

A GIS-based interactive map enabling data-driven decision-making in Nigeria's food supply chain

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Abstract

The accessibility of open-source data on fresh food supply chains provides key stakeholders from the public and private sectors with insights for better decision-making to drive food loss reduction. Nigeria has a fair amount of open-source agricultural and climate-related data. However, most of these datasets are not readily accessible. If they are open-access, they are often not easily digestible for the supply chain stakeholders to help them in decision-making. Using visually engaging interactive maps and graphs could help solve this challenge. This paper presents a detailed method used to develop an interactive web Geographic Information System (GIS) tool that collates and visualizes available open-source datasets for fresh food supply chains in Nigeria. Open-source data were acquired in various forms, including tabular, vector, and rasters, processed and uploaded as layers on the interactive web map. The gathered raw open-source data include crop production data, market prices, weather, road network, market locations, mobile coverage, water access, water scarcity, and food insecurity. Most of these data needed some processing on open-source geographic information system applications and web-based computing platforms to transform them into sources of actionable insights. These final processed layers were then uploaded to a consolidated interactive web map, built on the Google Earth Engine platform. This interactive map can lead to relevant insights that could help stakeholders in Nigeria optimize their supply chain of fresh produce. The method described here also allows for the reproduction of such maps for other countries.

Keywords: Data visualization, Google Earth Engine, smallholders, fresh produce, postharvest supply chain, cooling solution

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1 Specifications table

| | |
|--|---|
| Subject area | Agricultural and Biological Sciences |
| More specific subject area | Fresh food supply chain |
| Method Name | Visualizing the potential for sustainable cooling solutions across Nigeria via an interactive web-GIS tool |
| Name and reference of the original method | Our method was adapted from an early tool created for India: Increasing accessibility and usability of open-source data through a web map for better decision-making in India’s cold chain of fresh produce: K. Shoji, R. Evangelista, J. Gajardo, T. Motmans, T. Defraeye, Increasing accessibility and usability of open-source data through a web map for better decision-making in India’s cold chain of fresh produce, (2022). https://doi.org/10.5281/ZENODO.6448695 . |
| Resource availability | Google Earth Engine (GEE), QGIS (version 3.24 Tisler), ArcGIS Pro (version 2.9), Jupyter notebook, Google Colab, R (version 4.1.0), Python (version 3.8.3), etc. |

2 Method details

The agricultural sector represents approximately 22% of Nigeria’s GDP and about two-thirds of the labor force [1], yet the country experiences more than 40% percent loss of fresh produce post-harvest[2]. In Nigeria, the majority of fresh produce farms are located in the Northern region, and as such, fresh produce is transported through road networks to the markets in the southern region where they are consumed. Post-harvest loss occurs in the fresh food supply chain mainly due to inadequate cold storage and refrigerated transportation facilities when these products are being transported from the farms in the North to markets in the southern region. Open-access data, when utilized properly, could empower stakeholders to make their own decisions based on insights and stories embedded in the data. These stakeholders include smallholder farmers, cooling service providers, NGOs, financial institutions, policymakers, and government bodies. One way to do this is to make these data broadly accessible to the public via an interactive web-GIS tool. Availability of resources such as the interactive web map discussed in this paper will go a long way in mitigating this post-harvest loss. The web map comprises several GIS layers providing relevant information with actionable insights, the synergy of having all these data available is huge for decision makers. These layers include elevation, electrical grid, population, air temperature, solar radiation, precipitation, road network, market locations, mobile coverage, land cover, agro-ecological zones, food insecurity, blue water scarcity, water access, and crop production. This paper discusses the process of building an openly accessible Google Earth Engine (GEE) application. We highlight each layer on the web map and its sources and go into detail on the processing steps undergone in transforming the raw datasets into layers ready to convey information to stakeholders.

3 Data preprocessing steps

The open-source data we collected had various spatial coverage, temporal timespan, and data formats. The processing steps briefly discussed below were necessary to take these differences into account in order to produce layers to be displayed on the web map layer.

3.1 Global data preprocessing

Some open-source data collected consist of global data and therefore needed to be clipped to the extent of Nigeria. The datasets that fall under this category include; climate data (Section 3.3.1), elevation data (Section 3.3.2), water scarcity (Section 3.3.3), mobile broadband coverage data (Section 3.3.5), predicted electricity network lines (Section 3.3.6), agro-ecological zones (Section 3.3.10), and land cover (Section 3.3.11). These layers were clipped to Nigeria using a shapefile with state boundaries from 2020 [3] (Fig. 3). Note that we used these boundaries as they were the latest ones we could find. The elevation data were sourced from the Google Earth Engine data catalog [4] and were directly clipped for Nigeria in the GEE’s code editor. The predicted electricity network lines and mobile broadband coverage data were processed in QGIS (version 3.18.2) [5]. The land cover, agro-ecological zones, and blue water scarcity data were processed in QGIS (version 3.24 Tisler) [6] and ArcGIS Pro (version 2.9) [7]. The climate data were processed in R (version 4.1.0) [8].

3.2 Tabular data preprocessing

Some open-source data collected consist of tabular data containing metrics relative to a given state in each row. This is the case for crop production data sourced from the National Agricultural Sample Survey (NASS) of 2010 (see Section 1.4.9), water access levels data sourced from [9] (see Section 1.4.4), and market price data sourced from the National Bureau of Statistics (NBS) (see

Section 1.4.14). The crop production, market prices, and water access levels data were merged with the administrative layer at the state level (as of 2020) [3].

The merging was performed in Python (version 3.8.3) using the 'FuzzyWuzzy' (version 0.18.0) library [10] to match state names that might be spelled differently in the different data sources.

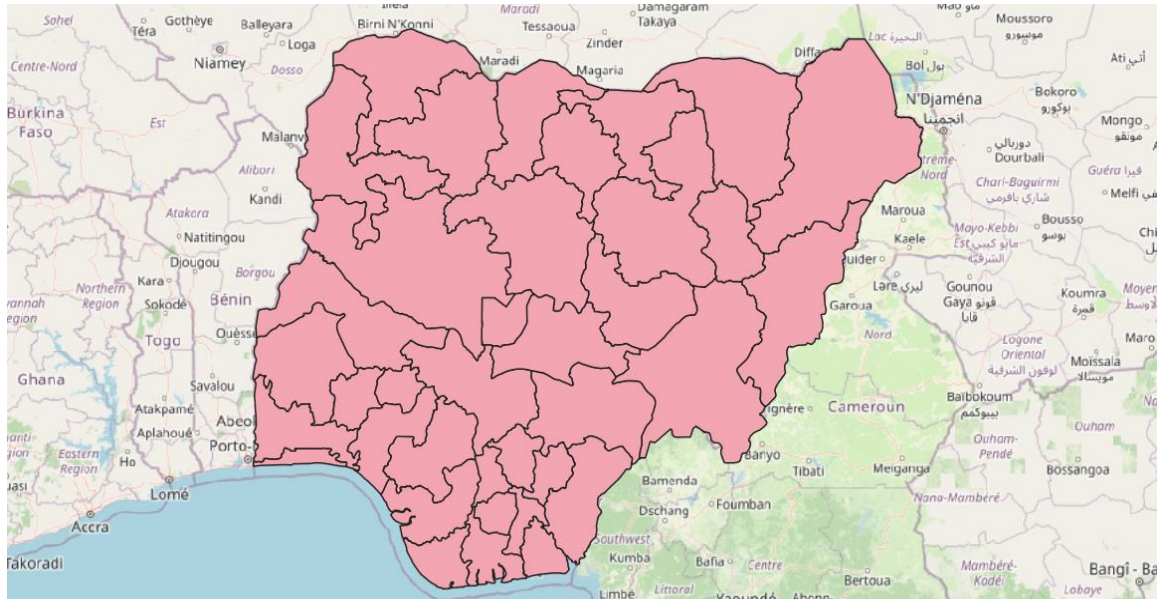


Figure 1. Shapefile of Nigeria map showing state administrative boundaries (from the year 2020). The shapefile was sourced from [3].

3.3 GIS layers

This section describes the layers that are shown on the interactive map. The license for each data source are referenced in the License sub-section of the respective layers.

3.3.1 Climate layers

This group of layers was downloaded from the ERA5 database [11]. The names of the extracted parameters are Total precipitation, 2m temperature, and Total sky direct solar radiation at the surface for total precipitation, temperature, and solar radiance, respectively. These data represent temperature, solar radiance, and total precipitation for each month in 2021. The data has a spatial resolution of approximately 30 km (0.25° latitude and 0.25° longitude). The datasets were downloaded in NetCDF format, imported in R (version 4.1.0), and clipped to the administrative boundary shapefile of Nigeria from 2020 sourced from [3]. Finally, the rasters per parameter for each month were exported as Geotiff files and uploaded to the assets on GEE. This processing was done via the 'ncdf4' and 'raster' packages. The datasets for this project were from 2021, as it is the latest year with complete data for the entire year. Details about the individual climate layers are discussed below.

The terms of use for this dataset can be found here: <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means?tab=overview>

3.3.1.1 Precipitation layer

This layer shows the total monthly averaged precipitation expressed as a combination of large-scale and convective rainfall and snowfall rates for the year 2021. The data was accumulated hourly for 24 hours per day for each month and then averaged. The original data were downloaded in m and converted to mm/day in GEE by multiplying the values by 86,400 (seconds in a day). The monthly layers were clipped to Nigeria and uploaded to the GEE repository as explained in Section 3.3.1.

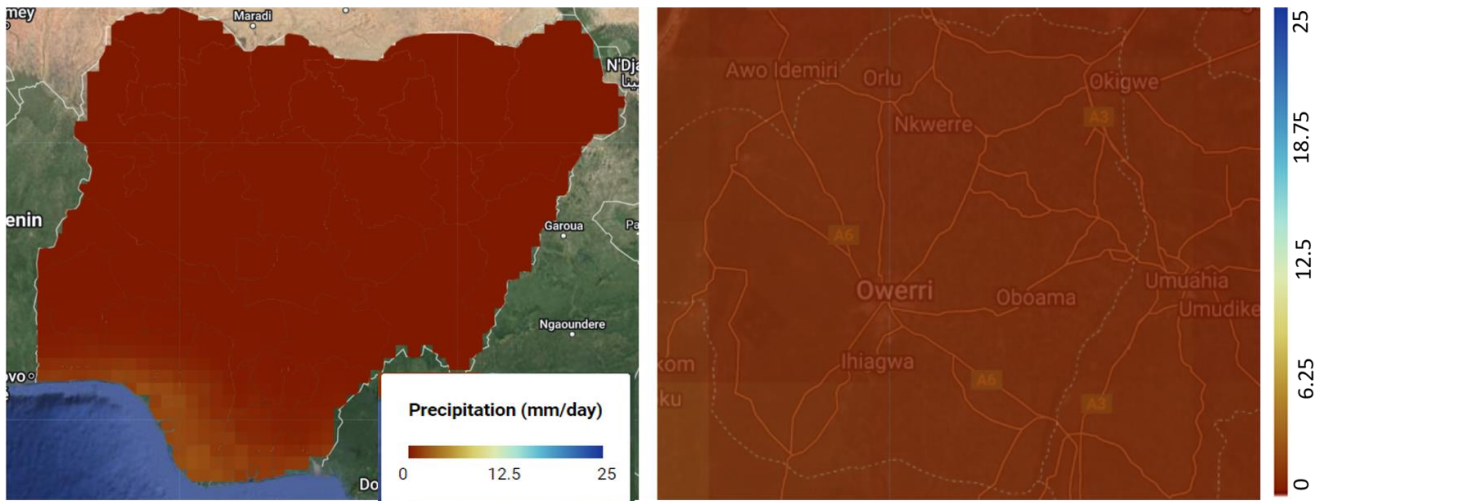


Figure 2. Precipitation layer, an example of January 2021 (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The precipitation data for the year 2021 were sourced from [11].

3.3.1.2 Temperature layer

This layer displays the monthly averaged air temperature data for the year 2021 measured at 2 m above the surface of land, sea, or inland waters. The original datasets were represented in K and were converted to °C. After clipping to the admin shapefile of Nigeria, each layer was uploaded to the GEE repository as explained in Section 3.3.1 above.

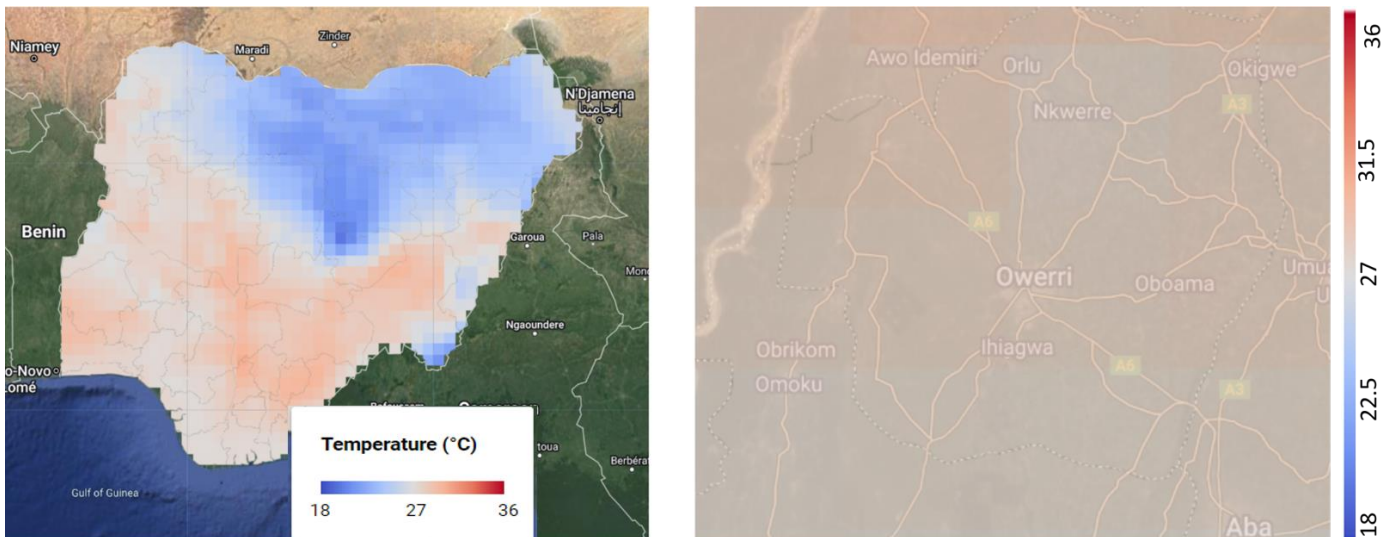


Figure 3. Air temperature layer, an example of January 2021 (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The temperature data for the year 2021 were downloaded from [11].

3.3.1.3 Solar radiance layer

This layer displays the monthly averaged direct and diffuse solar radiation accumulated for a single day per month as measured on the earth's surface in $W m^{-2}$. The original data were in $J m^{-2}$ per day and converted to $W m^{-2}$. After the processing steps mentioned in Section 3.3.1 were complete, each monthly layer was uploaded to GEE and compiled into a FeatureCollection. A UI panel was

designed with a slider component included such that as the slider changes value within the range 1 to 12 to account for each month of the year, a call-back is executed and the corresponding layer is overlaid on the GEE map.

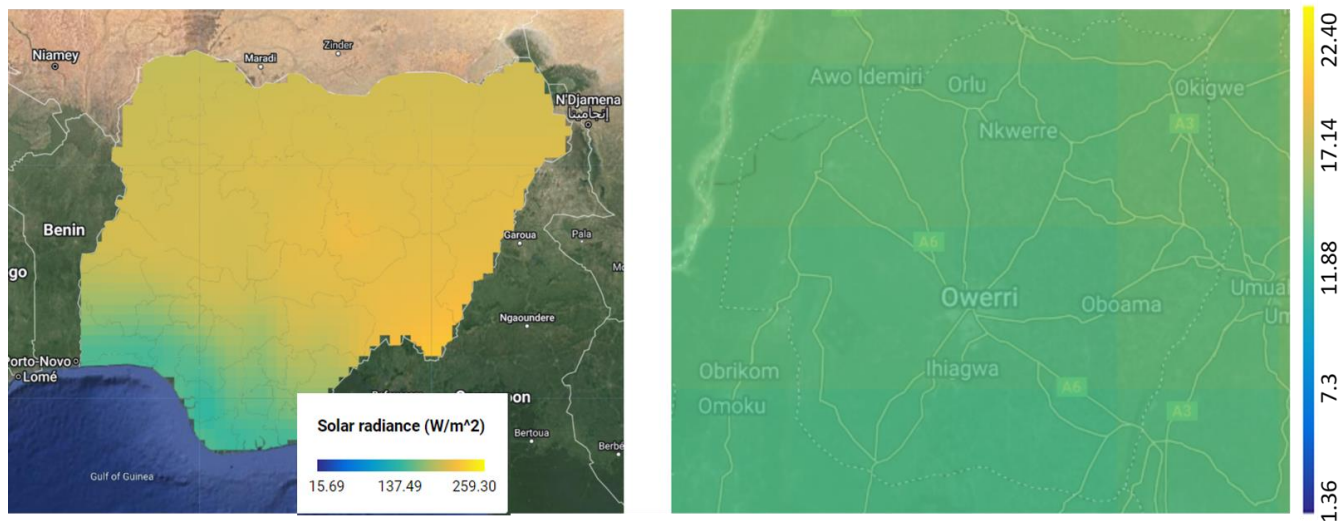


Figure 4. Solar radiance layer, an example of January 2021 (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The solar radiation data for the year 2021 were downloaded from [11].

3.3.2 Elevation layer

This layer displays the distance above sea level for the entire country. The data used in creating the elevation layer was sourced from the Japan Aerospace Exploration Agency (JAXA) Earth Observation Research Center [12]. This is a global digital surface model (DSM) dataset at a spatial resolution of 30 m prepared by JAXA for the ALOS World 3D - 30m (AW3D30) dataset. This layer was directly imported into the script from the GEE data catalog and clipped to Nigeria.

The terms of use for this dataset can be found here: <https://earth.jaxa.jp/en/data/policy/index.html>

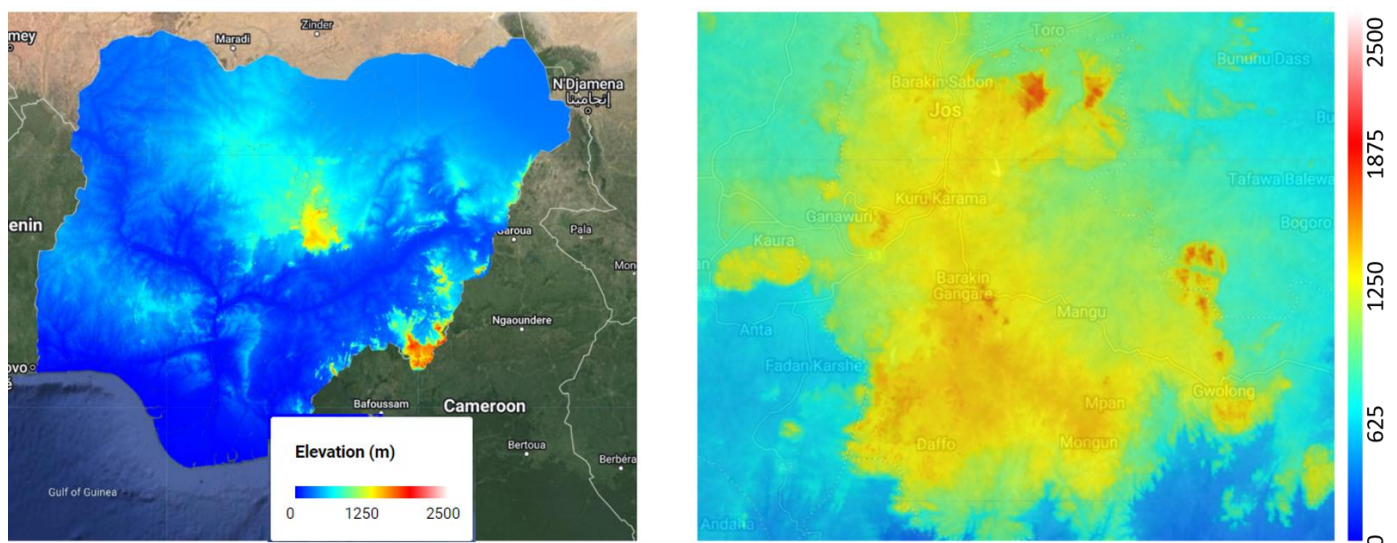


Figure 5. Elevation layer (Left: Nigeria, Right: Plateau state (Terrain background with 80% opacity)). The global elevation dataset was imported into GEE from [12].

3.3.3 Blue water scarcity layer

The water scarcity layer expresses the levels of blue water (fresh surface water and groundwater) scarcity in Nigeria on a monthly basis at a spatial resolution of 30 arc minutes (approximately 60 km). Blue water scarcity is expressed as the ratio of blue water footprint in a grid cell to blue water availability in the cell. The datasets were sourced from [13]. The research effort was to assess global blue water scarcity at a high spatial resolution using input data from 1996 and 2005. Details about the methodology and model validation are discussed in [13]. The global rasters were sourced from the authors of [13] on request and clipped to Nigeria on GEE.

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Figure 6. Blue water scarcity layer, an example of January (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The global rasters for blue water scarcity levels were sourced from [13].

3.3.4 Water access layer (WASH)

This layer displays household water and sanitation access levels across the country's 36 states, including the Federal Capital Territory. WASH stands for water, sanitation, and hygiene. The primary investigation was carried out in [9] to map the population's access to seven indicators of water and sanitation services in Nigeria using input data from the National Water Sanitation Survey 2015 (see [14] for a more detailed explanation of the NWSS survey). Geospatial covariates data included were vegetation index, aridity, land surface temperature, brightness of night-time lights, estimated travel time to nearest functioning water source, and a gridded population density map. Details about the methodology, model validation, and results are discussed in the paper [9]. The results were presented in the paper as tabular data estimating the percentage of total population per state with access to these seven indicators. For this project, we selected only the water indicators, which include "Improved water", "Basic water", "Improved source < 30 min trip", and "Piped water on premises". Each of these indicators is explained in detail in [9].

To process this layer, the metrics at the state level were merged with the Nigeria state-level boundaries (Figure 1) using the python 'FuzzyWuzzy' (version 0.18.0) library and geopandas (version 0.10.2) on Jupyter notebooks. This package enabled the matching of state names across the two datasets to create the shapefiles for the final layers. Note that for the indicators "Basic water" and "Improved source < 30 min trip" there was no data for Zamfara state.

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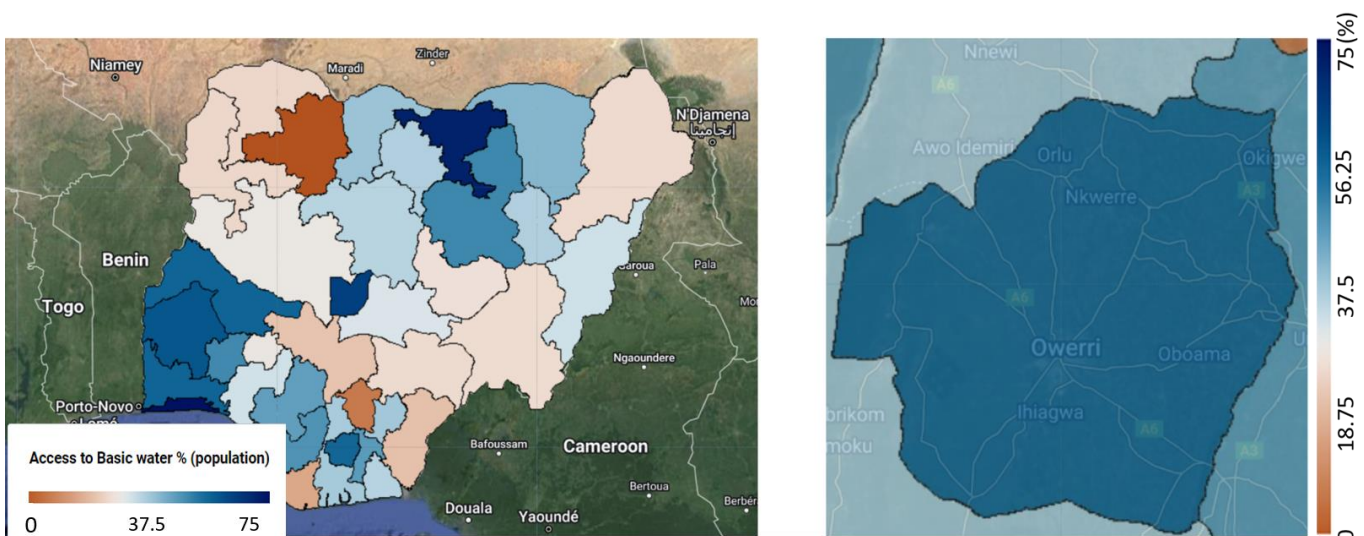


Figure 7. Water access layer, an example of Basic water access levels in January (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The tabular data containing water access statistics in population percentage per state for Nigeria was sourced from [9].

3.3.5 Mobile coverage layer

This layer represents the global mobile broadband coverage for Nigeria at a spatial resolution of 1 km. The grid was computed by merging coverage created from Open Cell ID cell tower database and operators' submission to Global System for Mobile Communication (GSMA). The datasets were sourced from [15]. Data processing was done on these data by clipping it to the extent of Nigeria and displaying it on the map.

The terms of use for this dataset can be found here:

<https://data.apps.fao.org/map/catalog/srv/eng/catalog.search#/metadata/7ee38f75-605f-4c88-9afc-64779e70e595>

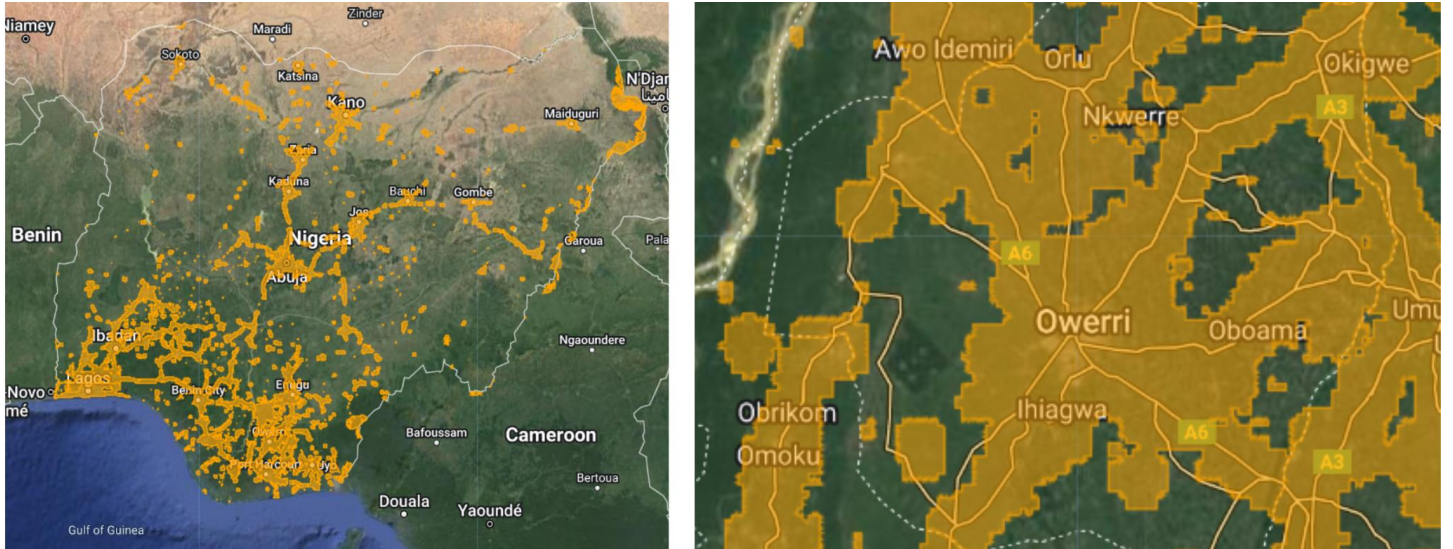


Figure 8. Mobile coverage layer (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The medium-dark yellow polygons represent the areas with mobile coverage as computed in [15].

3.3.6 Predicted electricity network lines layer

This layer displays Nigeria's predicted electricity network lines as computed by [16]. The layer was derived via a combination of OpenStreetMap data [16] and satellite imagery of Night time lights [16]. The lines are a vectorized representation of predicted Electrical transmission and distribution lines. This global dataset was clipped to Nigeria and uploaded to GEE.

The terms of use for this dataset can be found here: [Creative Commons Attribution 4.0 International](https://creativecommons.org/licenses/by/4.0/)

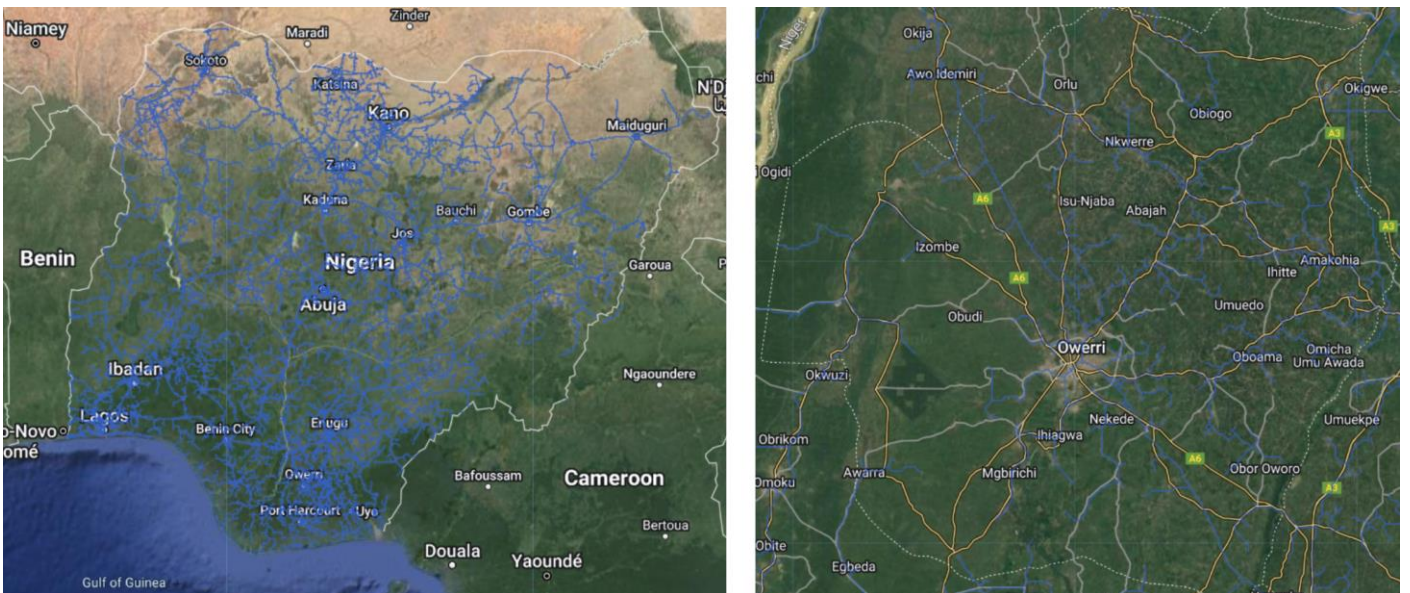


Figure 9. Predicted electricity network lines layer (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The blue color vectors represent the electrical transmission and distribution lines in Nigeria. The global electrical grid was sourced from [16] and clipped to the extent of Nigeria in QGIS (version 3.24 Tisler)

3.3.7 Acute food insecurity phase layer

This layer describes the anticipated severity of acute food insecurity using the Integrated Food Security Phase Classification (IPC 3.0) developed by the Famine Early Warning Systems Network (FEWS NET) [17]. FEWS NET is a leading provider of early warning and analysis on acute food Insecurity. They use a five-level scale developed by the IPC to describe the anticipated levels of acute food insecurity. This includes minimal, stressed, crisis, emergency, and famine levels of acute food insecurity. Classification is done based on individual access to food and income-generating activities. For the year 2022, FEWS NET has published a near-term projection for April - May and a medium-term projection for the months between June and September. We selected the far-term projection as it aligns with the timeframe for the release of the web map. Datasets are available for download in [17]. The layer was clipped to the Nigeria shapefile to ensure visibility of state boundaries for better visualization before addition to the Web Map.

The terms of use for this dataset can be found here: [Creative Commons Attribution 3.0 United States](https://creativecommons.org/licenses/by/4.0/)

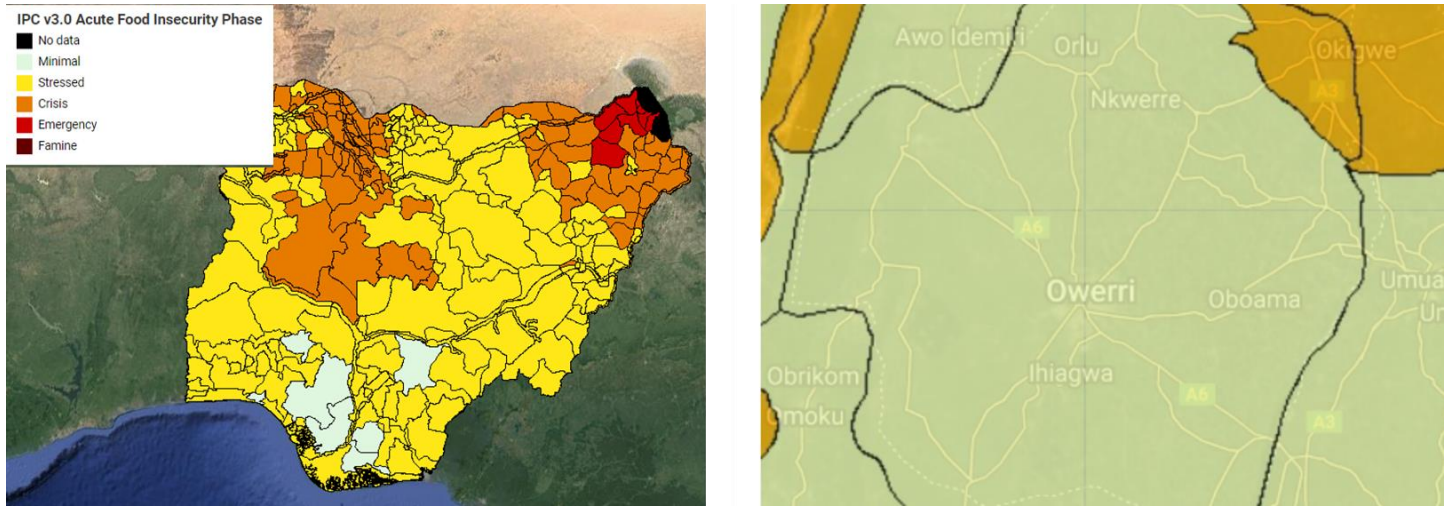


Figure 10. Acute food insecurity layer for the months in the range June – September for the year 2022 (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The Acute food insecurity shapefiles were sourced from [17].

3.3.8 Population per LGA layer

This layer displays the average population (in number of people) in each local government area (LGA) of Nigeria. The dataset was sourced from the official website of GRID3 Nigeria (Geo-referenced Infrastructure and Demographic Data for Development) [18]. It was officially released on the 29th of March, 2020. The data was generated as the output of statistical models developed by [19]. The values displayed by this layer represent the total posterior mean population estimate for each local government area in Nigeria. The model developed for this research utilized input population data from the Nigeria Microcensus survey of 2018 [20]. Details concerning model development, input datasets, and result validation are discussed in [19].

The terms of use for this dataset: Unknown

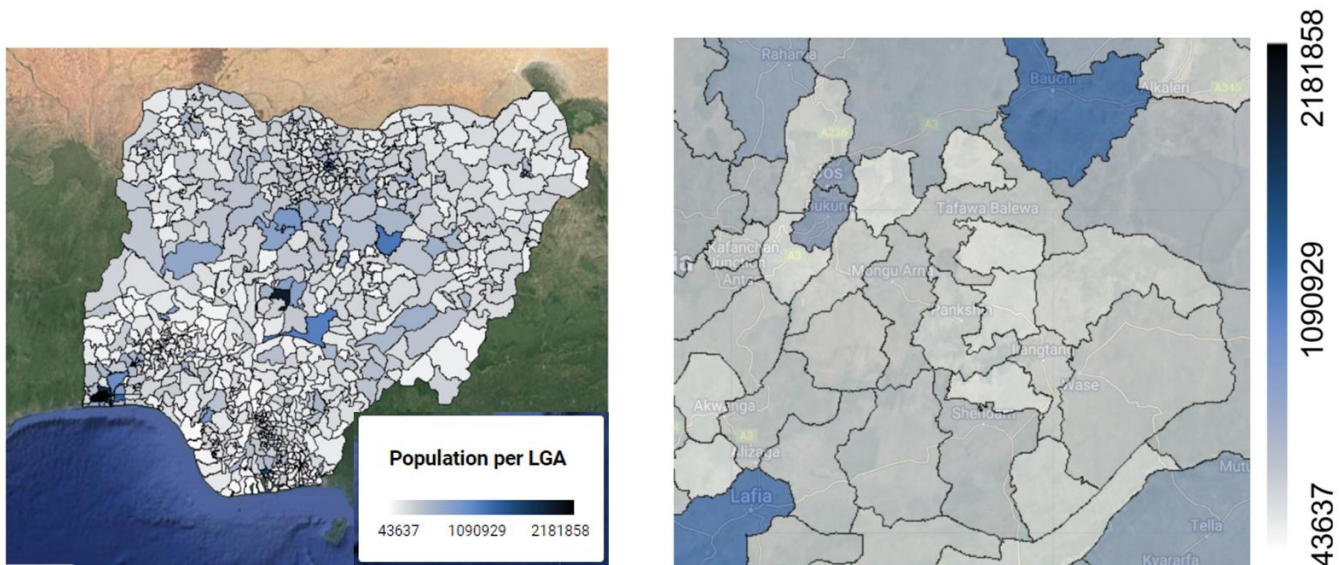


Figure 11. Mean LGA population layer (Left: Nigeria, Right: Plateau state (Terrain background with 80% opacity)). The population data per LGA in Nigeria was downloaded from [18].

3.3.9 Crop production layer

The crop production layer displays production statistics for various fresh produce, including bananas, beans, cocoyam, cucumber, garden egg, melon, okro, onion, pepper, pineapple, plantain, potato, pumpkin, and tomato at a state-level spatial resolution. These data were sourced from the National Agricultural Sample Survey (NASS) of 2010. The NASS is a survey conducted every ten years as recommended by the FAO. The survey covered all the 36 states of the federation, including the Federal Capital Territory (FCT), Abuja. The sample set of this survey covered over 35,000 households nationwide; the target population canvassed were peasant farming households and corporate farms. Extra details about the sampling methods, results, and conclusions can be found in the survey report available for download in [21].

The datasets were reported in tabular form. Each row displays a state name and crop production statistics in tonnes/year. In the report, it was stated that 960 farming households were surveyed for each state. Therefore, to make the data more representative, the reported production statistic for each state was divided by this value (960), and the unit was converted from tonnes to kilograms. The resulting final layers were in kg/year per household. These tabular datasets were then processed on Jupyter notebooks as described in Section 3.3.4. The final layers were uploaded to GEE. Note that the statistics presented in this layer are based on the NASS 2010 survey. Therefore, they are not fully representative of the actual crop production values in the states.

The terms of use for this dataset: Unknown

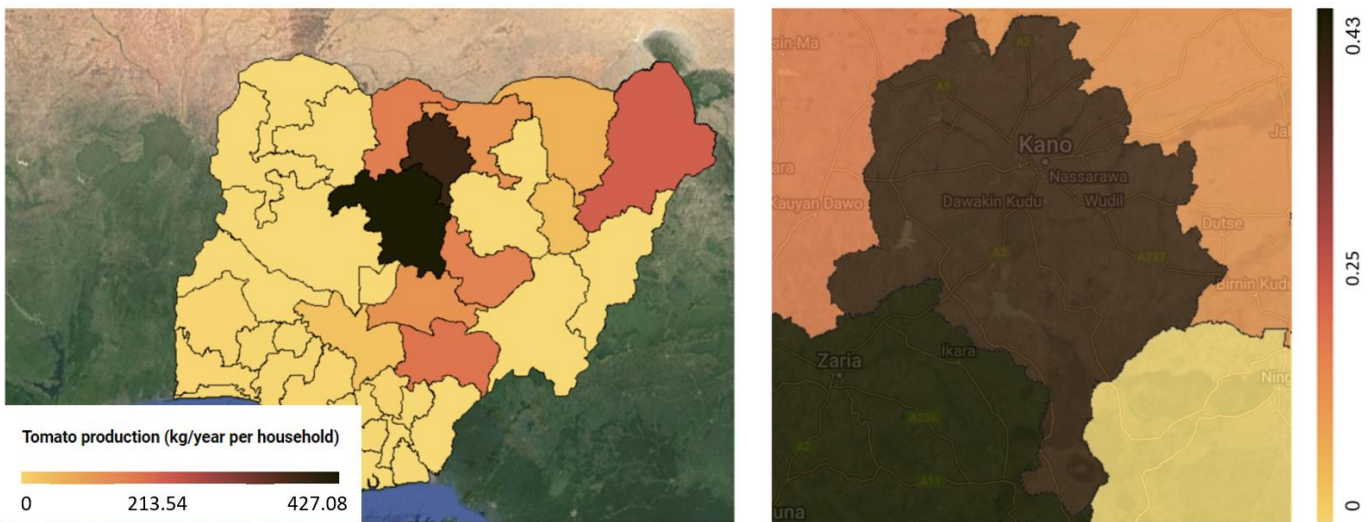


Figure 12. Crop production layer, an example tomato production (Left: Nigeria, Right: Kano state (Terrain background with 80% opacity)). The crop production tabular data with state statistics were sourced from [21].

3.3.10 Agro-ecological zones layer

The Agro-ecological zones layer represents the grouping of Nigeria's agro-ecological zones into 13 classes. Agro-ecological zones are geographical areas in a particular location with similar climatic conditions that is able to support rainfed agricultural activities. The data for this study was sourced from the Global Agro-Ecological Zoning version 4 (GAEZ v4) portal developed by the Food and Agricultural Organisation (FAO) of the United Nations in collaboration with the International Institute for Applied System Analysis (IIASA) [22]. The GAEZ v4 portal provides a standardized framework for the characterization of climate, terrain, and soil conditions relevant to agricultural production. This framework is subdivided into 6 themes, and for this project, we selected the land and water resources subtheme, which provides a characterization of bio-physical resources relevant to agricultural production systems. This theme groups the world's agro-ecological zones into 33 classes, and is available for download as a global raster with a spatial resolution of 5 arc minutes (approximately 9 km at the equator). The details concerning methodology and the development of the climatic models are discussed in [23]. Note that these models were combined with input data for different representative concentration pathways (RCP2.6, RCP4.5, RCP6, and RCP8.5) as defined by the Intergovernmental Panel on Climate Change (IPCC). We selected the ensemble climate model, essentially the ensemble mean of the 5 climatic models developed for the GAEZ v4 project, a projected timeframe of 2011-2040, and an RCP value of 4.5, which we believe corresponds to the middle value within the range of possible RCPs. The raster was downloaded from the GAEZ v4 portal, clipped to Nigeria, and uploaded to GEE. Note that the legend for this layer only displays 13 agro-ecological zones. This is because only 13 out of the 33 classes of Agro-ecological zones occur in Nigeria.

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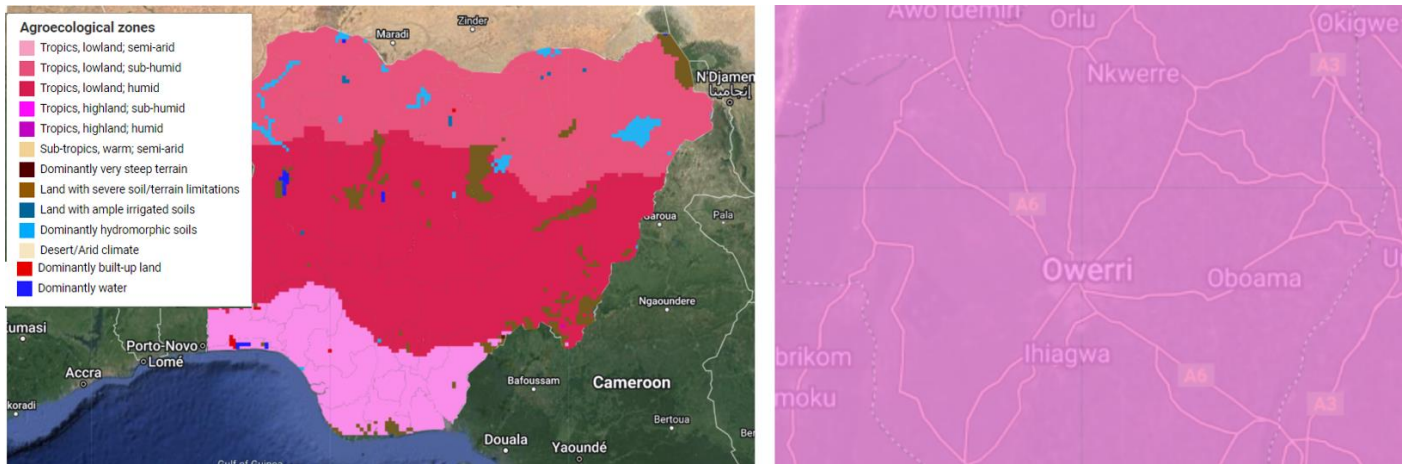


Figure 13. Agro-ecological zones layer (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The global Agro-ecological zones raster was sourced from [22].

3.3.11 ESRI landcover layer

The landcover layer displays the 10 classes of landcover in Nigeria as computed in [24]. These landcover classes include, water, trees, grass, flooded vegetation, crops, clouds, built area, bare ground, and scrub-shrub. The layer was sourced from the Environmental Systems Research Institute (ESRI) geodatabase for global land cover [24]. This global dataset consists of GeoTIFF tiles for all land masses on the planet grouped into 11 classes and offered at a high resolution of 10 meters. This global landcover map is generated with a deep learning model and yearly satellite images. To cover the complete extent of Nigeria, 5 tiles from 2021, collectively covering the areas between longitude 0°E - 18°E of the Greenwich meridian and latitude 0°N - 16°N of the equator, were downloaded from [25]. Each tile was imported into ArcGIS Pro (version 2.9) in our approach. Secondly, each tile was compressed using the LZ77 lossless compression and merged into one tile covering Nigeria's landmass. Finally, this tile was clipped to the shapefile of Nigeria and uploaded as a layer on GEE. Note that the legend for this layer only displays 10 land cover classes. This is because the class "snow" was removed from the legend for the GEE map as Nigeria does not experience snowfall, and no data was included for this class in the clipped landcover dataset.

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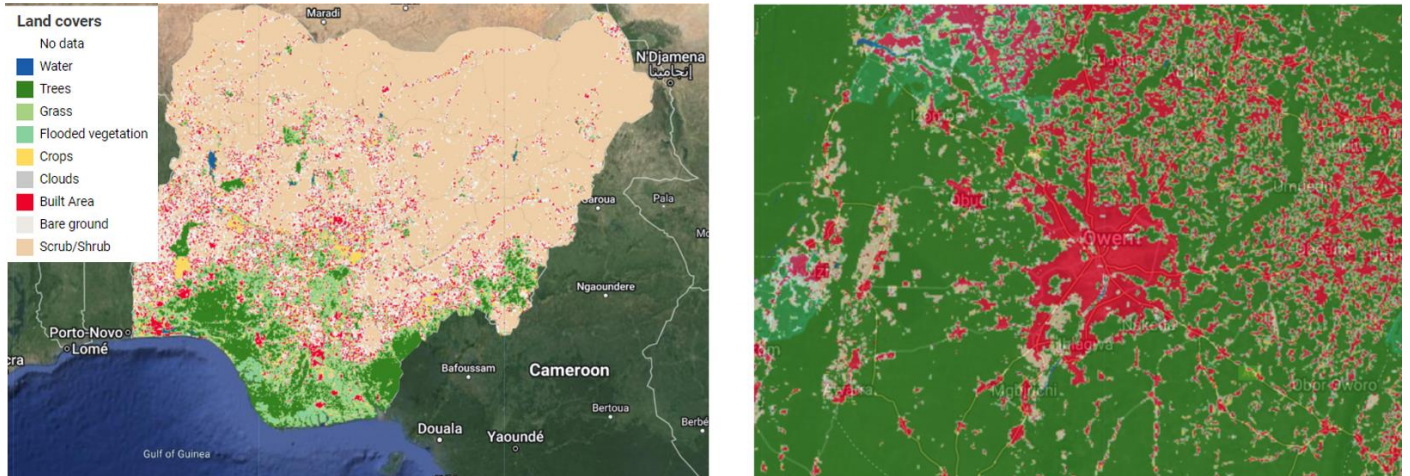


Figure 14. ESRI landcover layer (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The five landcover tiles used to generate this layer were sourced from [25]

3.3.12 Roads layer

This layer represents the road network in Nigeria based on OpenStreetMap. The dataset was downloaded from [26].

The terms of use for this dataset can be found here: [Open Database 1.0 License](https://openstreetmap.org/)

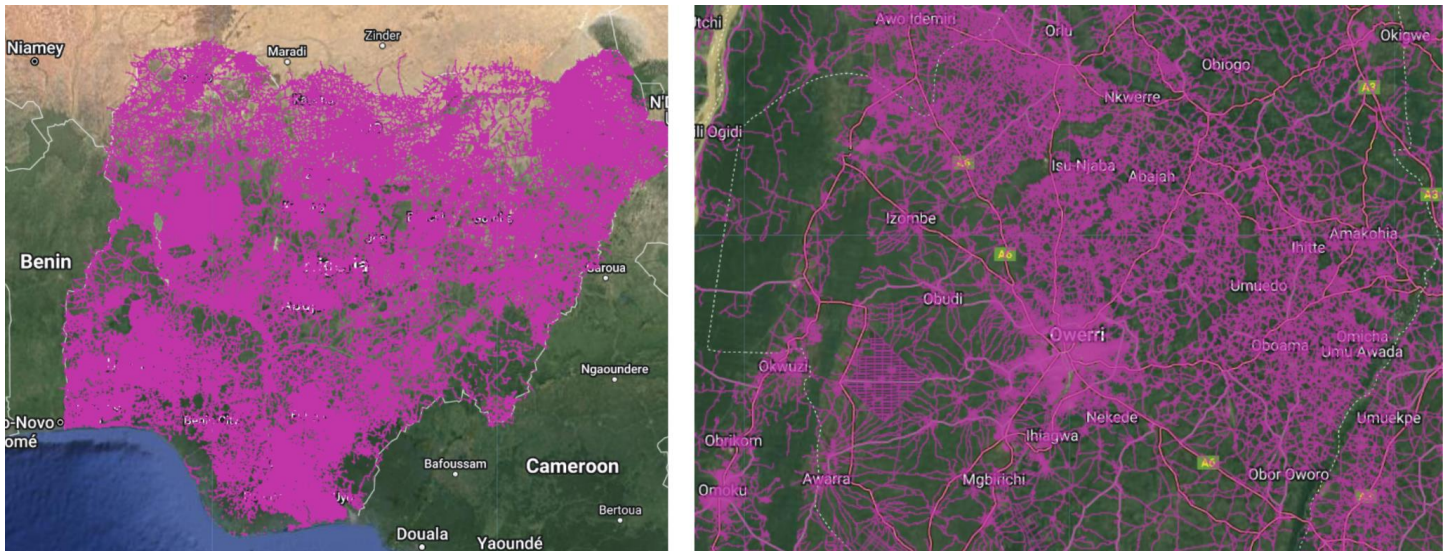


Figure 15. Roads layer (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The dark pink color vectors represent the road networks in Nigeria. The Nigeria road network was downloaded from [26].

3.3.13 Market locations layer

This layer represents geolocated data corresponding to over 11,000 markets across Nigeria, comprising both formal and informal markets. Although not specifically describing fresh produce markets, this layer will help stakeholders in the fresh food supply chain make informed market-related decisions as most Nigerian markets consist of mixed goods markets. The dataset was sourced from GRID3 [27].

The terms of use for this dataset: Unknown

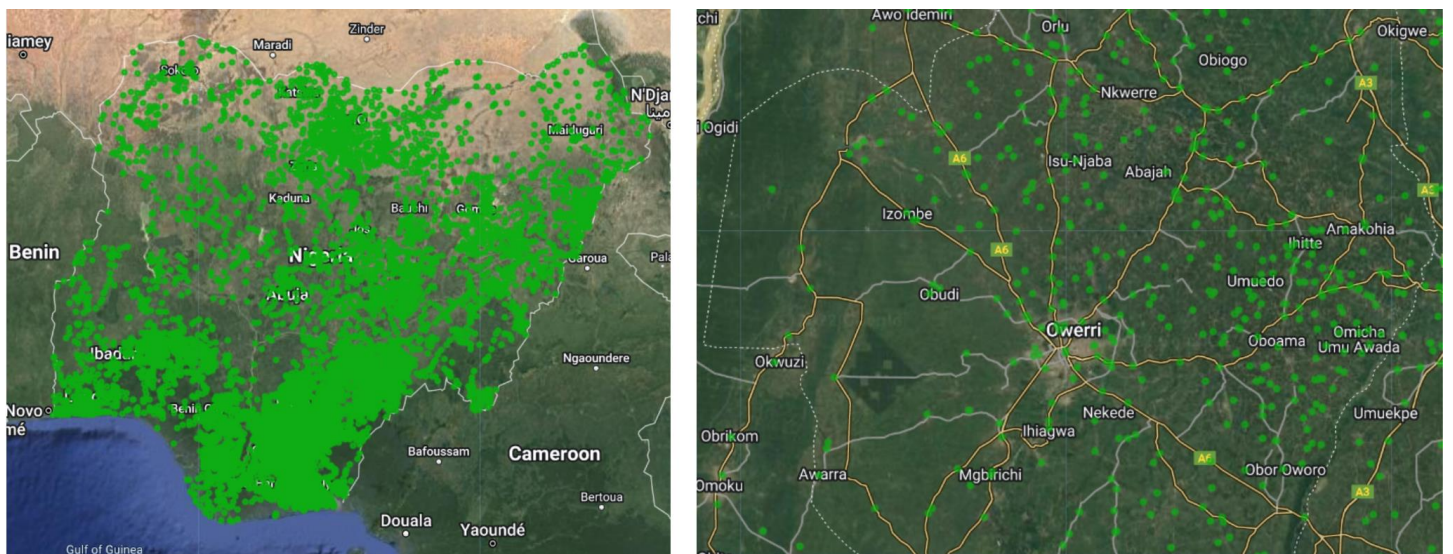


Figure 16. Market locations layer (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The green circular-shaped polygons represent the market locations in Nigeria. The market locations dataset was downloaded from [27].

3.3.14 Market prices time series layer

GEE has the functionality of displaying data as time series charts. The market price datasets were sourced from the official repository of the National Bureau of Statistics (NBS) and contain monthly averaged price data for some commodities from the year 2017 to 2021. The spatial granularity of these datasets is at the state administrative level. We decided to show this on the interactive web map as time series charts which can be exported after viewing. The aim is to visualize the seasonal variation in market prices of certain fresh produce across Nigeria. Commodities in this list include; onion, tomato, ripe plantain, unripe plantain, potato, and sweet potato. The data were downloaded from the E-library of the NBS [28] as Excel files containing price data for different products spread across 37 spreadsheets representing the 36 states in Nigeria, including the Federal Capital Territory.

The Excel files were processed on a Jupyter Notebook with the pandas package (version 1.4.2) to create properly structured data frames ready to be merged with the state administrative boundary shapefiles. Next, they were converted to Geodataframes using

the Geopandas (version 0.10.2) library and merged with the shapefiles by state name using the python 'FuzzyWuzzy' library (version 0.18.0). The 'FuzzyWuzzy' library accounts for state names that might be spelled differently in the two datasets. Final shapefiles were generated per commodity and uploaded to the GEE repository. A panel was created for the web map with selectors for commodity and state. When a combination of these inputs is selected, a time series chart showing the monthly market prices of the selected commodity in a selected state across the year range 2017-2021 is displayed on the map. This chart can be exported for further analysis.

The terms of use for this dataset: Unknown

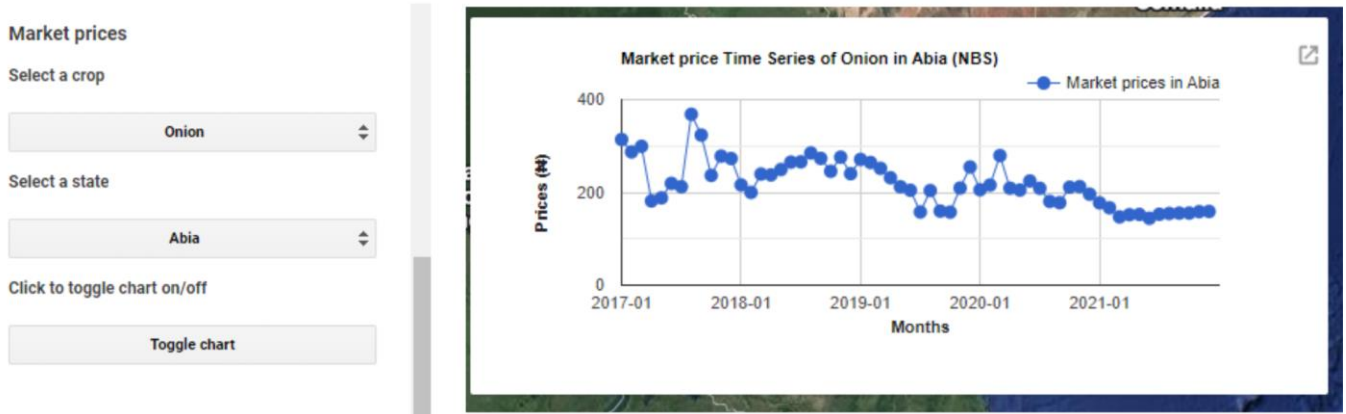


Figure 17. Market prices time series chart displaying the monthly market price time series for tomato in Abia state from January 2017 until December 2021 (Left: Market prices panel, Right: Market prices time series chart). The monthly market price tabular data were sourced from [28].

3.3.15 Shelf life gain layer

The shelf life of a commodity is calculated as the amount of time it can go without spoiling at a certain temperature, for example, the ambient temperature outside. This layer describes the gain in shelf life that can be achieved for selected commodities by keeping them at their optimal storage temperature instead of ambient temperature. The layer answers how long the shelf life can be extended by using cold storage. Thus, these layers express the potential benefits provided by cooling for selected key commodities in Nigeria. From a wider perspective, these key commodities can be seen as a representative set of fresh produce and therefore portray the advantage of storing fresh produce in cooling facilities. Five key commodities produced in large quantities in Nigeria were selected for this layer, including tomato, bell pepper, cabbages, green beans, and carrots. A temperature-based kinetic model was used for this calculation with input temperature data (Section 3.3.1.2). Other parameters used for the model, such as optimal temperature and shelf life under this optimal temperature for each key crop, were sourced from the Food and Agricultural Organisation of the United Nations. The details of the calculations and models are discussed in [29].

The terms of use for this dataset can be found here: [Creative Commons Attribution 4.0 International](#)

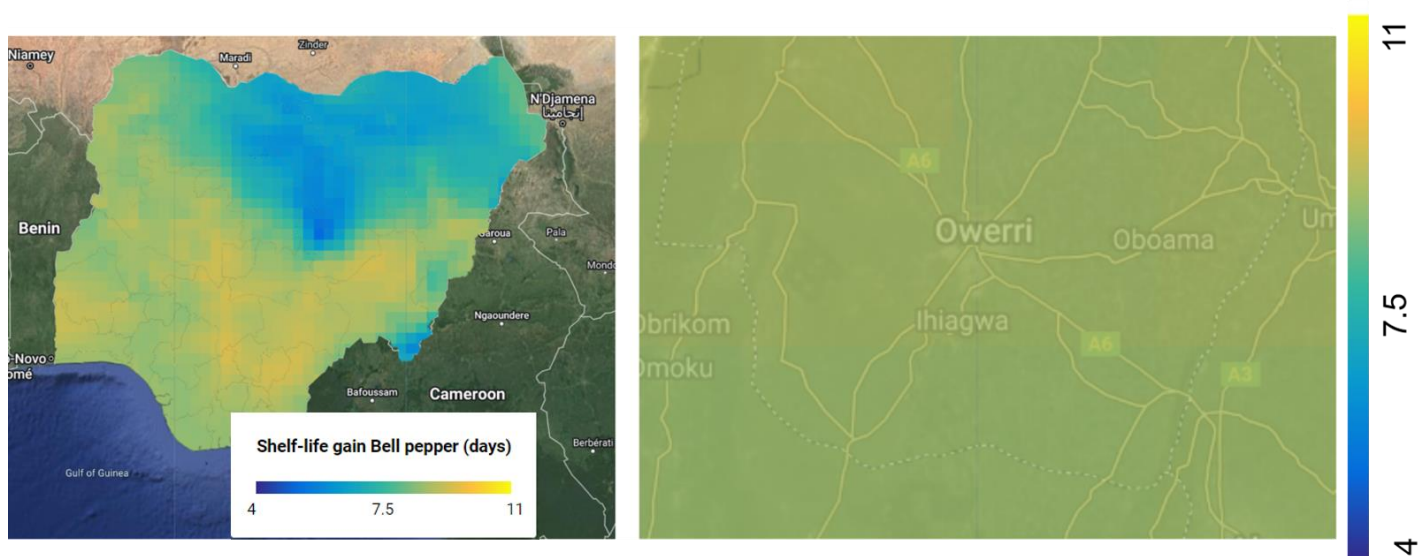


Figure 18. Shelf life gain layer, an example of bell peppers in January 2021 (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The shelf life rasters were developed by the YVCCA team [29].

3.3.16 Predicted cold room locations layer

This layer on the web map represents suitable areas for siting cooling units in Nigeria based on important available open-source data. Layers of importance were selected based on the need of a particular cooling service provider in Nigeria. This means that we used an algorithm that mimics the decision-making of a certain stakeholder to select areas that met certain pre-determined threshold criteria suitable for installing new cooling units. Some of these criteria required by a cooling service provider in Nigeria on which a threshold value is set, include; sun orientation, sunshine intensity, noise pollution, health hazard, land topography, market location and road accessibility. To calculate promising locations for installing new cold rooms, we used some layers discussed above in a model developed on the Graphical modeler tool on QGIS (version 3.24 Tisler). The input layers for this model were the following:

- Roads (Section 3.3.12)
- Market locations (Section 3.3.13)
- ESRI Landcover (Section 3.3.11)

In this model, we made key assumptions derived from insights provided to us by a certain stakeholder to filter out areas in the map that did not meet said assumptions. These assumptions are as follows;

- We selected areas that are no more than 2 km from a market
- Areas that are at a distance of 500 m from a road (access route proximity)
- Areas that are no more than 2 km from cropland.

Note that this assumption may vary depending on the service provider and the geographical location of the country of interest.

The merged and clipped ESRI landcover raster discussed in Section 3.3.11 was used to generate a binary cropland raster where cropland pixels were represented with values of one and the rest classes with zeroes. This was done using the 'raster calculator' tool on QGIS (version 3.24 Tisler). This raster was then polygonized with the 'polygonize' tool on QGIS (version 3.24 Tisler) to generate a vector showing cropland features in Nigeria. Some of these features had invalid geometries so, the 'Fix geometries' tool on QGIS (version 3.24 Tisler) was used to correct these features. The resulting cropland vector is then used in the model to calculate the distance from cropland pixels. In this model, the state boundary for the selected state is extracted by state name from the state boundary shapefile [3] using the 'Extract by attribute' algorithm from the processing toolbox in QGIS (version 3.24 Tisler), the roads in the selected state are extracted using the 'Extract by location' algorithm and the Roads layer (Section 3.3.12) as input. The same algorithm is used to extract the croplands in the selected state with the cropland vector as input. The markets and croplands in the selected state are then buffered by a distance of 2 km using the 'Buffer' tool in the processing toolbox in QGIS (version 3.24 Tisler), while a distance of 500 m buffers the roads. These buffered vectors are then intersected using the 'Intersection' algorithm to derive the final predicted cold room locations in the selected state. For the final step, the predictions for all 36 states, including the FCT, were merged into a single layer on QGIS (version 3.24 Tisler) and uploaded to Google Earth Engine. There are some limitations of this layer that are worth mentioning. The 2 km condition for markets is the major limiting factor for the output predicted locations of the model. Furthermore, note that this cropland vector is based on the Esri Landcover layer which is generated from machine learning models [22] and therefore is not completely accurate. Lastly, the roads layer (section 3.3.12) sourced from [19] does not cover all roads in Nigeria and, therefore, might exclude some dirt roads.

This layer was created to suggest to cooling service providers the best areas for locating future cooling units. However, the Your VCCA team declines any responsibility for any errors or omissions in the information provided. For the next version of this application, we plan to introduce more interactivity by allowing users to compute layers using their own selected input layers and thresholds.

The terms of use for this dataset can be found here: [Creative Commons Attribution 4.0 International](#)

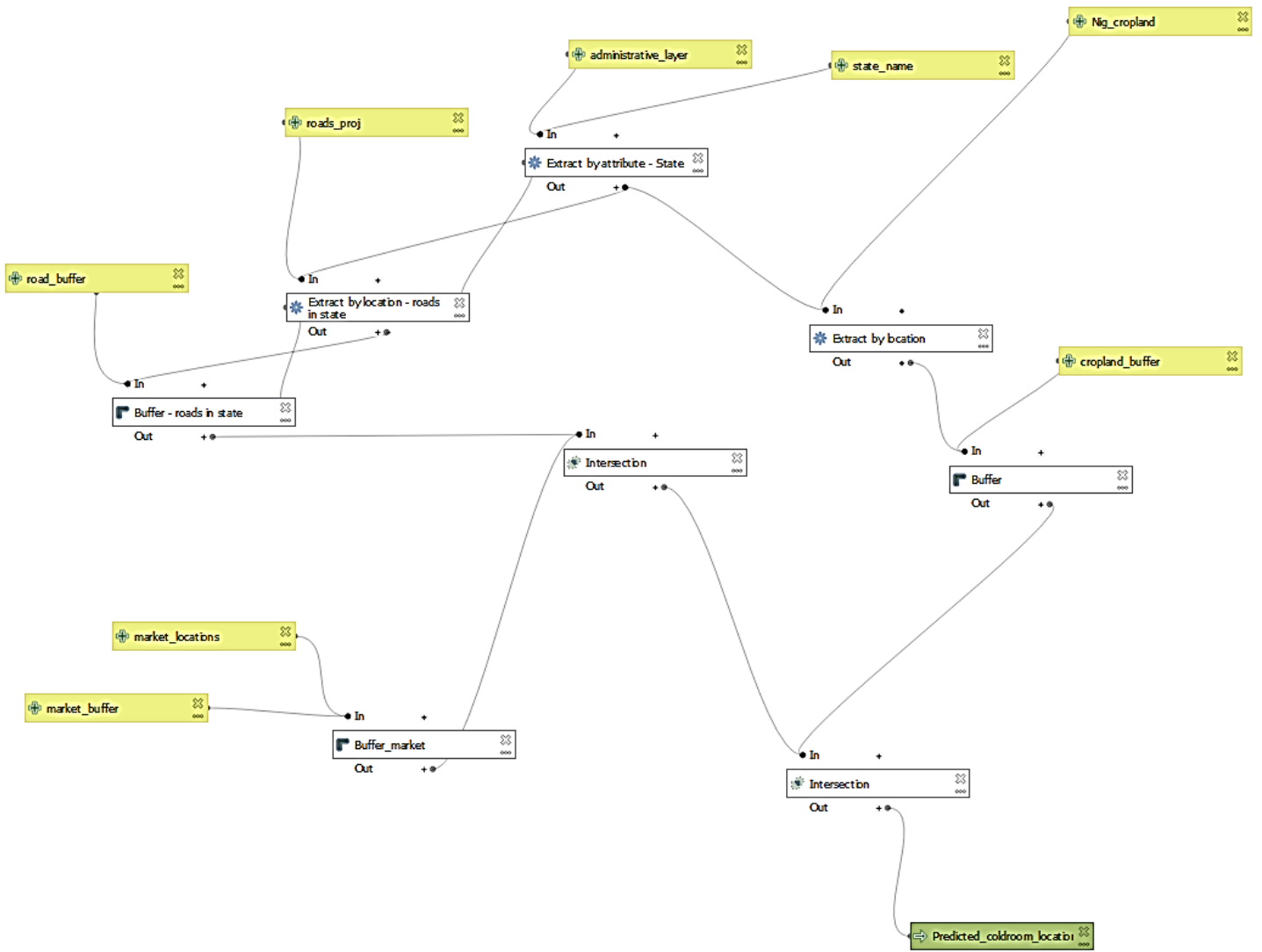


Figure 19. Graphical model used to generate the Predicted cold room locations for each state in QGIS (version 3.24 tislter). The yellow boxes represent the vector input layers, including the administrative layer showing state boundaries (Section 1.4.1), cropland (Section 1.4.16), roads (Section 1.4.12), and market locations (Section 1.4.13). The yellow boxes with “_buffer” attached to the titles represent the input buffer distance thresholds for the roads (Section 12), market locations (Section 1.4.13), and cropland (section 1.4.16) layers. The white boxes represent the algorithms used to process these input layers. The green colored box represents the final Predicted cold room locations layer for each state (final output of the model).

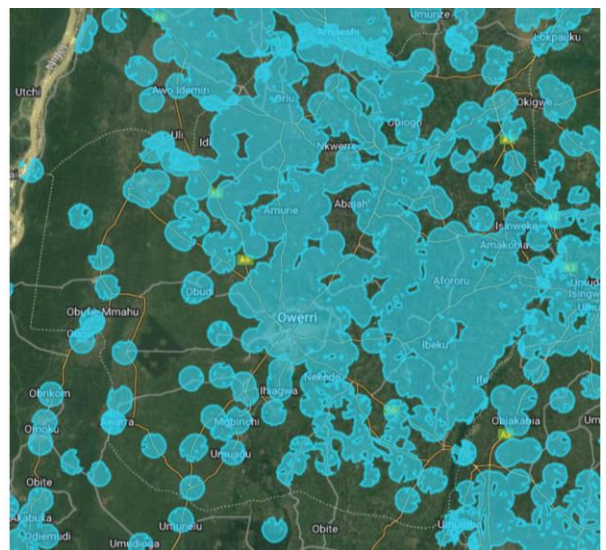
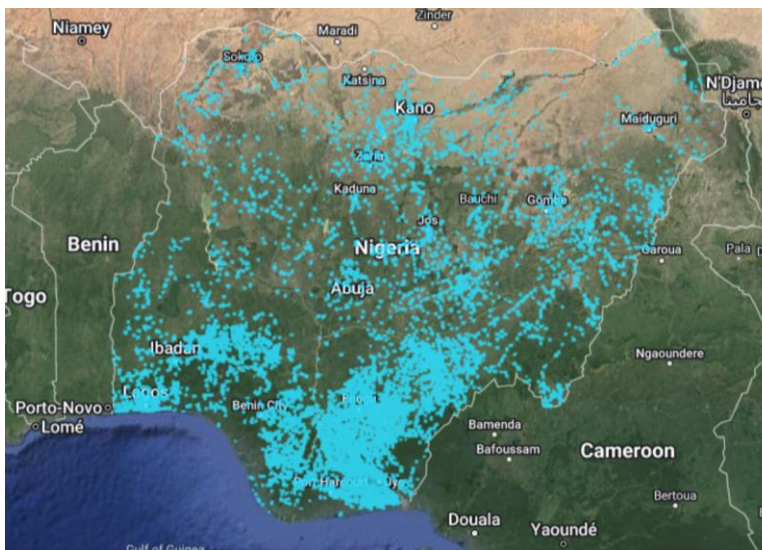


Figure 20. Potential cold room location layer (Left: Nigeria, Right: Imo state (Terrain background with 80% opacity)). The blue colored polygons represent the suitable areas in Nigeria for installing cold room facilities as computed by the Your VCCA team.

3.4 Google Earth Engine web map

GEE is an open-source platform combining a multi-petabyte catalog of satellite imagery and geospatial datasets for planetary-scale analysis. The user interface (UI) template for organizing the code contained in the GEE script for this project was sourced from [11]. Following the instructions from the framework template specified by [11] above, the code is divided into six sections; Model, Components, Composition, Styling, Behaviours, and Initialization sections, as follows:

1. **Model:** In this section, all the data displayed on the map and other relevant information are defined. This includes all Images, Image collections, Feature, and Feature collections. Image collections and Feature collections are stacks or sequences of related images and features respectively that are grouped together to allow operations to be carried out on the entire group, such as sorting and filtering. In GEE, raster data are uploaded as Images and Image collections, while vector data are uploaded as Features and Feature collections
2. **Components:** In this section, all the UI widgets are defined, including panels, selectors, sliders, buttons, and charts.
3. **Composition:** In this section, all the UI components defined in the components section above are arranged to give a complete UI. An example is the control panel. This scrollable panel contains all the widget groups for controlling how the layers are displayed, located at the left corner of the GEE web map. Here, all the other defined panels, including shelf-life gain, crop production, water access, water scarcity, market prices, climate panels, etc, are arranged to give a clean look and promote a great user experience.
4. **Styling:** The style properties of all widgets are defined in this section
5. **Behaviors:** This section contains the majority of the call-back functions that dictate how the app behaves when a user interacts with it. These functions are tied to the widgets using event listeners such as Onclick for buttons and the map, and onChange for the selectors and sliders.
6. **Initialization:** The app is initialized with certain predefined properties in this section. All except the topmost layer are kept invisible to improve the map loading speed.

The color palette for visualizing most of the layers was taken from the palette package and can be found here [12]. The UI components for this web map are grouped into 4 major component groups, the control panel, the map, the value panel, and the legends.

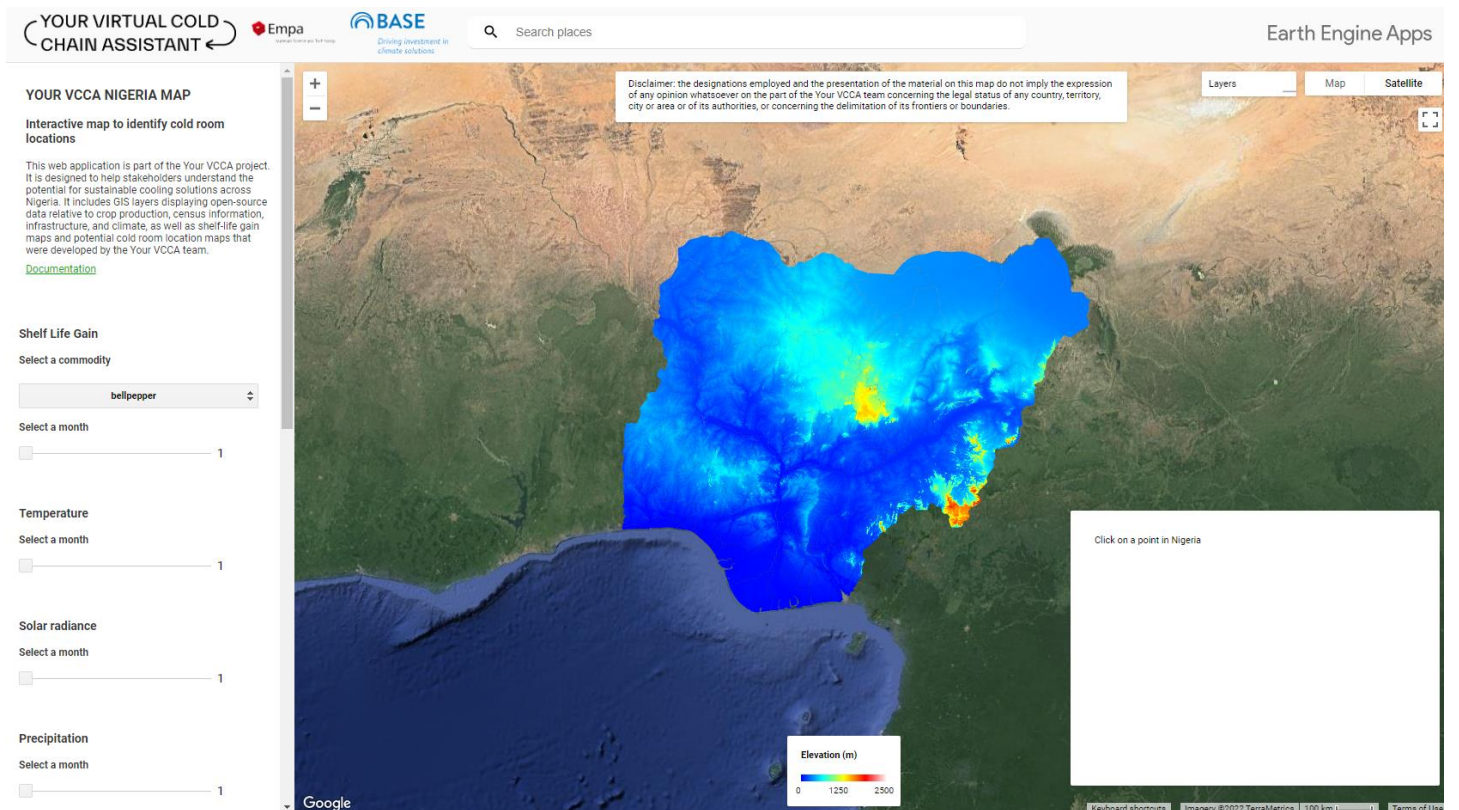


Figure 21. Google Earth Engine web map showing the elevation layer (Section 1.4.2).

4 CRediT author statement

TD, TM and DO [Onwude] conceptualized the project and acquired funding. TD and DO [Onwude] did the project administration. KS, RE, JG, DO [Onwude], and DO [Odion] collected the data, performed the investigation, and developed the methodology; DO [Odion], RE, and KS, JG did the processing of the data and analysis; DO [Odion] did the visualization, with key input from DO [Onwude], TD, KS, JG, and RE. DO [Odion] developed the web map with key inputs from JQ, KS, RE, DO [Onwude], and TD; DO [Odion] wrote the original draft of the paper with key input from DO [Onwude], and all authors performed critical review and editing of the paper.

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6 Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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