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Mapping and Estimating the Impact of Drought on Food Crop Farmers Using Remote Sensing in East Nusa Tenggara Province

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Abstrak: Nusa Tenggara Timur (NTT) merupakan daerah dengan iklim kering dengan kapasitas curah hujan kurang dari 2.000 mm/tahun, yaitu sekitar 72%, sehingga tergolong daerah rawan kekeringan. Karakteristik bahaya kekeringan sangat berbeda dengan bahaya bencana lainnya karena tidak muncul secara tiba-tiba tetapi terjadi secara perlahan dan mudah terabaikan. Dampaknya akan mulai terasa ketika produksi pertanian, misalnya tanaman pangan, pemenuhan kebutuhan minum, mulai berkurang, berujung pada hilangnya mata pencaharian akibat kurangnya pasokan air. Data kekeringan, terutama mengenai luas areal pertanian tanaman pangan dan jumlah petani yang terkena dampak kekeringan, masih sangat jarang. Penelitian ini bertujuan untuk memetakan dan mengklasifikasikan kabupaten dan kota di Provinsi NTT berdasarkan tingkat kekeringan, memperkirakan luas panen dan produksi sektor pertanian tanaman pangan yang terdampak kekeringan serta memperkirakan jumlah petani tanaman pangan yang terdampak kekeringan yang terdeteksi oleh data penginderaan jauh. Estimasi ini menggunakan pendekatan MOD13Q1 penginderaan jauh dengan mengukur Indeks Kesehatan Vegetasi (VHI) lahan yang terkena dampak kekeringan. Hasil penelitian menunjukkan bahwa dampak kekeringan yang paling signifikan terjadi di Kabupaten Timur Tengah Selatan, dengan jumlah petani terdampak sebesar 20231 jiwa. Persentase petani tanaman pangan yang mata pencahariannya terkena dampak kekeringan cukup besar di Kabupaten Malaka, Sumba Barat Daya, Sabu Raijua, Timor Tengah Selatan, dan Sumba Barat.

Kata kunci: kekeringan, tanaman pangan, ketahanan pangan, kehilangan, penginderaan jauh, SFDRR

Abstract: *East Nusa Tenggara (NTT) is an area with a dry climate with a rainfall capacity of less than 2,000 mm/year, which is around 72%, so it is classified as a drought-prone area. The characteristics of drought hazards are quite different from those of other disaster hazards because they do not appear suddenly but occur slowly and are easily overlooked. The impact will begin to be felt when agricultural production, for example, food crops, meeting drinking needs, begins to decrease, leading to a loss of livelihood due to a lack of water supply. Data on drought, especially regarding the area of food crop farming and the number of farmers affected by drought, is still very rare. This study aims to map and classify districts and cities in NTT Province based on the level of drought, estimating the harvest area and production of the food crop agricultural sector affected by the drought and estimating the number of food crop farmers affected by the drought as detected by remote sensing data. This estimate uses the MOD13Q1 remote sensing approach by measuring the Vegetation Health Index (VHI) of land affected by drought. The results of the study show that the most significant impact of the drought occurred in Timur Tengah Selatan district, with the number of affected farmers amounting to 20231 people. The percentage of food crop farmers whose livelihoods have been affected by the drought is quite large in the districts of Malaka, Sumba Barat Daya, Sabu Raijua, Timor Tengah Selatan, and Sumba Barat.*

Keywords: *drought, food crops, food security, loss, remote sensing, SFDRR*

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INTRODUCTION

Indonesia is a country with a tropical climate and high rainfall, but there are still droughts in several areas for various reasons. Drought is a condition where the available water supply is unable to meet normal water needs. Drought conditions over a long period of time will trigger various effects of drought, such as a water crisis, disruption of the socio-economic sector, and environmental sustainability due to climate change (Zarch et al., 2015). The danger of drought is quite different from the dangers of other disasters because the characteristics of the danger of drought come slowly, but the impact does not appear immediately and is easily overlooked. The impact will begin to be felt when agricultural production, meeting drinking needs, and industrial use decrease drastically due to a lack of water supply. The most dangerous impact is damage to the land system, which leads to optimal land use not being used, destruction of the agricultural sector, and even starvation.

One of the provinces in Indonesia that often experiences drought phenomena is East Nusa Tenggara (NTT) Province. This phenomenon is a challenge for the economy in NTT, an island region with a steep topography and dry climate that still relies heavily on the agricultural sector. The contribution of the agricultural sector to the formation of Indonesia's GRDP is 28 percent, supported by the food crops subsector at 8.15 percent (BPS, 2023). Quantitatively, this figure makes a significant contribution to creating conditions that support the implementation of development and forming collaborative relationships with other sectors. However, the drought disaster has had the impact of decreasing food crop production, especially paddy, corn, and soybeans, in recent years due to the high frequency of the El Nino phenomenon and the decreasing intensity of rainy days (Bates et al. 2018). On the other hand, 48.70 percent of NTT's population works in the agricultural sector. This figure is large enough to trigger the Open Unemployment Rate (OUT) if drought conditions are prolonged.

Sendai Framework for Disaster Risk Reduction 2015–2030 or better known as SFDRR, adopted at the United Nations Third World Conference on disaster risk reduction, held from 14 to 18 March 2015 in Sendai, Miyagi, Japan, which represents a unique opportunity for countries, namely (a) To adopt a concise, focused, forward-looking and action-oriented post-2015 framework for disaster risk reduction; (b) Complete an assessment and review of the implementation of the Hyogo Framework for Action 2005–2015: Building the Resilience of Nations and Communities to Disasters; (c) Consider the experience gained through regional and national strategies/institutions and disaster risk reduction plans and their recommendations, as well as relevant regional agreements for implementation of the Hyogo Framework for Action; (d) To identify modalities of cooperation based on commitments to implement the post-2015 framework for disaster risk reduction; (e) To determine the modalities for periodic review of the implementation of the post-2015 framework for disaster risk reduction (UNISDR, 2015)

. In its publication, UNISDR divided the SFDRR targets into seven. Two of them are Targets B and C, which can be used to calculate estimated losses due to drought (UNISDR, 2018).

Target B stated in it is to substantially reduce the number of people affected globally by 2030 and lower the global average per 100,000 between 2020 and 2030 compared to 2005 and 2015. The indicators consist of 5, namely B-1, to measure the number of people directly affected by the disaster per 100,000 population. Then B-2 measures the number of people injured or sick due to the disaster per 100,000 people. Next, B-3 measures the number of people whose houses were damaged by the disaster. Finally, B-4 measures the number of people whose houses have been destroyed by the disaster, and B-5 measures the number of people whose livelihoods have been disrupted or destroyed due to the disaster.

There is a definition of livelihood to measure indicators B-5, namely capacity, productive assets (both living and material), and activities needed to secure means of living, in a sustainable manner, with dignity. Some of the most important productive assets needed to secure means of livelihood are those correlated with labor and sources of income. There are sub-indicators in this discussion. One is B-5a, to measure the number of agricultural workers whose crops were damaged or destroyed by the disaster. The number of damaged plants can be estimated with the C-2Ca sub-indicator. This methodology requires data and metadata related to indicators for Target C, specifically C-2Ca (number of hectares of plantations damaged or destroyed by the disaster). Target C contained in the SFDRR is to reduce economic losses due to direct disasters related to global gross domestic product (GDP) by 2030. Indicator C-2 is direct agricultural losses caused by disasters. Agriculture covers the food crop sector, livestock, fisheries, animal husbandry bees, aquaculture, and forest and related facilities and infrastructure. In order to support the calculation of the B-5a target, the C-2Ca sub-indicator is used, namely the number of hectares of plantations damaged or destroyed as a result of the disaster.

The Sustainable Development Goals (SDGs) aim to achieve development that supports sustainable growth of people’s economic well-being. This goal also involves efforts to maintain the sustainability of the community’s social life, preserve the quality of the environment, and ensure justice and effective governance. In order to achieve this goal, it is important to maintain the quality of life from generation to generation so that the development carried out not only benefits the current generation but also pays attention to future interests (Ministry of National Development Planning, 2020). TPB or SDGs are global and national commitments that aim to improve people’s welfare. It involves 17 different objectives. In the SDGs, there is an indicator that supports the implementation of SFDRR. This indicator is indicator 1.5.3 on the planning and implementation of a national strategy for disaster risk reduction in line with the Sendai Framework for Disaster Risk Reduction 2015–2030. This indicator is contained in target 1.5: By 2030, build the resilience of people experiencing poverty and those in vulnerable situations, and reduce their vulnerability to extreme events related to climate and economic, social, environmental, and disaster shocks (Ministry of National Development Planning/Bappenas, 2020).

Apart from that, the second goal of the SDGs is "to eliminate hunger, achieve food security and good nutrition, and improve sustainable agriculture" (Bappenas, 2022). Food is one of the primary needs; therefore, the government must ensure that its people have food security. According to the Law of the Republic of Indonesia Number 18 of 2018, food security is a condition where food is met for the country and individuals, which is reflected in the availability of sufficient food, both in quantity and quality, that is safe, diverse, nutritious, evenly distributed, affordable, and not in conflict with the religion, belief, and culture of society, to be able to live a healthy, active, and productive life in a sustainable manner. Food security is a multidimensional and very complex issue, covering social, economic, political, and environmental aspects. Political aspects are often the dominant factor in the decision-making process to determine food policy (Suryana, 2014).

Based on this background, this study aims to map and classify districts/cities in NTT Province based on the level of drought, estimating the harvest area and production of the food crop agricultural sector affected by the drought and estimating the number of food crop farmers affected by the drought in the NTT province as detected by remote sensing data. The limitations of this research are the impact of the drought that occurred in NTT province in 2019, the estimated harvest area, and the number of farmers affected by the drought only in the food crop sector. Estimation of the number of food crop farmers affected by drought using the SFDRR Indicator B-5a methodology The year 2019 was used as the focus of the research because in that year there was an extreme drought, and the death toll from the drought increased to 1.15 million people (BPS, 2020).

This study adds to the body of knowledge about the effects of natural catastrophes by demonstrating how to monitor plant growth and productivity using remote sensing of vegetation changes, which is a method for detecting drought. This study makes use of temperature (MOD11A2) and vegetation index (MOD13Q1) remote sensing satellite data products from the Moderate Resolution Imaging Spectroradiometer (MODIS), which are produced every 16 days at a 250-meter spatial resolution and used for the period 2000 to March 2023. The Vegetation Condition Index (VCI) was developed to determine the level of drought hazards in NTT's food crop farm sector. Drought detection is not the only application for remote sensing. The use of remote sensing is not only used to detect drought but is also used to estimate the harvest area, the amount of food crop production, and the number of agricultural sector workers affected by the drought. Previous studies used remote sensing to determine the distribution of wetland agricultural drought areas and their relationship with rainfall in Indramayu Regency (Zuhro et al., 2020); detecting agricultural drought in Central Europe in water-limited areas for vegetation growth (Kloos et al., 2021); identifying drought characteristics such as duration, severity, and area (Amalo et al., 2018); mapping the vegetation health index using remote sensing data and geographic information systems under El Nino, La Nina, and normal conditions in Bali Province (Tropika et al., 2021). It is hoped that this study will provide benefits for the government and National Statistics Office (NSO) to use big data as a new data source to complement official statistics. Apart from that, predictions of the impact of drought are not only on harvest area, production and number of farmers but can be extended to other sectors so that the impact of drought can be mitigated earlier. In this way, national food security is maintained.

METHODS

The Open-ended Intergovernmental Expert Working Group (OIEWG) identified that natural disasters, especially droughts, can affect people directly or indirectly. Affected persons may experience short-term or long-term consequences for their lives, livelihoods, or health in the economic, social, physical, cultural, and environmental fields. The following two definitions are recommended within the SFDRR's scope of reporting terminology from OIEWG:

1. Directly affected: Persons who have experienced injury, illness, or other health impacts; evacuated, transferred, transferred persons; or suffer direct damage to their livelihoods, economic, social, physical, cultural, and environmental assets.
2. Indirectly affected: Persons who suffer consequences, in addition to or in addition to the direct effects, from time to time due to disturbances or changes in economic, critical infrastructure, basic services, trade, employment, or social, health, and physiological consequences (UNISDR, 2018).

The European Commission for Latin America and the Caribbean (ECLAC) proposed a methodology designed to carry out disaster impact assessments on the economy, divided into three groups: direct damage, indirect damage, and secondary effects (Artiani, 2011). The macroeconomic impacts of natural disasters are divided into two groups, namely real impacts and intangible impacts, which are divided into direct and indirect impacts, respectively (AusAID, 2005). The two groups below will affect changes in macroeconomic variables. One of the macroeconomic indicators affected by the disaster is employment. Disasters can cause changes in employment structure due to damaged and destroyed productive capacity and social infrastructure and changing conditions during the reconstruction and rehabilitation process. Even if possible, changes in employment also impact people's incomes. In the case of drought in the NTT region, the impact is in the form of job losses for farmers.

C-2 assesses the direct losses in the agricultural sector due to the disaster and considers the specificities of each sub-sector, namely food crops, livestock, forestry, aquaculture, and fisheries. This indicator measures the direct effects of various disasters of different types, duration, and severity. In addition, it applies to disasters of various scales, from large-scale shocks to small and medium-scale events with cumulative impacts. In line with C-2, SFDRR B-5 can be used to estimate the number of people whose livelihoods are disrupted or destroyed associated with disasters. (UNISDR, 2018).

Remote Sensing

Remote sensing, often called *remote sensing,* is the art and science of obtaining information about objects, areas, or phenomena through data analysis using tools without direct contact with the object being studied (Lillesand & Kiefer, 1979). The tool is a sensor generally carried by rides in the form of aircraft, satellites, and other types of rides. The results of the recording by the tool are, from now on, referred to as remote sensing data. *Remote sensing* devices capture information that is divided into two types, namely passive and active sensors. Passive sensors are sensors that receive reflected light from the observed object. Passive sensors depend on other energy sources, such as sunlight. At the same time, active sensors send energy to the observed object to be reflected and received by the sensor. Therefore, active sensors can work day and night because they can transmit energy to the observed object.

Remote sensing image data has different qualities and depends on the resolution of the sensor carried by the device. Satellite image data has several characters, namely:

1. Spatial Resolution. The spatial resolution has the smallest area that the sensor can record. According to Purwadhi (2001), spatial resolution is good if it can identify the object of observation in detail.
2. Spectral Resolution. Spectral resolution is a measure that refers to the *remote sensing ability* to record over a certain range of wavelengths. Generally, each satellite carries more than one type of sensor, and each sensor will carry more than one type of sensor with the ability to record a certain range of wavelengths.
3. Temporal Resolution. Temporal resolution is the ability of satellite imagery to record an area repeatedly within a certain time. The temporal resolution is affected by the time it takes for the remote sensing device to circle the earth back to its original orbital point.
4. Radiometric Resolution. Radiometric resolution is a measure that states the sensor's ability to distinguish objects of observation based on various brightness (Lillesand & Kiefer, 1979). Satellite imagery data is provided by official institutions such as NASA, NOAA, and LAPAN and is also available at the EOG Payne Institute (BPS, 2021).

The results obtained from remote sensing can be in the form of images or images, reference data, or other results in digital form. These data are converted into objects that can be analyzed in Geographic Information System (GIS) processing software in the form of vector or raster data. Vector data represents the shape of a region with certain coordinates in digital points, lines, and polygons. Vector data can be operated based on logical functions to obtain information as material for decision-making from remote sensing results (Indarto, 2017). At the same time, raster data is data whose information is collected in a collection of tiles where each tile has a value that represents a certain brightness or color code.

Moderate Resolution Imaging Spectroradiometer (MODIS)

Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices Data, often called MOD13Q1 Version 6.1, is generated every 16 days at a spatial resolution of 250 meters as a level 3 product. MOD13Q1 data produces two main vegetation layers, namely the Normalized Difference Vegetation Index (NDVI), which is called a continuity index of the National Oceanic and Atmospheric Administration-Advanced Very High-Resolution Radiometer (NOAA-AVHRR) derived from the NDVI, and the Enhanced Vegetation Index (EVI), which has better sensitivity in areas with high biomass. With both layers, a Hierarchical Data Format (HDF) file will have MODIS reflectance bands 1 (red), 2 (near-infrared), 3 (blue), and 7 (mid-infrared), as well as four observation layers.

NDVI is an excellent index to observe changes in vegetation productivity. It is based on the difference in the reflectance of near-infrared (NIR) and visible red (RED) light emitted and absorbed by plants. Chlorophyll in plants reflects low-intensity red light and absorbs high-intensity NIR light. Therefore, healthy and productive plants tend to have higher NIR reflectance and lower RED reflectance. NDVI combines the two wavelengths and directly indicates the amount of chlorophyll and photosynthetic activity occurring in the plant. Changes in chlorophyll count and photosynthetic activity can reflect changes in vegetation productivity.

When plants experience stress, be it drought, nutrient deficiencies, or disease attacks, they tend to show decreased photosynthetic activity and productivity. Vegetation stress can cause changes in the reflectance of NIR and RED, which are reflected in NDVI values. Monitoring changes in NDVI over a certain period can be used to monitor and analyze changes in vegetation productivity caused by these stress factors. The NDVI value is the ratio between the reflectance of near-infrared (NIR) and the reflectance of visible red light (RED), which can be calculated using the following formula:

$$NDVI = \frac{(NIR - RED)}{(NIR+RED)} \quad \textbf{(1)}$$

NDVI values range from -1 to +1, with values close to zero indicating no green vegetation and values close to +1 indicating high vegetation density. A higher NDVI value indicates healthier and more productive vegetation. Areas of barren rock, sand, and snow yield NDVI values < 0.1, whereas scrub and grassland typically produce NDVI values 0.2–0.3, and temperate and tropical rainforests produce values in the range 0.6–0, 8. The NDVI data generated by MOD13Q1 provide important information about vegetation productivity, land cover change, and plant response to environmental conditions.

The data product generated by another MODIS sensor is MOD11A2. MOD11A2 data generates ground surface temperature data globally and a spatial resolution of approximately 1 kilometer. The data is taken twice a day and can be used to observe variations in ground surface temperature throughout the year. MOD11A2 can be applied in climate modeling, earth surface temperature monitoring, agricultural prediction, drought risk evaluation, natural resource management, and other scientific research. MOD11A2 data can be accessed through public archives such as Earthdata Search or NASA’s Land Processes Distributed Active Center (LP DAAC).

Vegetation Condition Index (VCI)

The Vegetation Condition Index (VCI) is one of the most frequently applied indices to measure the severity of drought hazards in the agricultural sector (Jiao et al., 2016). VCI provides information about the relative vegetation condition in an area by comparing current conditions with normal or baseline conditions measured over a certain period. VCI is generally calculated using NDVI data obtained from *remote sensing*. VCI can be written in the following equation:

$$VCI_j = \frac{(NDVI_j - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \times 100 \quad \textbf{(2)}$$

Where $NDVI_{min}$ is minimum value of NDVI calculated from a predetermined baseline or reference period, $NDVI_{max}$ is Normalized Difference Vegetation Index value obtained from satellite imagery or remote sensing, and $NDVI_j$ is NDVI for the current period.

VCI has many uses, especially in drought monitoring, plant health evaluation, and natural resource management. By monitoring changes in VCI over time, researchers can identify areas experiencing drought stress and take appropriate mitigation measures to protect vegetation, ensure the sustainability of natural resources, and minimize the risk of drought victims.

Temperature Condition Index (TCI)

Temperature Condition Index is an index obtained from a good thermal radiation band used as an indicator to monitor temperature conditions in weather and climate monitoring as well as the energy balance of the earth's surface because temperatures can rise quickly and in conditions of water shortages. TCI is an early indicator of water stress and drought. This index provides the temperature deviation relative to normal or baseline conditions. The TCI is obtained using the monthly LST (Land Surface Temperature) of MOD11A2 and is calculated by the following equation:

$$TCI = \frac{(LST_{max} - LST)}{(LST_{max} - LST_{min})} \text{x100} \quad \textbf{(3)}$$

Where TCI is Temperature Condition Index, LST is Land Surface Temperature obtained from thermal radiation data, LST_{min} is The minimum Land Surface Temperature value determined from the previous reference period or baseline, LST_{max} is Maximum value of Land Surface Temperature determined from the previous reference period or baseline. TCI values range from 0 to 1. Low TCI values or close to 0 indicate unfavorable conditions, while high TCI values or close to 1 indicate optimum conditions.

Vegetation Health Index (VHI)

The Vegetation Health Index (VHI) combines the constructed VCI and TCI and can be used effectively for drought assessment. VHI monitors plants' or vegetation's health, vigor, and vitality because it incorporates information about soil and vegetation moisture indices. VHI can be obtained using the following equation:

$$VHI = \alpha \times VCI + \alpha \times TCI \quad \textbf{(4)}$$

Where α is the weight to measure the contribution of VCI and TCI in assessing drought status, generally α applied as 0.5. Numerical values or VHI maps reflect the health of vegetation relative to soil moisture. Higher VHI values indicate healthier vegetation and adequate soil moisture, while lower VHI values indicate vegetation experiencing moisture stress or water shortages.

This research has the scope of analysis of vegetation change to monitor plant growth and productivity, which is then used to detect drought. The locus of this research is the districts and cities in the Province of East Nusa Tenggara (NTT). In its analysis, this research utilizes remote sensing satellite data products the vegetation index (MOD13Q1) from the Moderate Resolution Imaging Spectroradiometer (MODIS), which is generated every 16 days at a spatial resolution of 250 meters and is used for the period 2000 to March 2023. This data set is used to assess the severity of the hazard drought in NTT for the food crop agriculture sector based on the Vegetation Condition Index (VCI) with agricultural land as the study area. 2019 is the focus of research because that year, there was an extreme drought and an increase in the number of drought victims to 1.15 million people (BPS, 2020). The data and data sources applied to this study as seen in Table 1.

Table 1. Data and data sources

No.	Data	Source
1.	MOD13Q1	https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MOD13Q1
2.	SUTAS 2018	https://www.bps.go.id/publication/2019/01/02/c7cb1c0a1db444e2cc726708/hasil-survei-pertanian-antar-sensus--sutas--2018.html
3.	RBI Map of NTT Province	http://nttprov.ina-sdi.or.id/pencarian?categori=Batas%20Wilayah

Processing on *Google Earth Engine*

Before calculating the drought index, prepare a shapefile for the province of NTT. Set the variables for the month ('MM' format) and year ('YYYY' format) for which you want to calculate the index. In this study, October 2019 was chosen as the time used to calculate the drought index. This is to the research of Amalo et al. (2018), which stated that the highest drought occurred in October. Next, a historical period is selected for analysis. The period selected is from October 2000 to October 2018. Load the Terra Vegetation Index (250m resolution, global, 16 d) using MOD13Q1 data and filter by predefined historical period. Do a factor scale for NDVI, then calculate the minimum and maximum values of NDVI. Load Terra Vegetation Index (250m resolution, global, 16 d) using MOD13Q1 data and filtered by a predefined analysis period, i.e., October 2019. Perform VCI calculations and map *clipping according to AOI.* Next, load the collection for TCI using MOD11A2 data and filter by predefined historical periods. Compute the minimum and maximum LST values of a preloaded collection. Collect LST collections based on the drought monitoring period, October 2019, using MOD11A2 data. Perform TCI calculations and *clipping* according to AOI. Calculate the VHI value based on the VCI and TCI values. Classify VHI values based on threshold values for calculating Drought Index, and export Drought Index to SHP file.

$$VCI_j = \frac{(NDVI_j - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \times 100 \quad \textbf{(5)}$$

$$TCI = \frac{(LST - LST_{min})}{(LST_{max} - LST_{min})} \quad \textbf{(6)}$$

$$VHI = 0.5\,VCI + 0.5TCI \quad \textbf{(7)}$$

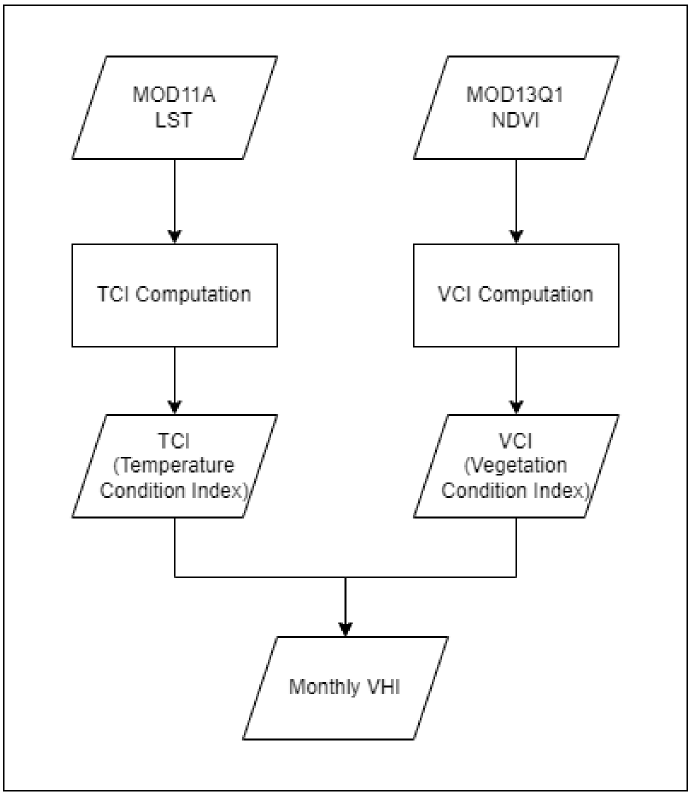


Figure 1. VHI processing steps

Processing on QGIS

Add a *shapefile layer* for the NTT province map with boundaries between districts/cities in QGIS. Perform area calculations with the $area formula on *the table attribute*. Load the drought index maps obtained from GEE into the QGIS *software*. Combine the NTT provincial map with the drought index map with intersection features to produce a drought index map based on districts/cities. Also, add the previously obtained land cover map. Then, filter the legend column so it only contains land cover related to food crops such as wetland agriculture, dry land agriculture, and paddy fields. Combine the land cover map for food crops with the drought index map per district/city. Then calculate the area of each food crop area for each drought index in each district/city. The drought index labeled 5 (no drought) can be removed to measure losses due to drought. Then it can continue calculating the area with $area. Thus, data on the area of food cropland affected by drought has been obtained in each district/city. Furthermore, the following calculation can measure the number of farmers affected by drought.

$$B5a = C - 2Ca\ x\ \frac{Jumlah\ petani\ per\ kabupaten\ kota}{luas\ kabupaten\ kota} \quad \textbf{(8)}$$

where B5a is number of affected farmers, and C-2Ca = area of agricultural land for food crops affected by drought. Finally, calculate the percentage of food crop farmers affected by drought in each district/city.

Mapping of Areas Experiencing Drought

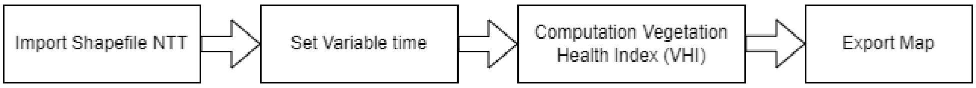


Figure 2. VHI processing flow

The initial step in estimating the number of affected food crop farmers is to identify areas of the NTT province experiencing drought. MOD13Q1, as an *open-source satellite*, is used to obtain drought hazard information. VHI, a combination of VCI and TCI values, is usually used to analyze the effect of greenery in agriculture to assess drought. Meanwhile, TCI is used to assess vegetation stress due to temperature. Therefore, VCI and VHI can be used for drought monitoring and assessment. However, VHI is more powerful and effective due to its good representation of drought occurrence phenomena.

The TCI is derived using the LST (Land Surface Temperature) of the monthly MOD11C3 LST with a spatial resolution of 0.05 degrees and is calculated by the following equation:

$$TCI = \frac{(LST - LST_{min})}{(LST_{max} - LST_{min})} \text{x} 100 \qquad \textbf{(9)}$$

Where LSTi, LSTmin, and LSTmax are defined as the LST of the current month and the maximum and minimum LST values in multiyear. TCI values range from 0-100, while low TCI indicates unfavorable conditions and high TCI indicates optimum conditions

The output raster from the previous steps needs to be categorized into drought severity zones to analyze drought levels in the affected area. VHI values vary between 0 and +1(100), and raster images are classified according to the criteria and implemented in the code in the Table 2.

Table 2. TCI, VCI, and HVI drought severity classes

Drought severity class	Mark
Extreme Drought	<10
Severe Drought	<20
Moderate Drought	<30
Mild Drought	<40
No Drought	≥40

Furthermore, the classified image is encoded according to the criteria in the Figure 3.

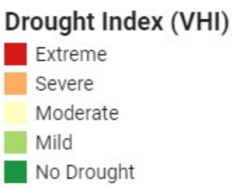


Figure 3. Drought Classification with VHI

Estimating the Area of Agricultural Land Affected by Drought

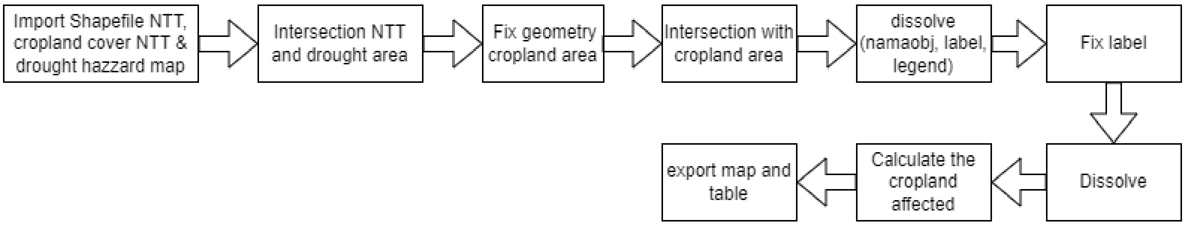


Figure 4. Processing flow for drought-affected areas

To measure the area of agricultural land affected by food crops can be obtained by combining the results of the drought hazard assessment for each urban district with land cover data for food crops. The merging process is called *intersection.* However, before *the intersection is carried out, a fixed geometry* process is carried out for agricultural land cover to make it easier to measure its area. After the *intersection process* with the map of the province of NTT, *dissolve it,* in this case, using the attribute name obj table, drought label, and land type legend. After the process is complete, the area of agricultural land for food crops affected per district/city in the province of NTT can be obtained.

Estimating the Number of Farmers whose Livelihoods are Disrupted due to Drought

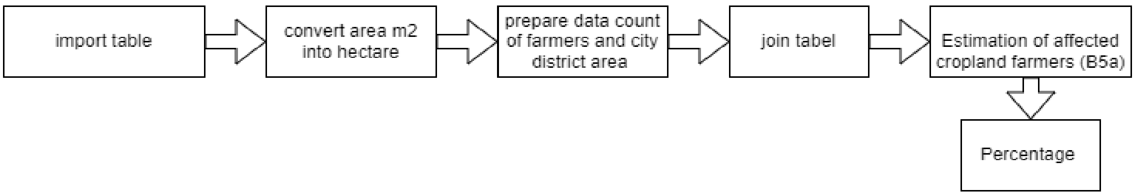


Figure 5. The processing flow in estimating the number of farmers affected by drought

To measure the number of people affected by agricultural drought can be obtained by combining the results of the drought hazard assessment with remote sensing land cover data, agricultural statistics, and 2018 Inter-Census Agricultural Survey (SUTAS) data. Land cover data is extracted for agricultural land by hazard severity classification drought by extracting exposed plant areas per severity class. To relate this to the number of workers affected, this study refers to the Sendai Framework for Disaster Risk Reduction (SFDRR) methodology, which estimates the number of people affected by a disaster and measures the achievement of Target B of the SFDRR. The next step is to calculate the B-5a indicator (Number of Workers Affected by Drought in the Agriculture Sector), which is based on the assumption that the characteristics of "plants damaged or destroyed" are met when the drought hazard assessment detects extreme, severe, moderate, and mild classes.

RESULT AND DISCUSSION

Estimated area of agricultural land for food crops affected by drought

Drought mapping in East Nusa Tenggara Province was carried out using the VHI calculation method, which consists of five drought classes: extreme, severe, moderate, mild, and no drought. In Figure 6, it can be seen that Sumba Island and Timor Island have the most drought. Meanwhile, Flores Island, Alor Island, and the surrounding areas are dominated by areas that are not affected by drought.

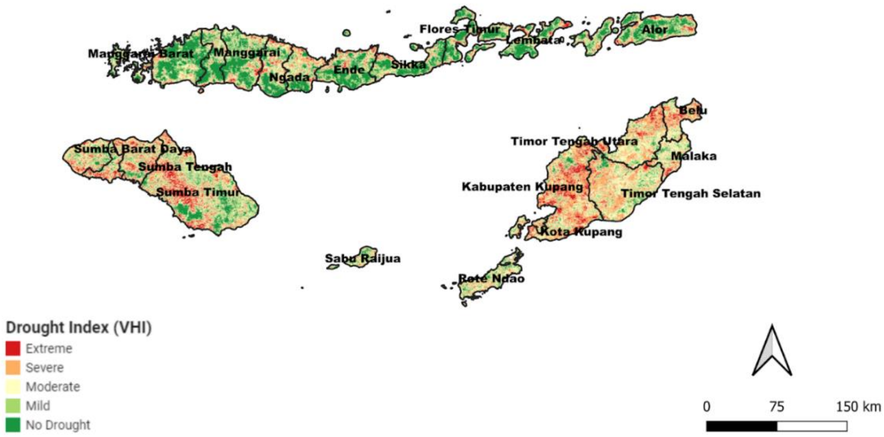


Figure 6. Mapping of drought areas based on drought classes

Data visualization based on the distribution of drought groups and the area of each district or city can be seen in Figure 6. Each district or city has a pie chart that represents drought groupings, which are differentiated based on color type. The size of the pie chart represents the area of the district or city. The larger the size, it means that the district or city has a larger area. Based on this visualization, it appears that East Sumba Regency has the largest area. The distribution of drought in the region also tends to be evenly distributed.

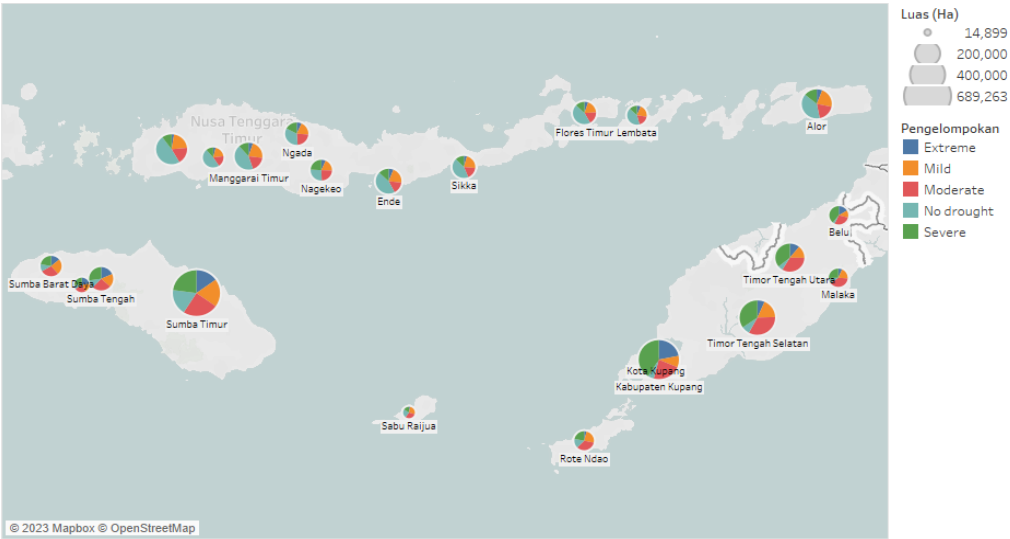


Figure 7. Map of the distribution of drought areas in districts/cities

Mapping of agricultural land for food crops in areas experiencing drought in the districts and cities of East Nusa Tenggara Province was carried out using the VHI calculation method. The severity of drought is divided into 4 classes: extreme (extreme drought), severe (severe drought), moderate (moderate drought), and mild (mild drought). A visualization of food crop drought can be seen in Figure 7. Visually, there are many food crop farming areas in East Nusa Tenggara Province that are experiencing drought. The agricultural land for food crops that experienced the greatest drought was on Timor Island, which is located in South Central Timor district. Meanwhile, the district with the largest area of food crop land but the least impact from drought is East Sumba district.

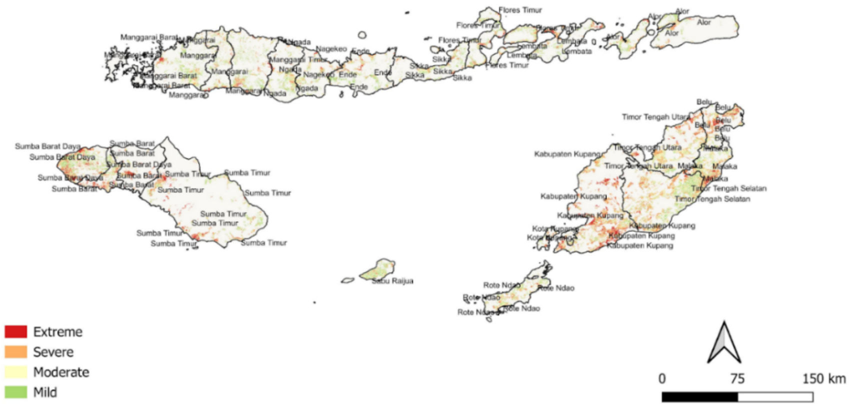


Figure 8. Mapping of food crop agricultural areas affected by drought

It can be seen in Figure 8 that the area of food crop farming that is affected by drought does not exceed the area that is not affected by drought. However, agricultural land that experiences drought during a dry climate needs special attention, especially regarding water sources and management, because water availability is the main limiting factor due to very low rainfall. Therefore, it is very logical that areas with dry climates are associated with pockets of poverty and thus become food-insecure areas, especially in NTT. Areas with a high food security category are characterized, among other things, by the relatively limited capacity of agricultural land for food production needs, low human resources, limited facilities and infrastructure, limited agricultural land management, etc., average income below the poverty line, and a very high share of food expenditure (BPS 2014).

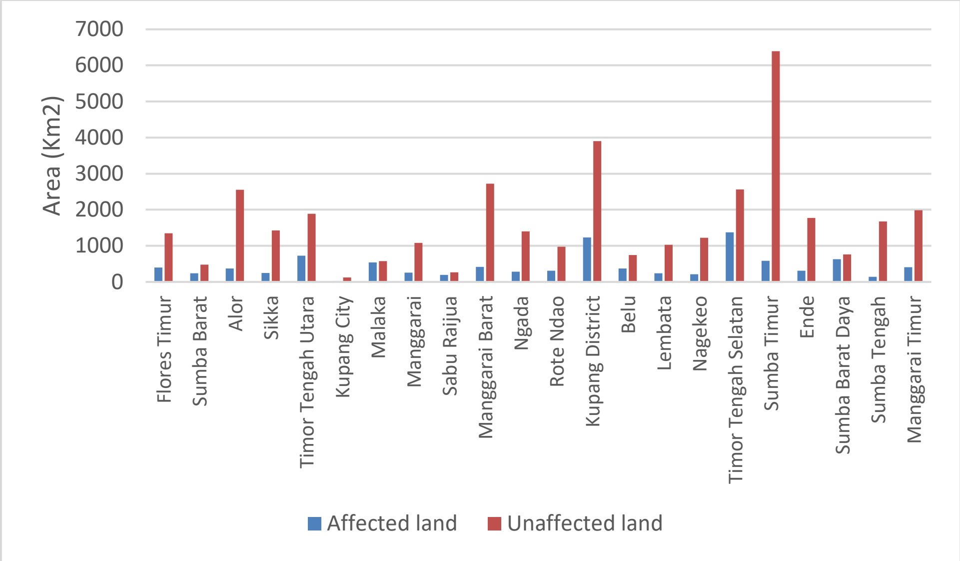
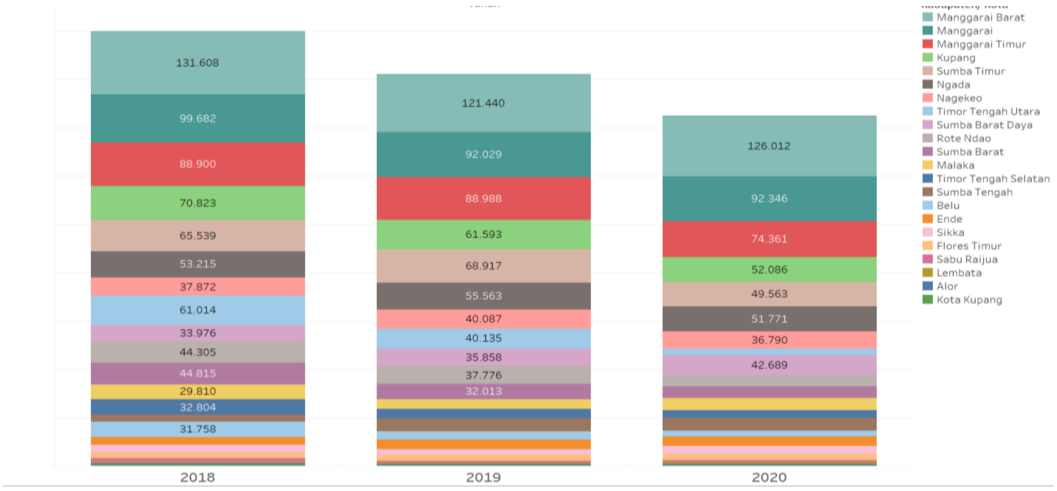
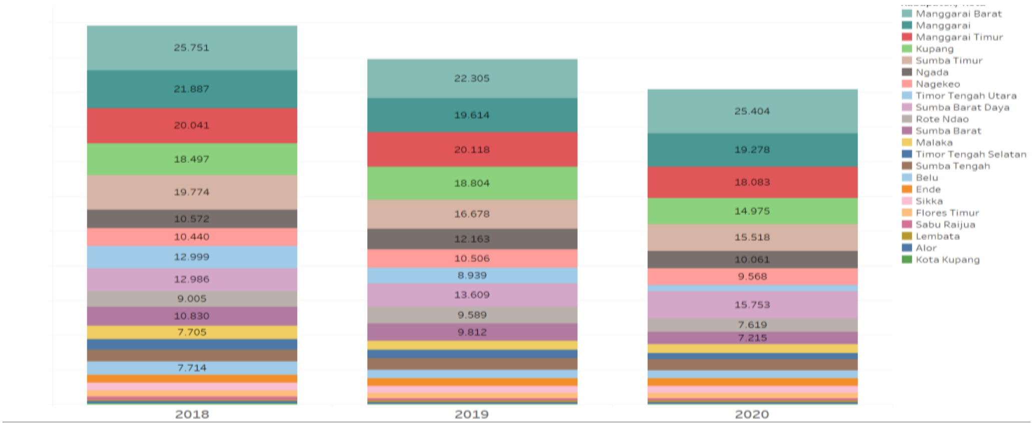


Figure 9. Comparison of food cropland affected and not affected by drought

The paddy/paddy commodity is the backbone of the development of the food crops sub-sector because paddy is the population's staple food and is cultivated a lot. In 2019, paddy production in NTT amounted to 1,292,300 tons of dry-milled grain with a harvested area of 335,608 ha. Compared to the previous year, paddy production increased by 1.80 percent, but there was a decrease in the harvested area of 3,453 ha, or 1.02 percent. The following is a visualization of paddy production and harvested area in each district or city in the province of East Nusa Tenggara. South Central Timor District is the largest contributor to corn production in the province of NTT. Corn production and harvested area have increased in several districts and cities because the dry climate is very suitable for corn farming.



(a) Production (Ton)



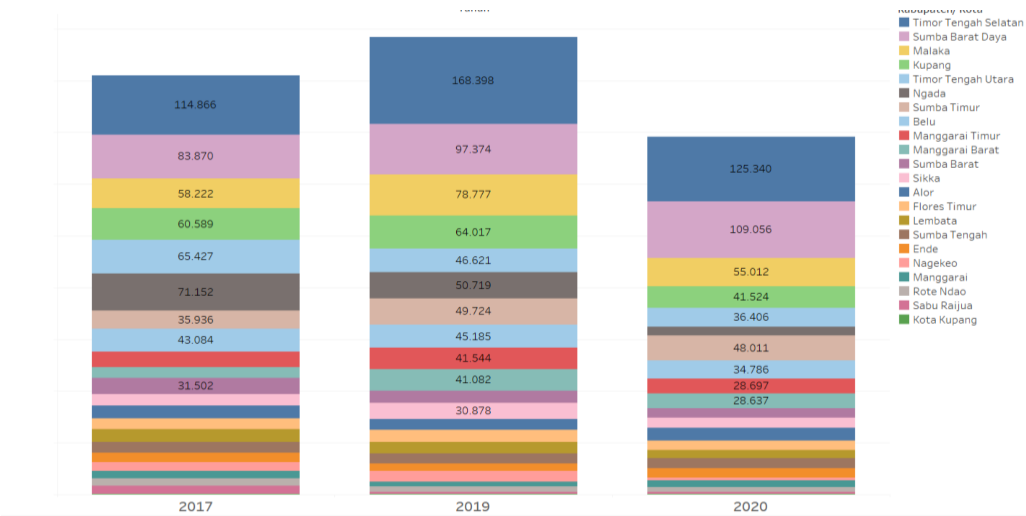
(b) Harvested area (Hectares)

Figure 10. Production and harvested area of paddy by district/city in NTT, 2018-2020

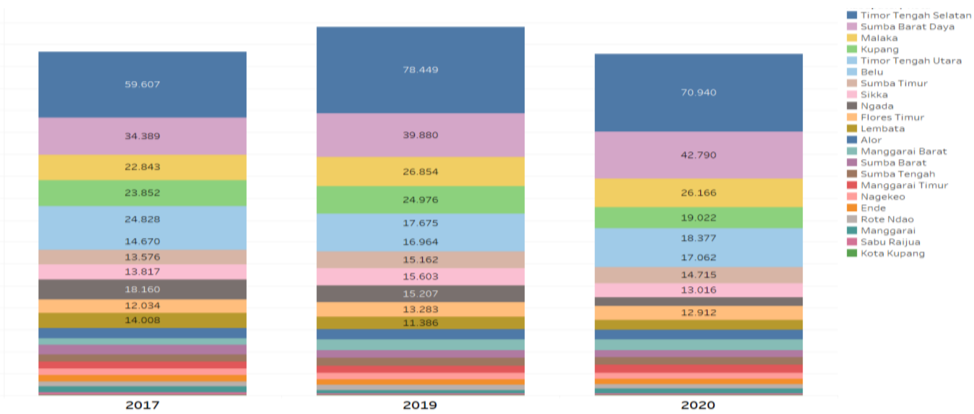
The largest paddy producer in 2018, 2019, and 2020 in West Manggarai Regency has the largest paddy harvest area among other districts/cities. It can be seen from the graph above that paddy production decreased from 2018 to 2019 in several urban districts except for East Manggarai, East Sumba, Ngada, Nagekeo, and Southwest Sumba Regencies, which have experienced an increase in paddy production. Meanwhile, in terms of harvested land area, most urban regencies experienced a reduction in the area of paddy harvested land.

The palawija crops cultivated by NTT farmers include corn, soybeans, peanuts, mung beans, cassava, and sweet potatoes. In addition to comparing the production and area of palawija plantations on a provincial scale, a comparison of the production and area of pawpaw plantations in each regency or city will be carried out. The periods used in the visualization include 2017, 2019, and 2020. 2017 was used due to insufficient available data regarding production and harvested area in 2018.

The type of palawija plant in the cereal group (grains) that is mostly cultivated in NTT is corn, because corn is suitable for the climate and soil conditions of NTT. In 2019, corn production was 884,326 tons of dry-shelled corn from a harvested area of 335,901 hectares. Compared to 2018, corn production has increased by 4.16 percent, but not as much as in 2018 and 2017. The harvested area has also increased by 2.22 percent.



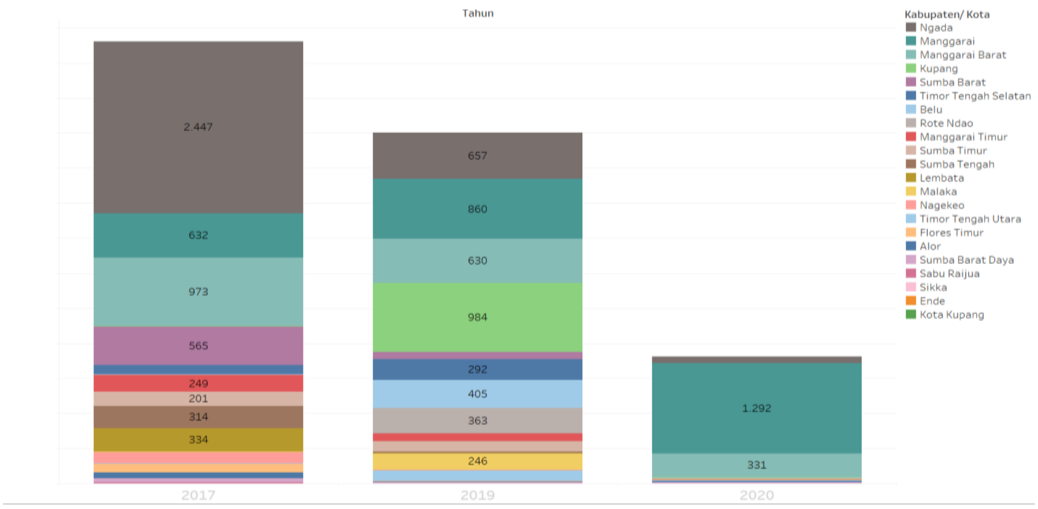
(a) Production (Ton)



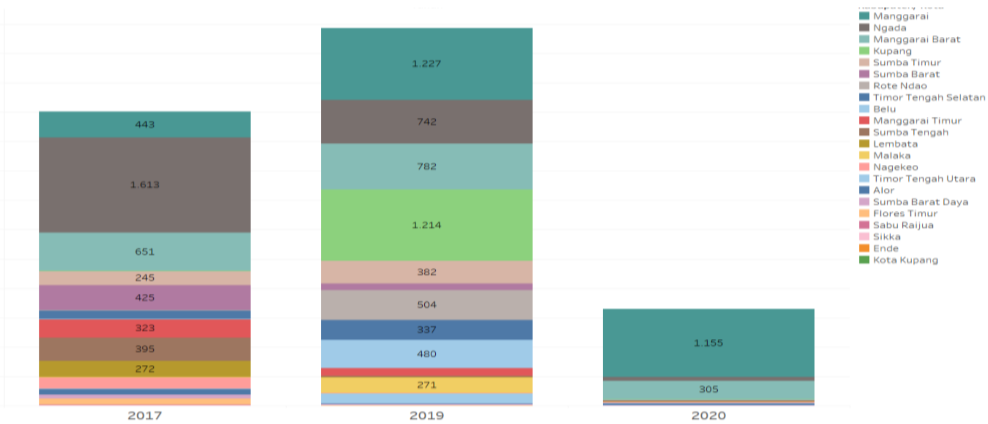
(b) Harvested area (Hectares)

Figure 11. Production and harvested area of corn by district/city in NTT, 2017-2020

In 2019, soybean production in NTT was 5,003 tons from a harvested area of 6,429 hectares. Soybean production in 2019 decreased by 76.27 percent compared to 2018. In 2017, Ngada Regency became the largest contributor to soybean production. In 2019, Kupang Regency and Manggarai Regency produced the largest number of soybeans, in line with the significant increase in harvested area compared to 2017. From the two graphs above, there is an anomaly where production in 2019 has decreased compared to 2017, but the harvested area is the opposite, showing an increase compared to 2017. This indicates a decrease in paddy productivity, which causes production to also decrease.



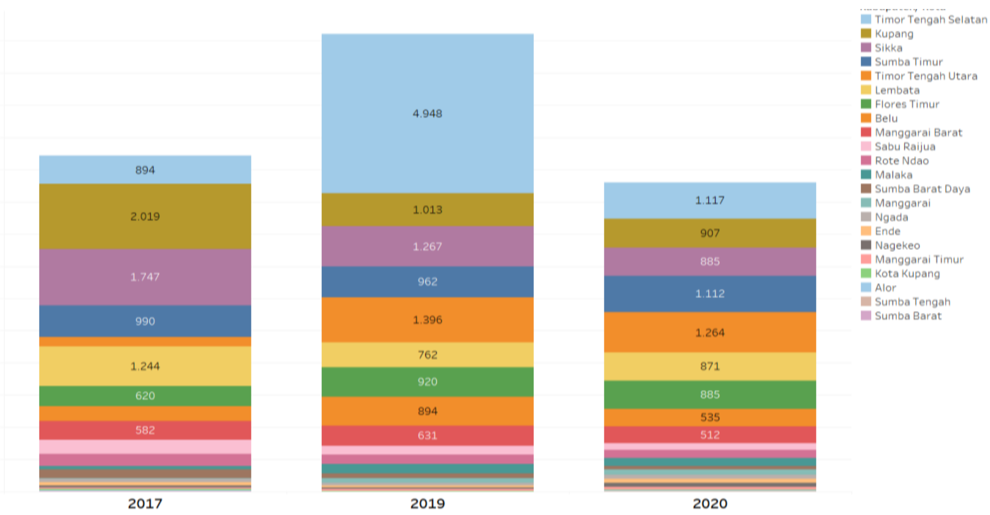
(a) Production (Ton)



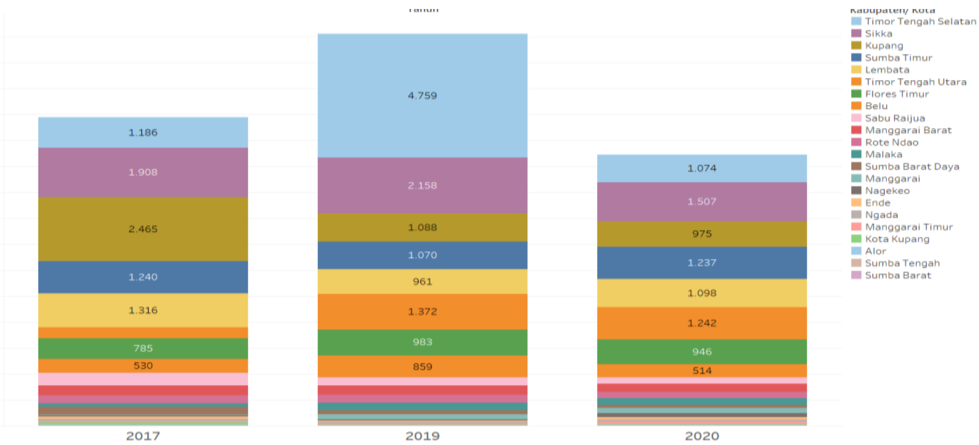
(b) Harvested area (Hectares)

Figure 12. Production and harvested area of soybean by district/city in NTT

Peanuts are the second-most important crop after soybeans. In 2019, peanut production in NTT was 14,212 metric tons of dry seeds from a harvested area of 15,104 hectares. When compared to the situation in 2018, peanut production has increased by 41.55 percent due to an increase in harvested area of 30.61 percent. Peanut production in 2019 in NTT tends to increase; this is evidenced by the increase in peanut production in each district or city, which has increased accompanied by an increase in the area of harvested land. The South Timor Tengah Regency contributed the largest production of peanuts in 2019, accompanied by an increase in harvested land. However, in 2020, the production and harvested area of the peanut plant decreased significantly. This is indicated by the impact of the extreme drought that hit NTT.



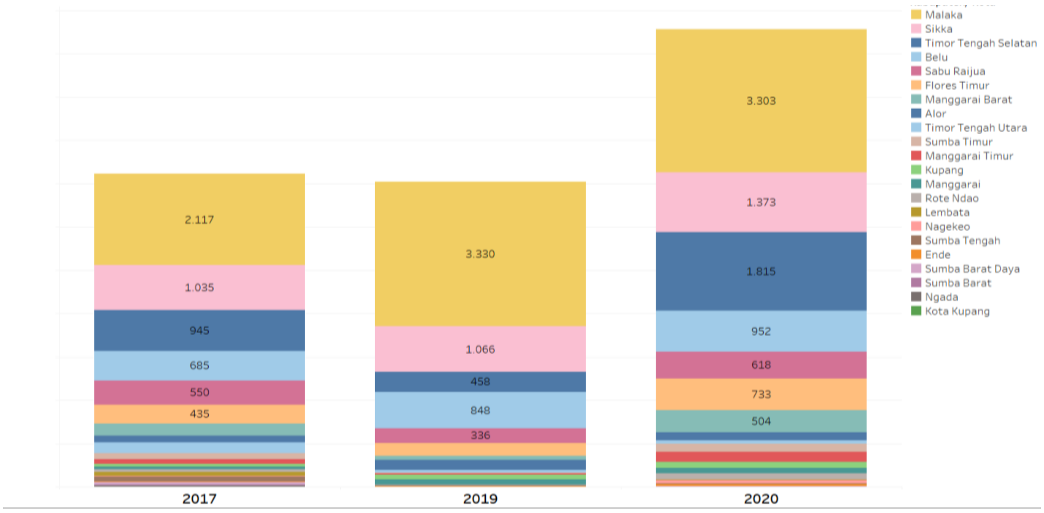
(a) Production (Ton)



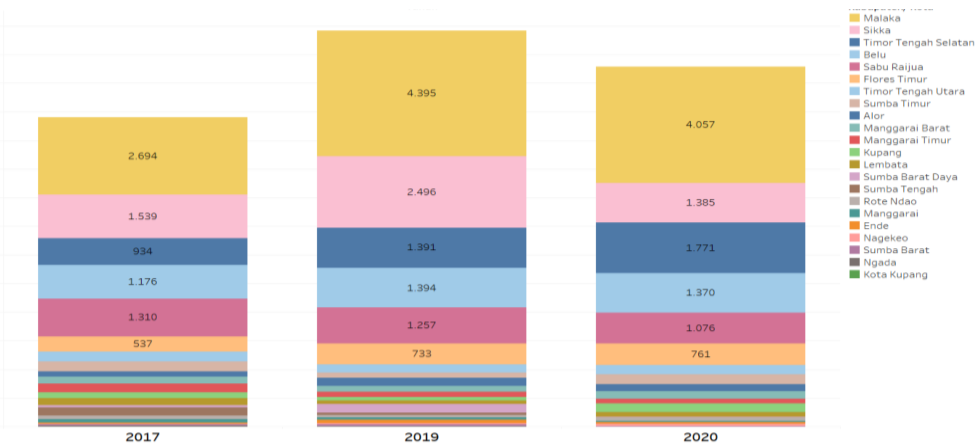
(b) Harvested area (Hectares)

Figure 13. Production and harvested area of peanut by district/city in NTT

Mung beans, which belongs to the leguminous family (Fabaceae), has many benefits in everyday life as a source of high-protein vegetable food. After soybeans and peanuts, mung bean in Indonesia ranks third most important as a legume food crop. In 2019, NTT green bean production was 7,042 tons of dry beans from a harvested area of 13,830 hectares with a 5.09 ku/ha productivity. The largest mung bean-producing district was Malacca Regency from 2017 to 2020. Mung bean production in 2019 fell by 11.60 percent compared to 2018. This was due to decreased productivity, even though the harvested area increased. In 2019, most city regions experienced an increase in production but remained within the level of mung bean production in 2017.



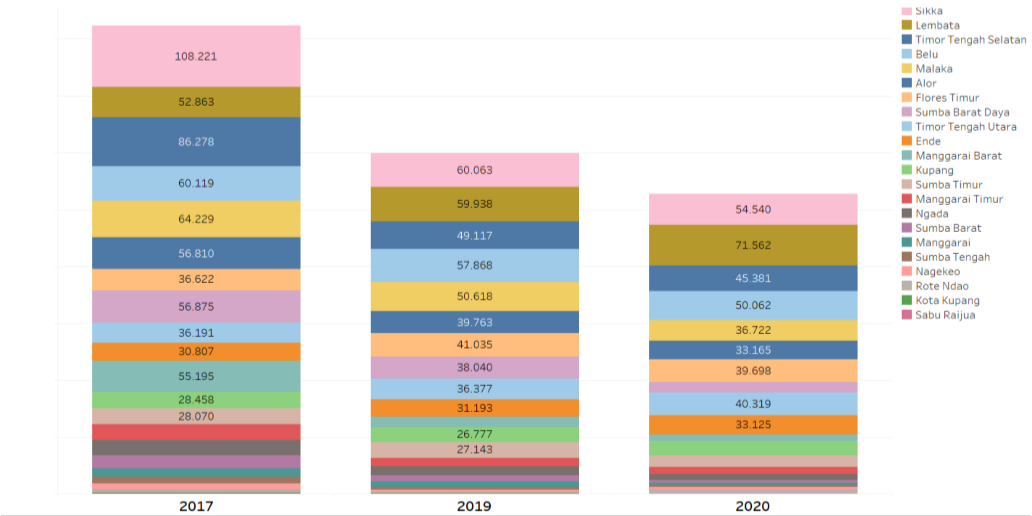
(a) Production (Ton)



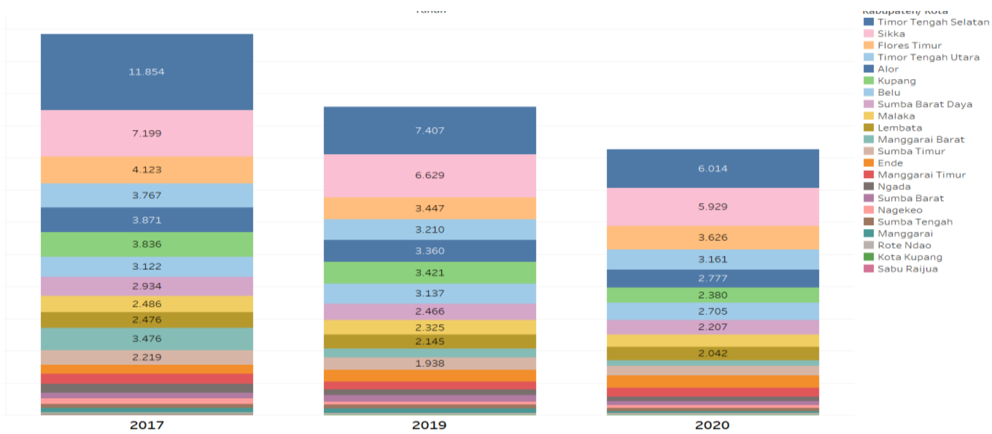
(b) Harvested area (Hectares)

Figure 14. Production and harvested area of mung beans by district/city in NTT

As a food crop commodity, cassava has roles and prospects as a source of food, industrial raw materials, and feed. As food, cassava is consumed in the form of fresh cassava, cassava, tapioca, and cassava flour. In 2019, cassava production in NTT was 599,304 tons of fresh tubers from a harvested area of 47,904 hectares. Cassava production decreased by 1.38 percent compared to 2018 due to a decrease in cassava harvested area of 6.40 percent. The largest cassava-producing district was Sikka Regency consecutively from 2017 to 2019, while in 2020, the largest producer of mung beans was the Lembata district.



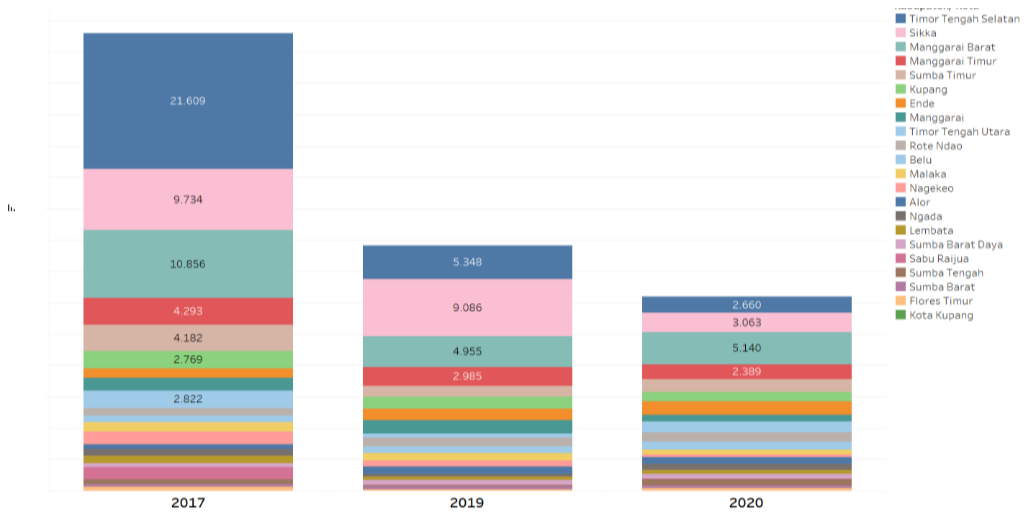
(a) Production (Ton)



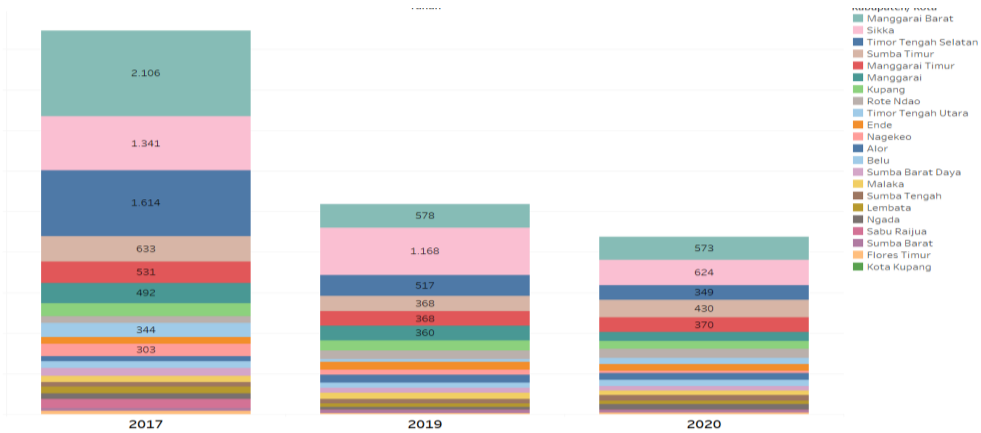
(b) Harvested area (Hectares)

Figure 15. Production and harvested area of cassava by district/city in NTT

Sweet potato has various advantages, including being easy to cultivate, fast to produce, resistant to flooding, highly nutritious, and tasting good. Sweet potatoes also have various benefits: food, animal feed, and industrial raw materials. Although sweet potatoes have an important role, their production is still low. In 2019, sweet potato production in NTT was 39,097 tons of fresh tubers from a harvested area of 5,178 hectares with a productivity of 75.51 ku/ha. Sweet potato productivity in 2019 decreased by 14.76 percent compared to the previous year.



(a) Production (Ton)



(b) Harvested area (Hectares)

Figure 16. Production and harvested area of sweet potato by district/city in NTT

It can be seen from the graph above that South Central Timor Regency has experienced a very significant decrease in production compared to 2017, initially producing 21609 tons of sweet potatoes in 2017 and 5348 tons in 2019. This was exacerbated by a decrease in the harvested area and the productivity of sweet potato food crops. In 2019, South Central Timor Regency became one of the areas affected by the worst drought in East Nusa Tenggara.

Estimated number of agricultural workers affected by drought

Estimating the number of people affected by disaster phenomena is, in many cases, difficult to determine precisely. According to the National Disaster Management Agency, people affected by natural disasters can be defined as individuals or groups who are directly or indirectly affected by disasters, including physical, material, economic, and psychological losses. However, this definition is not easily applied to the phenomenon of drought, as it is a slow and slowly occurring event where people gradually reach a point where they need help, and the main focus is protecting livelihoods rather than morbidity and mortality. Estimating the number of people affected indirectly is very important to apply to the drought phenomenon, which is a slow event but has a significant impact because of the various indirect impacts, especially in the economic, environmental, and community sectors. Tennis guidelines from SFDRR and remote sensing modeling approaches can be used to estimate the number of workers affected by drought in the agricultural sector. The results of data processing are presented in Figures 17 and 18.

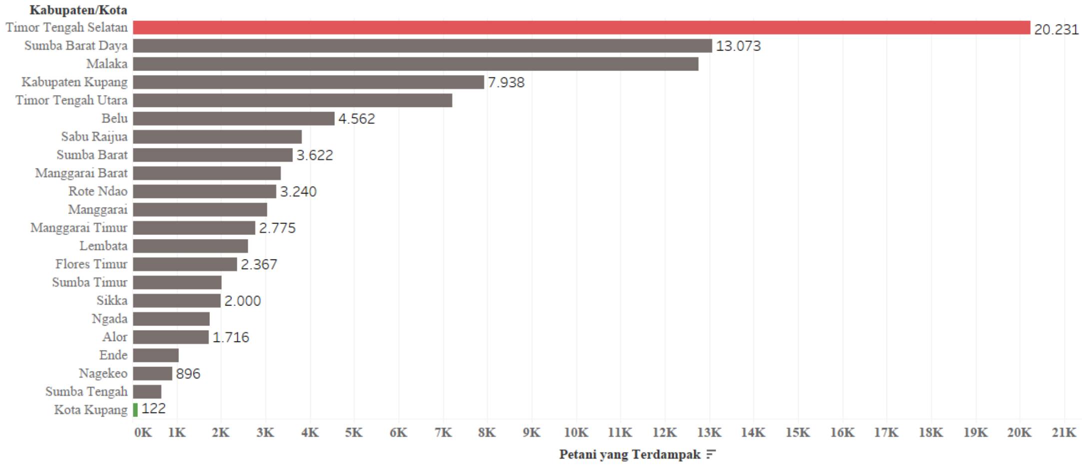


Figure 17. Estimated Number of Farmers Affected by Drought

Timor Tengah Selatan District area contributed the most to the number of food crop farmers whose livelihoods were affected by drought, amounting to 20,231 people (see Figure 17). The Timor Tengah Selatan region still experiences 202 days without rain in the extreme drought category. Meanwhile, the City of Kupang has the smallest number of food crop farmers whose livelihoods have been disrupted due to the impact of the drought among other regions in the province of East Nusa Tenggara, namely 122 people.

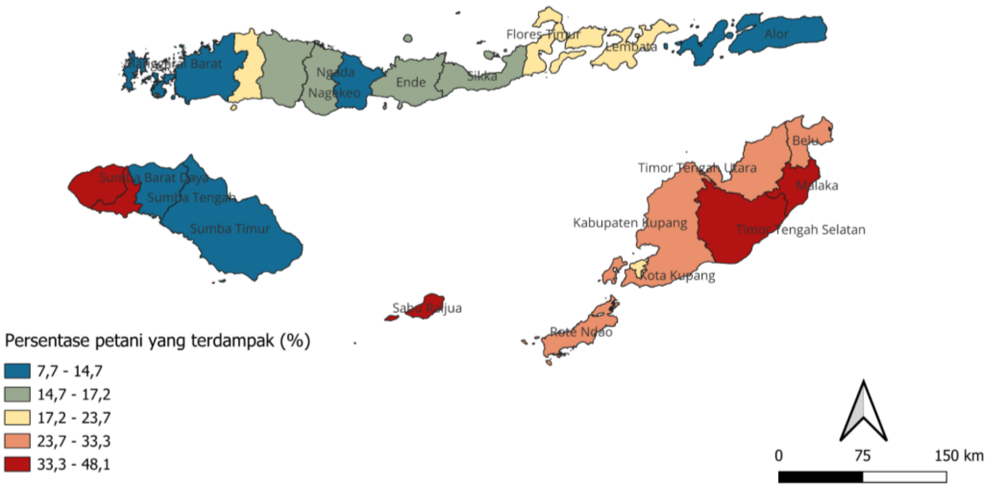


Figure18. Percentage of farmers affected by drought

The percentage of the number of food crop farmers whose livelihoods are affected by the drought is a comparison of the number of food crop farmers affected by the drought with the total number of farmers in a particular district or city area. In this research, the data source for the number of farmers in a region was obtained from the 2018 Inter-Census Agricultural Survey (SUTAS). Based on Figure 18, it can be seen that the number of food crop farmers whose livelihoods were affected by the drought in Malaka, Sumba Barat Daya, Sabu Raijua, Timor Tengah Selatan, and Sumba Barat is 48%, 45%, 42%, 35%, and 33%, respectively.

CONCLUSION

This study uses the Vegetation Health Index to map areas experiencing drought in NTT Province based on districts and cities. Drought areas are grouped into 5 classes based on the VHI value, namely extreme, severe, moderate, mild, and no drought. The drought distribution map shows that Sumba Island and Timor Island are dominated by areas experiencing drought. Meanwhile, Flores Island, Alor Island, and the surrounding areas are dominated by areas that are not affected by drought. The results of the study show that the most extensive agricultural land for food crops is on Timor Island, located in Timur Tengah Selatan district. Meanwhile, the district with the largest area of food crop land but the least impact from drought is Sumba Timur district. The drought in agricultural land for food crops had an impact on food crop production in 2019. The decline in production occurred in secondary crops such as soybeans, green beans, cassava, and sweet potatoes.

The research succeeded in showing that the Sendai Framework for Disaster Risk Reduction (SFDRR) indicator B-5a can be measured using a remote sensing approach and geospatial models as a new data source for estimating the number of food crop farmers whose livelihoods were affected by the drought in East Nusa Tenggara Province in 2019. The results of the study show that the most significant impact of the drought occurred in Timur Tengah Selatan district, with the number of affected farmers amounting to 20231 people. This is also supported by the phenomenon of days without rain lasting 202 days. The percentage of food crop farmers whose livelihoods have been affected by the drought is quite large in the districts of Malaka, Sumba Barat Daya, Sabu Raijua, Timor Tengah Selatan, and Sumba Barat.

The limitation of this study is that it only covers the food crop subsector, especially paddy and secondary crops. It is hoped that future research will include calculations of other subsectors so as to obtain a more complete estimate of the impact of drought on the agricultural sector and other sectors. The results of estimates of the area harvested for food crops and the number of agricultural sector workers affected by the drought cannot be compared traditionally because there is no official statistics available.

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