size and administrative status on the structuring of food supply chains.

The model we developed has several limitations. One major limitation is the assumption that weekly demand is evenly distributed across all weeks of a season due to the lack of detailed weekly data. This does not reflect actual fluctuations in demand, which can vary due to seasonal, economic, or event-specific factors. A more accurate approach would involve modeling demand as a stochastic variable with a probabilistic distribution, allowing for weekly variations.

Additionally, the current model does not take into account that vehicles transport both food products and other goods. The lack of data on the volumes of other items complicates the accurate estimation of vehicle load capacity, which can lead to an overestimation of transport costs. To refine these estimates, it would be beneficial to develop a model capable of allocating costs proportionally or to use reliable data on vehicle load capacity.

The use of the DBSCAN algorithm for clustering introduces subjectivity, particularly in determining the epsilon parameter from a distance graph. This subjectivity could lead to variability in results. To address this, more objective methods or alternative algorithms should be considered.

Finally, the model does not account for toll route costs, which can represent a significant portion of transport costs. Incorporating these fees would improve the accuracy of cost estimations and better reflect the economic realities of transportation.

## Conclusion

This study demonstrates that the dynamics of food supply flows in the West African cities studied are largely influenced by geographical and seasonal factors, with markets and farms playing a key role. Supply distances and transport choices vary depending on product type, perishability, the geographic origin of the supply source, seasons, and the status of the cities, reflecting both vulnerabilities and flexibility in their food systems. The management of these flows supports Von Thünen's model, highlighting the importance of local supplies for perishable products, while non-perishable goods travel longer distances, providing flexibility but also potential vulnerabilities for national capitals.

The transport cost optimization model is currently under development, and preliminary results suggest promising avenues for further analysis. The established methodology provides a solid foundation for future research and improvement of the model.

Firstly, integrating more recent and longer-term data would help validate and further refine the model, taking into account the rapid evolution of cities and their food systems. Expanding this analysis to other West African cities would allow us to verify whether the observed patterns are generalizable across the region.

A promising avenue would be to incorporate the identification of intermediate points in the model. Currently, the model predicts product flows from a source to the city without considering possible intermediate stops. Adding these points could optimize routes in terms of energy and financial costs by breaking the journey into more efficient segments, while enabling GAMS to generate an optimal routing network.

Another perspective would be to integrate a function that models the "shelf life" of products into the model. This function would allow better management of perishable products by considering their remaining lifespan, not only based on the distance traveled but also by optimizing the time and cost of transport. The idea would be to introduce a multi-objective model, where the optimization aims to minimize both transport costs and the time required to deliver products to the city before they deteriorate.

## References


Ahumada, Omar, et J. Rene Villalobos. 2009. « Application of planning models in the agri-food supply chain: A review ». *European Journal of Operational Research* 196 (1): 1-20. https://doi.org/10.1016/j.ejor.2008.02.014.

Akoto-Danso, Edmund Kyei, Hanna Karg, Pay Drechsel, George Nyarko, et Andreas Buerkert. 2019. « Virtual water flow in food trade systems of two West African cities ». *Agricultural Water Management* 213 (mars):760-72. https://doi.org/10.1016/j.agwat.2018.11.012.

Amprako, Louis, Hanna Karg, Regina Roessler, Jennifer Provost, Edmund Kyei Akoto-Danso, Seydou Sidibe, et Andreas Buerkert. 2021. « Vehicular Livestock Mobility in West Africa: Seasonal Traffic Flows of Cattle, Sheep, and Goats across Bamako ». *Sustainability* 13 (1): 171. https://doi.org/10.3390/su13010171.

Barruga, peachsanchez. 2022. « Classifications of Food According To: Classification of Food Based On Perishability ». 2022. https://www.scribd.com/document/571397744/HORT#:~:text=It%20divides%20foods%20into%20three,medium%2C%20and%20high%20acid%20foods.

Bortolini, Marco, Maurizio Faccio, Mauro Gamberi, et Francesco Pilati. 2016. « Multi-Objective Design of Multi-Modal Fresh Food Distribution Networks ». *International Journal of Logistics Systems and Management*, mai. https://www.inderscienceonline.com/doi/10.1504/IJLSM.2016.076470.

De Steenhuijsen Piters, Bart, Joost Nelen, Bertus Wennink, Verina Ingram, Fabien Tondel, Froukje Kruijssen, et Jenny Aker. 2021. « West African Food System Resilience ». Wageningen: Wageningen Economic Research. https://doi.org/10.18174/543127.

Drechsel, Pay, Sophie Graefe, et Michael Fink. 2007. *Rural-Urban Food, Nutrient and Virtual Water Flows in Selected West African Cities*. Research Report / IWMI 115. Colombo: IWMI.

Gao, Kun, Hassan Ali Khan, et Wenwen Qu. 2022. « Clustering with Missing Features: A Density-Based Approach ». *Symmetry* 14 (1): 60. https://doi.org/10.3390/sym14010060.

Hemerijckx, Lisa-Marie, Gloria Nsangi Nakyagaba, Hakimu Sseviiri, Katarzyna Janusz, Michelle Eichinger, Shuaib Lwasa, Julian May, Peter H. Verburg, et Anton Van Rompaey. 2023. « Mapping the Consumer Foodshed of the Kampala City Region Shows the Importance of Urban Agriculture ». *Npj Urban Sustainability* 3 (1): 11. https://doi.org/10.1038/s42949-023-00093-1.

Huriot, Jean-Marie. 1994. « Von Thünen économie et espace ». *(No Title)*. https://cir.nii.ac.jp/crid/1130000798096772352.

Karg, Hanna, Edmund K. Akoto-Danso, Louis Amprako, Pay Drechsel, George Nyarko, Désiré Jean-Pascal Lompo, Stephen Ndzerem, Seydou Sidibé, Mark Hoschek, et Andreas Buerkert. 2023. « A Spatio-Temporal Dataset on Food Flows for Four West African Cities ». *Scientific Data* 10 (1): 263. https://doi.org/10.1038/s41597-023-02163-6.

Karg, Hanna, Edmund K. Akoto-Danso, Pay Drechsel, Abdul-Halim Abubakari, et Andreas Buerkert. 2019. « Food- and Feed-Based Nutrient Flows in Two West African Cities ». *Nutrient Cycling in Agroecosystems* 115 (2): 173-88. https://doi.org/10.1007/s10705-018-9944-4.

Karg, Hanna, Jill Bouscarat, Edmund Kyei Akoto-Danso, Philipp Heinrigs, Pay Drechsel, Louis Amprako, et Andreas Buerkert. 2022. « Food Flows and the Roles of Cities in West African Food Distribution Networks ». *Frontiers in Sustainable Food Systems* 6 (mai). https://doi.org/10.3389/fsufs.2022.857567.

Karg, Hanna, Pay Drechsel, Edmund Akoto-Danso, Rüdiger Glaser, George Nyarko, et Andreas Buerkert. 2016. « Foodsheds and City Region Food Systems in Two West African Cities ». *Sustainability* 8 (12): 1175. https://doi.org/10.3390/su8121175.

Kumar, Vishal, Suresh Chandra, Kapil Kumar, S.K. Goyal, Lalit Kumar, et Amit Kumar. 2017. « Perishable and non-perishable food products roles in environment- A review ». *South Asian Journal of Food Technology and Environment* 03 (01): 465-72. https://doi.org/10.46370/sajfte.2017.v03i01.01.

Lamsal, Kamal, Philip C. Jones, et Barrett W. Thomas. 2016. « Harvest logistics in agricultural systems with multiple, independent producers and no on-farm storage ». *Computers & Industrial Engineering* 91 (janvier):129-38. https://doi.org/10.1016/j.cie.2015.10.018.

Lemeilleur, Sylvaine, Mohammed Aderghal, Oumaïma Jenani, Abdelali Binane, Bruno Romagny, et Paule Moustier. 2019. « La distance est-elle toujours importante pour organiser l'approvisionnement alimentaire urbain ? Le cas de l'agglomération de Rabat ». *Systèmes alimentaires / Food Systems*. https://ird.hal.science/ird-02465344.

Lin, Xiaowen, Paul J. Ruess, Landon Marston, et Megan Konar. 2019. « Food Flows between Counties in the United States ». *Environmental Research Letters* 14 (8): 084011. https://doi.org/10.1088/1748-9326/ab29ae.

Mkondiwa, Maxwell, et Jeffrey Apland. 2022. « Inter-district food flows in Malawi ». *Food Security* 14 (août). https://doi.org/10.1007/s12571-022-01302-y.

Moustier, Paule. 2017. « Short urban food chains in developing countries: signs of the past or of the future? » *Natures Sciences Sociétés* 25 (1): 7-20.

Moustier, Paule, Michelle Holdsworth, Dao The Anh, Pape Abdoulaye Seck, Henk Renting, Patrick Caron, et Nicolas Bricas. 2023. « The diverse and complementary components of urban food systems in the global South: Characterization and policy implications ». *Global Food Security* 36 (mars):100663. https://doi.org/10.1016/j.gfs.2022.100663.

Mullin, Tara. 2020. « DBSCAN Parameter Estimation Using Python ». *Medium* (blog). 15 juillet 2020. https://medium.com/@tarammullin/dbscan-parameter-estimation-ff8330e3a3bd.

Nadal-Roig, Esteve, et Lluís M. Plà-Aragonés. 2015. « Optimal Transport Planning for the Supply to a Fruit Logistic Centre ». In *Handbook of Operations Research in Agriculture and the Agri-Food Industry*, édité par Lluis M. Plà-Aragonés, 163-77. New York, NY: Springer. https://doi.org/10.1007/978-1-4939-2483-7_7.

Nakandala, Dilupa, Henry Lau, et Jingjing Zhang. 2016. « Cost-optimization modelling for fresh food quality and transportation ». *Industrial Management & Data Systems* 116 (avril):564-83. https://doi.org/10.1108/IMDS-04-2015-0151.

Nguyen, Tri-Dung, Tri Nguyen-Quang, Uday Venkatadri, Claver Diallo, et Michelle Adams. 2021. « Mathematical Programming Models for Fresh Fruit Supply Chain Optimization: A Review of the Literature and Emerging Trends ». *AgriEngineering* 3 (3): 519-41. https://doi.org/10.3390/agriengineering3030034.

Pingali, Prabhu, Anaka Aiyar, Mathew Abraham, et Andaleeb Rahman. 2019. *Transforming Food Systems for a Rising India*. Springer Nature. https://doi.org/10.1007/978-3-030-14409-8.

Raoui, Hanane El, Mustapha Oudani, et Ahmed El Hilali Alaoui. 2020. « Perishable food distribution in urban area based on real-road network graph ». In *2020 5th International Conference on Logistics Operations Management (GOL)*, 1-6. Rabat, Morocco: IEEE. https://doi.org/10.1109/GOL49479.2020.9314721.

Raton, Gwenaëlle, et Céline Raimbert. 2019. « Livrer en circuits courts : les mobilités des agriculteurs comme révélateur des territoires alimentaires émergents. Étude de cas dans les Hauts-de-France ». *Géocarrefour* 93 (3). https://doi.org/10.4000/geocarrefour.13993.

Sander, Jörg, Martin Ester, Hans-Peter Kriegel, et Xiaowei Xu. 1998. « Density-Based Clustering in Spatial Databases: The Algorithm GDBSCAN and Its Applications ». *Data Mining and Knowledge Discovery* 2 (2): 169-94. https://doi.org/10.1023/A:1009745219419.

Schubert, Erich, Jörg Sander, Martin Ester, Hans Peter Kriegel, et Xiaowei Xu. 2017. « DBSCAN Revisited, Revisited: Why and How You Should (Still) Use DBSCAN ». *ACM Transactions on Database Systems* 42 (3): 1-21. https://doi.org/10.1145/3068335.

Soto-Silva, Wladimir E., Marcela C. González-Araya, Marcos A. Oliva-Fernández, et Lluís M. Plà-Aragonés. 2017. « Optimizing Fresh Food Logistics for Processing: Application for a Large

Chilean Apple Supply Chain ». *Computers and Electronics in Agriculture* 136 (avril):42-57. https://doi.org/10.1016/j.compag.2017.02.020.
Soto-Silva, Wladimir E., Esteve Nadal-Roig, Marcela C. González-Araya, et Lluis M. Pla-Aragones. 2016. « Operational research models applied to the fresh fruit supply chain ». *European Journal of Operational Research* 251 (2): 345-55. https://doi.org/10.1016/j.ejor.2015.08.046.