

Faculty of Engineering and the Built Environment

Department of Land and Spatial Sciences



PROJECT REPORT

Integrated Context Analysis (ICA)

By

Sibungo Pride Manvwali

218101600

Supervisor

Mr Miguel Orti

Course coordinator

Erich Naoseb

## Acronyms and Abbreviations

ICA	Integrated Context Analysis
WFP	World Food Programme
GIS	Geographic Information System
SLP	Seasonal Livelihood Programming

## 1. Introduction

The Integrated Context Analysis (ICA) is a WFP corporate programme design tool used in over 20 countries around the globe. The ICA is one of the pillar's of WFP's three-pronged approach (3PA), which combines the risk of natural shocks (droughts, floods, landslides) with the recurrence of food insecurity to identify priority areas for resilience interventions (WFP, West and Central Africa Regional Integrated Context Analysis (ICA), 2023). This is an analytical process that contributes to the identification of broad national programmatic strategies, including resilience building, disaster risk reduction, and social protection for the most vulnerable and food insecure populations. The ICA is based on principles of historical trend analyses across a number of technical and sectorial disciplines, the findings of which are overlaid to identify areas of overlap (WFP, Integrated Context Analysis (ICA) Technical Paper Jordan, 2019).

The World Food Programme (WFP) has carried out ICA's in different countries, some of these include Zimbabwe, Somalia, Niger and Mozambique. The analysis was to assess the vulnerability of communities in these countries to food insecurity by considering factors like climate variability, natural disasters, conflict, and economic instability. The goal is to inform targeted and context-specific interventions that contribute to improved food security outcomes (WFP, Integrated Context Analysis (ICA) ZIMBABWE, 2021).

No Integrated Context Analysis (ICA) has been carried out in Namibia to date. This presents a unique opportunity for stakeholders to conduct a thorough examination of the factors influencing food security, livelihoods, and overall well-being in the country. By undertaking this project, we can gain valuable insights that will contribute to more informed and targeted interventions to address the specific needs and challenges faced by communities in Namibia, fostering sustainable development and resilience.

### 1.1 Objectives:

The primary objective of this project was to carry a part of the Integrated Context Analysis (ICA) that focused on two natural shocks, Drought and Evapotranspiration that occur in Namibia. The aims of this project are threefold: first, to spatially analyse and map occurrences of natural shocks in Namibia, with a specific focus on fire incidents and transpiration patterns. Second, to create a composite map that integrates the impact of these natural shocks, aiding in understanding the combined effects on different regions. Third, to overlay the natural shock findings with the food insecurity results produced by fellow student to create a final map that shows regions in Namibia that are most vulnerable to food insecurity. The project aimed to provide a comprehensive view of the two natural shocks in Namibia.

### 1.2 Contribution to Problem Solving:

In addressing the issue of food security in Namibia, this project's outcomes offer an understanding of the spatial dynamics of natural shocks. By examining the correlation between fire incidents and transpiration patterns, decision-makers can better create strategies to mitigate the potential risks to agriculture and food production. The project's results contribute to an informed and proactive approach to managing the impact of natural shocks on food security in Namibia.

### 1.3 Background:

Namibia, with its diverse ecosystems, faces challenges related to climate variability and natural disasters (Climate Risk Country Profile : Namibia, 2021). The project was initiated to assess the natural shocks affecting Namibia's food security, with a particular focus on fire incidents and evapotranspiration patterns. According to Britannica, fire is described as the “rapid burning of combustible material, producing heat and usually accompanied by flame” (Britannica, 2003). Tanner defines evapotranspiration as “the conversion to vapor and mixing with the atmosphere of the liquid water at the earth-atmosphere boundary; this may be soil moisture, ponded water, water intercepted on surfaces, and water in plants” (Tanner, 2015). Understanding the patterns of these two natural shocks in relation to Namibia is crucial for informed decision-making and sustainable development.

## 2. Context

### 2.1 Project Context:

This is a pilot project that has been carried out by myself but it can be used by WFP for further analysis. The ICA is based on two core factors: trends of food insecurity and main natural shocks. I did 50% of the work by focusing on the natural shocks and another student did the other 50% of the work by focusing on

food insecurity. By overlaying these findings on each other, combinations of recurring food insecurity and shock risk can be identified (WFP, Integrated Context Analysis (ICA) Technical Paper Jordan, 2019). The project revolves around the geographical context of Namibia, analysing the natural shocks in various regions. The study encompasses spatial analysis, utilizing Geographic Information System (GIS) technology to create maps and to integrate and interpret fire and transpiration data.

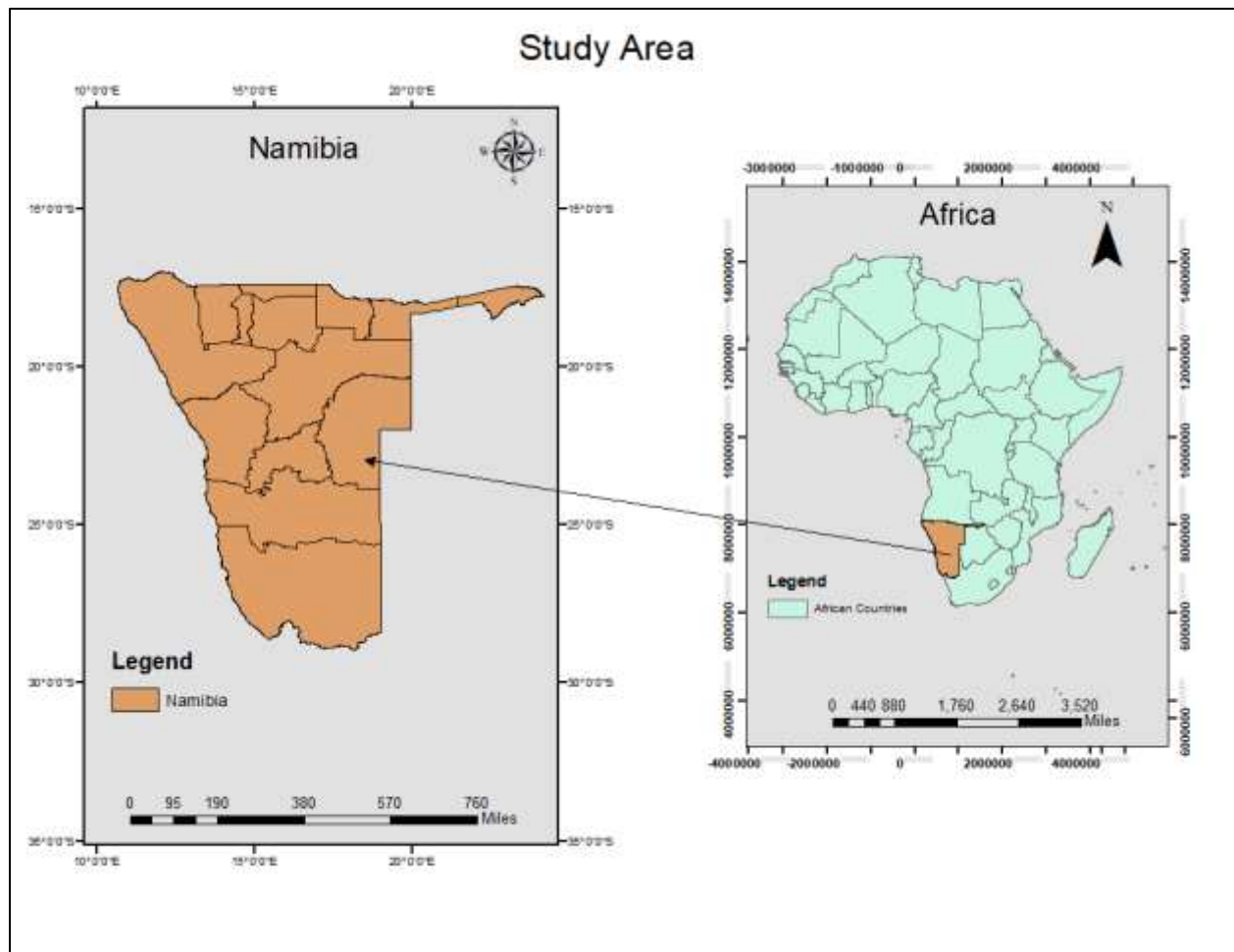


Figure 1: Map showing the study area, Namibia (left).

## 2.2 Technology Employed:

The primary technology employed in this project is ArcMap version 10.8, a powerful GIS software. ArcMap facilitates the integration of spatial datasets, allowing for the creation of composite maps that represent the combined impact of fire and transpiration on Namibian regions.

### 3. Theoretical Considerations

#### 3.1 Applicable Theoretical Aspects:

The theoretical framework for this project draws on the guidelines and instructions of the ICA at regional level. It includes principles of spatial analysis (e.g. Overlay Analysis, Spatial Relationships), GIS (e.g. Map Overlay and Spatial Data Layers ) and environmental science (e.g. Climate Patterns). It involves understanding the spatial relationships between natural shock events and their potential impact on food security.

#### 3.2 Norms and Standards:

**Projection:** Ensuring that both fire and transpiration data are using the same coordinate system. This is fundamental for maintaining spatial accuracy, consistency, and meaningful analysis in GIS.

**Data Standardisation:** Standardizing all data from zero to one ensures Consistency and Accuracy, Interoperability and Data Integration.

### 4. Process Description

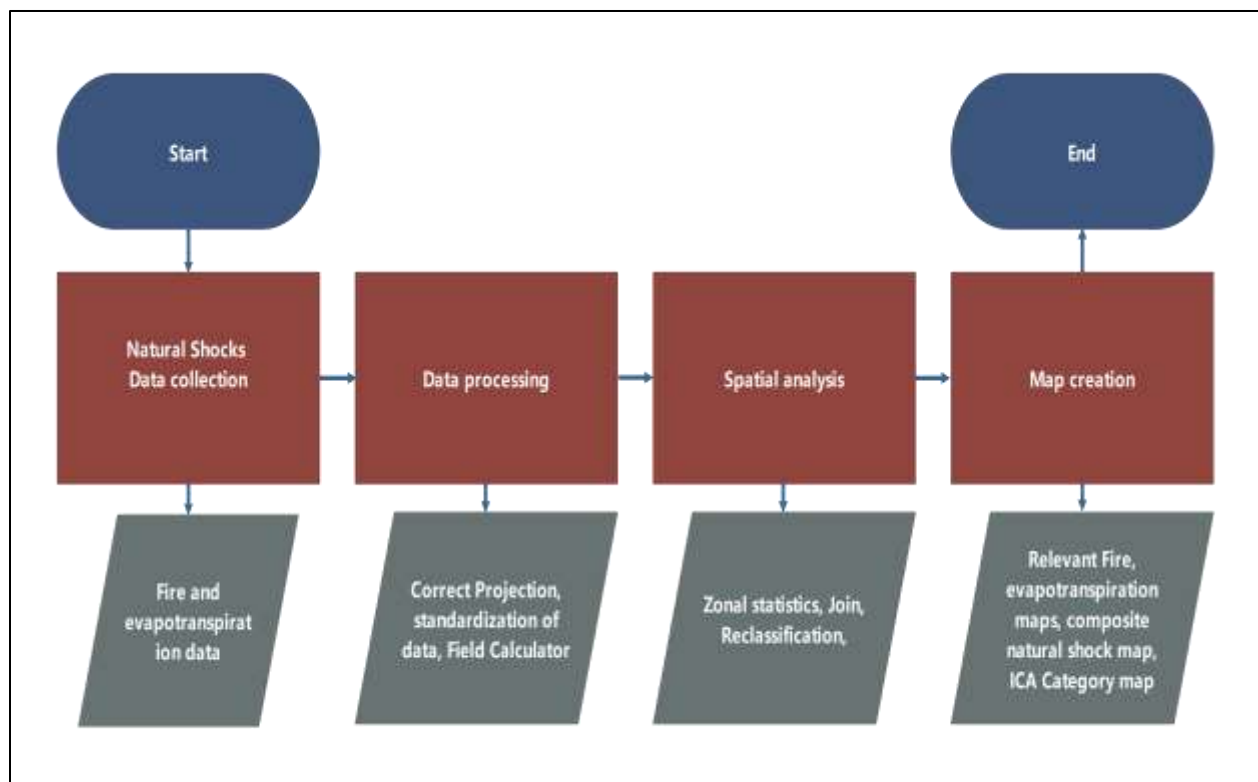


Figure 1: Flow Chart showing Project Process

### 3.3 Activities Executed:

- Data collection

*Table 1: Landscape overview of data availability and acquisition*

Sector/Topic	Description	Source
Evapotranspiration	This file contains data on annual evaporation rates (mm per year) for 24 stations across the country.	<a href="http://www.digitalnamibia.nsa.org.na">www.digitalnamibia.nsa.org.na</a>
Fire Data	Temporal data of Burned Areas from 2012 shown as a percentage.	<a href="http://www.digitalnamibia.nsa.org.na">www.digitalnamibia.nsa.org.na</a>

### 3.4 Data processing

**Projection:** The fire, evapotranspiration and region data were loaded into ArcMap. The datasets are transformed to WGS 1984 coordinate system for accurate analysis.

**Standardization:** Converting values to a common scale (e.g., 0 to 1) is a form of standardization. This is useful when integrating data from different sources or when preparing data for analysis that requires consistent units or scales.

In order for the datasets to be integrated and interpreted, they have to be standardised to a common numerical format, which makes them compatible and allows them to be overlaid. The formula used for the standardisation is follows:  $(\text{value} - \text{min} / \text{max} - \text{min})$ , this standardizes the data to range from 0 to 1 with 0 being good and 1 being bad. For the fire data, the “fire3” column was standardized and for the evapotranspiration layer the “mean” column was selected. The output of the standardisation is found below:

FID	Shape *	region_nam	area	fire3	stand
3	Polygon	Karas	181274.7	0.053722	0
2	Polygon	Hardap	109617.7	0.487403	0.015225
7	Polygon	Ohangwena	10703.2	0.94439	0.031268
1	Polygon	Erongo	63579.9	1.112867	0.037183
5	Polygon	Khomas	36943.7	1.954325	0.066724
6	Polygon	Kunene	115273.9	2.405124	0.08255
8	Polygon	Omaheke	84552.5	10.195654	0.356051
11	Polygon	Oshikoto	38668.3	11.912497	0.416324
9	Polygon	Omusati	28571.2	13.531794	0.473172
12	Polygon	Ojozondjupa	105203.2	17.637676	0.617317
4	Polygon	Kavango West	48455.2	21.992934	0.770216
13	Polygon	Kavango East	48455.2	22.499548	0.788062
0	Polygon	Zambezi	14480.3	23.035711	0.806825
10	Polygon	Oshana	8652.4	28.538209	1

FID	Shape *	region_nam	area	MEAN	stan
6	Polygon	Kunene	115273.9	1261.457761	0
0	Polygon	Zambezi	14480.3	1375	0.174708
7	Polygon	Ohangwena	10703.2	1375	0.174708
13	Polygon	Kavango East	48455.2	1375	0.174708
4	Polygon	Kavango West	48455.2	1376.022794	0.176619
11	Polygon	Oshikoto	38668.3	1481.320015	0.373281
9	Polygon	Omusati	28571.2	1535.712351	0.474871
10	Polygon	Oshana	8652.4	1523.086735	0.474871
12	Polygon	Ojozondjupa	105203.2	1570.012332	0.538933
8	Polygon	Omaheke	84552.5	1585.64002	0.56812
1	Polygon	Erongo	63579.9	1586.952327	0.570572
5	Polygon	Khomas	36943.7	1757.196748	0.88854
2	Polygon	Hardap	109617.7	1791.902288	0.953356
3	Polygon	Karas	181274.7	1816.876795	1

Figure 2: Standardized values for the fire and evapotranspiration layer.

### 3.5 Spatial analysis

#### Methodology

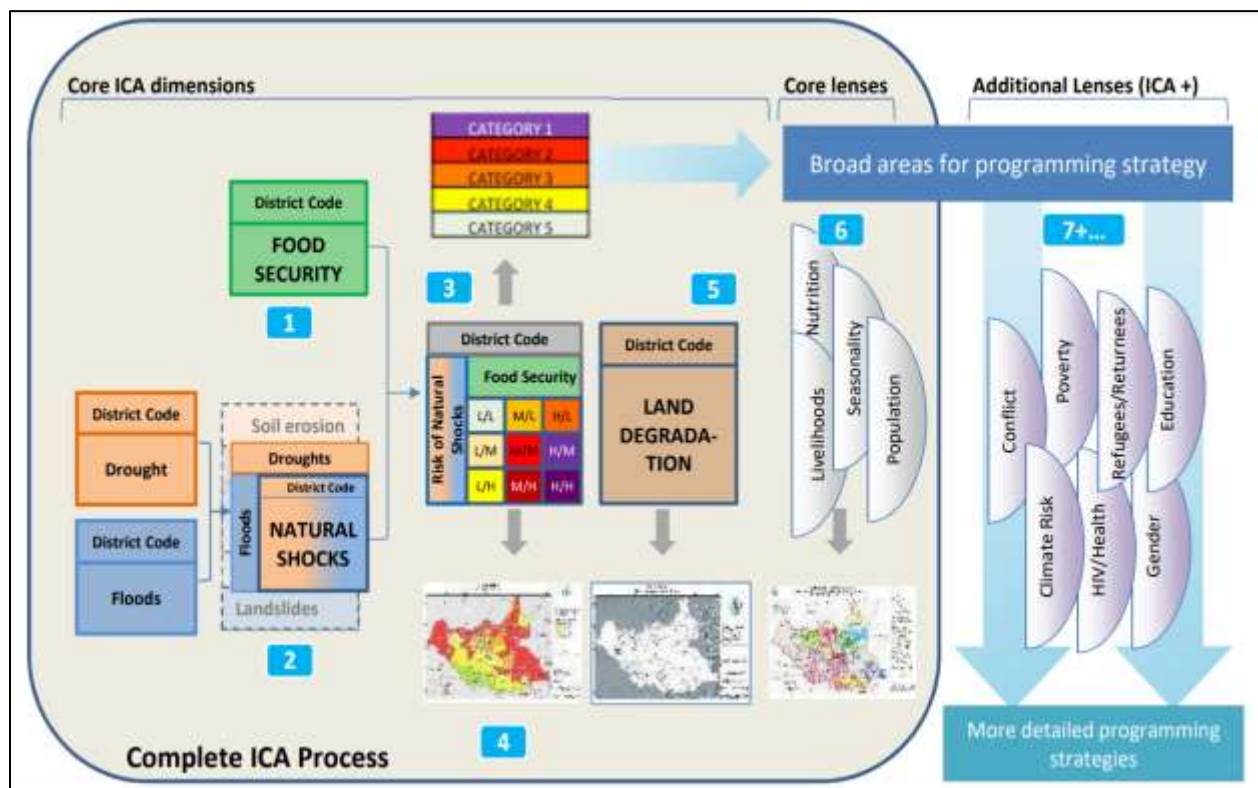


Figure 3: ICA Methodology Source: World Food Programme (World Food Programme Part 1: Integrated Context Analysis)

Compatibility with Spatial Analysis Tools: Many spatial analysis tools and operations in GIS are designed to work with raster data. Some data in this project was reclassified into categories (e.g., Low, Medium, High) allows you to use these tools for further analysis, such as risk assessment.

To understand the statistical relationship between the regions and both the fire and evapotranspiration layers, we need to understand the statistical connection between them. We derive this information by using the zonal statistics as a table tool that generates a table of statistics for each region. Zonal statistics, which involve calculating statistics for raster data within specified zones (usually polygons), typically require raster input. An illustration on how the tool operates is found below:



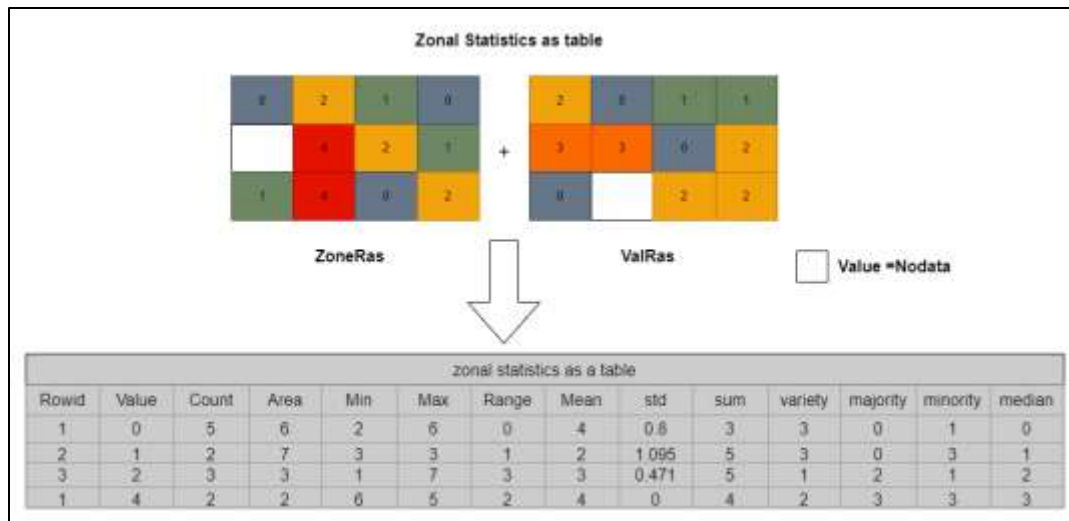


Figure 4 Illustration: Zonal Statistics as a table

This tool requires that we have at least one raster layer as input before it can be run. Due to this requirement, we convert the Fire and Evapotranspiration layers into rasters that will be used in the zonal statistics as a table tool. The conversion for both layers is found below:

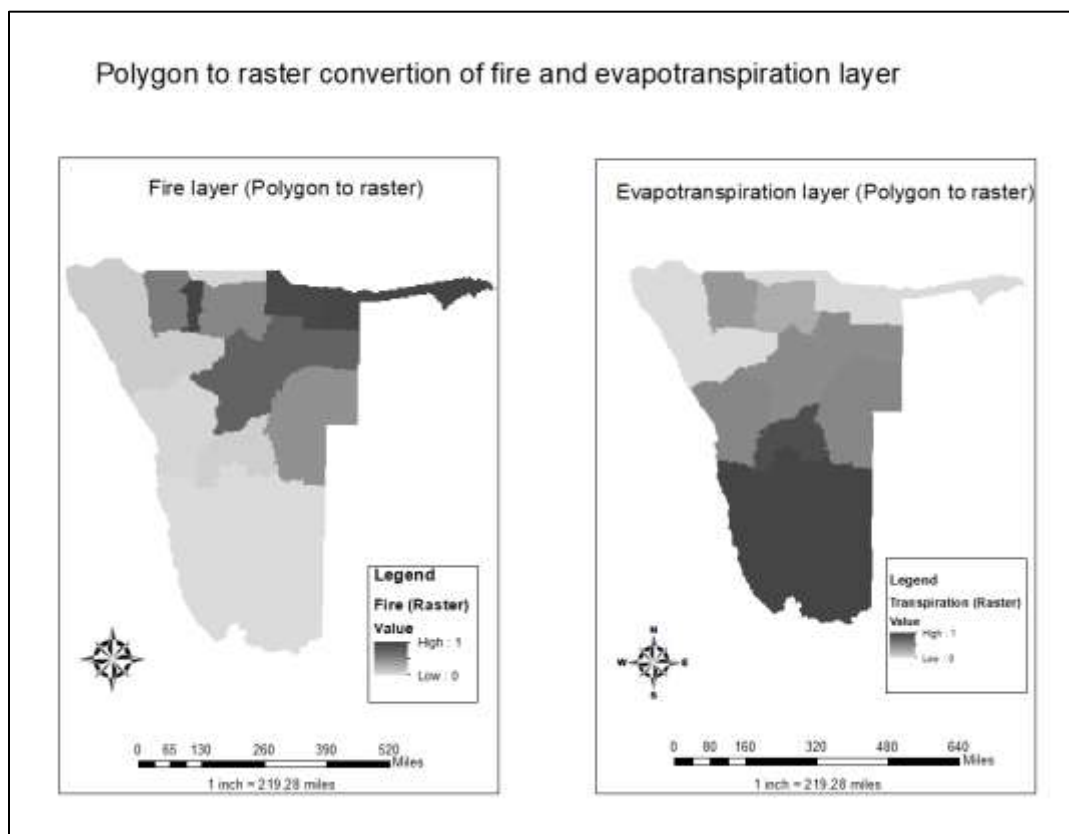


Figure 5: Fire and evapotranspiration polygon to raster conversion.

After deriving the needed raster outputs, they are then utilised in the zonal statistics a table tool. This tool calculates statistics for each zone, such as the mean, sum, maximum, minimum. The output can be exported for further analysis. In the tool the input raster was the regions layer and the input value raster was fire and evapotranspiration layers when running the tool respectively for both layers. The output is shown below:

**ZonalStats\_fire**

OBJECTID	VALUE	ZONE_CODE	COUNT	AREA	MIN	MAX	RANGE	MEAN	STD	SUM	VARIETY	MAJORITY	MINORITY	MEANAB
1	Fire	4	11144	18391830000	500	2150	1650	1816.87676	342.716227	20247270	10	2090	1890	1890
2	Fire	3	7894	149801700000	500	2350	1850	1791.902288	206.152884	13629520	9	1890	1990	1890
3	Fire	6	2050	36920840000	1850	1850	0	1797.195740	79.740831	3681400	5	1790	1890	1790
4	Fire	2	14425	42602200000	500	1850	1350	1836.802377	264.824388	26400000	7	1790	1375	1790
5	Fire	8	1887	84719400000	1850	1750	0	1882.84822	35.845717	8542980	3	1890	1760	1890
13	Fire	13	1286	105303100000	1375	1750	375	1875.812332	81.831181	11457980	4	1890	1760	1890
14	Fire	14	1886	28496240000	1375	1850	275	1828.712361	76.450213	3434820	3	1890	1890	1890
15	Fire	11	589	8490720000	1375	1880	275	1823.884726	83.450126	898875	3	1890	1890	1890
16	Fire	12	2878	3867020000	1375	1880	175	1881.820678	88.450126	3988975	2	1890	1375	1890
17	Fire	5	1711	2470840000	1375	1850	175	1878.822794	13.33852	2054375	2	1375	1890	1375
18	Fire	1	1032	14488880000	1375	1375	0	1375	0	1377750	1	1375	1375	1375
19	Fire	8	757	10921080000	1375	1375	0	1375	0	1046875	1	1375	1375	1375
20	Fire	14	1409	2365580000	1375	1375	0	1375	0	1918125	1	1375	1375	1375
21	Fire	7	3022	11824830000	500	1750	1250	1384.457781	436.423883	10294225	9	1890	1760	1375

**ZonalStats\_evap**

OBJECTID	region name	ZONE_CODE	COUNT	AREA	MIN	MAX	RANGE	MEAN	STD	SUM
1	Zambia	1	518	14454440000	0.490788	0.490788	0	0.490788	0	253.235113
2	Botswana	2	2288	83788120000	0.383875	0.383875	0	0.383875	0	888.194448
3	Malawi	3	3811	10988990000	0.484291	0.484291	0	0.484291	0	1884.260136
4	Kenya	4	5741	16126490000	0.5	0.5	0	0.5	0	2870.5
5	Kenya West	5	989	24470210000	0.475417	0.475417	0	0.475417	0	471.388788
6	Kenya East	6	1318	3878780000	0.477632	0.477632	0	0.477632	0	625.898819
7	Rwanda	7	4115	11853410000	0.541275	0.541275	0	0.541275	0	189.764896
8	DRC	8	366	1536210000	0.182888	0.182888	0	0.182888	0	38.802862
9	DRC	9	3824	8494410000	0.482085	0.482085	0	0.482085	0	1267.348538
10	Uganda	10	850	2688500000	0.474621	0.474621	0	0.474621	0	455.32942
11	DRC	11	309	3878610000	0.737436	0.737436	0	0.737436	0	227.861576
12	DRC	12	1375	3862770000	0.394883	0.394883	0	0.394883	0	542.853452
13	DRC	13	3787	10852410000	0.576128	0.576128	0	0.576128	0	2172.919825
14	Kenya East	14	844	2378790000	0.487385	0.487385	0	0.487385	0	488.26385

Figure 6: Zonal statistics as a table output. Fire layer being bottom and the evapotranspiration layer being on top.

The next step is to create two joins comprising of two datasets. The Join Features tool will transfer attributes from one layer or table to another based on spatial and attribute relationships in our case, the common attribute between the region layer and the fire and evapotranspiration zonal statistics outputs are the regions, therefore the joins will be based on the names of the regions. An illustration of the tool is found below:

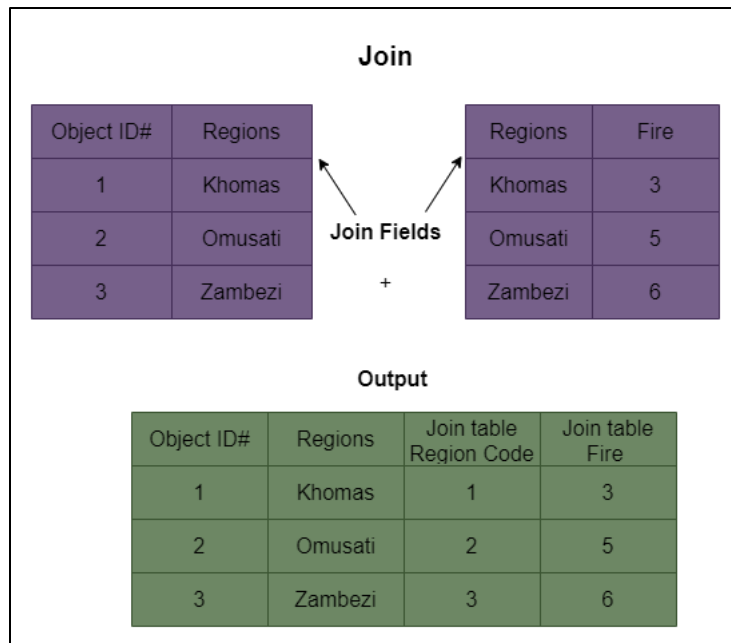


Figure 7: Illustration Join tool

The columns which were not deemed necessary for further analysis were deleted. The output of the spatial join for both fire and evapotranspiration layer is found below:

FID	Shape *	region_nam	area	fire3	stan
3	Polygon	Karas	161274.7	0.053722	0
2	Polygon	Hardap	109617.7	0.487403	0.015225
7	Polygon	Ohangwena	10703.2	0.94439	0.031268
1	Polygon	Erongo	63579.9	1.112087	0.037183
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8	Polygon	Omaheke	84552.5	1585.64802	0.56812
12	Polygon	Otjozondjupa	105203.2	1570.012332	0.538933
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11	Polygon	Oshikoto	38868.3	1481.320615	0.373281
4	Polygon	Kavango West	48455.2	1376.022794	0.176619
0	Polygon	Zambezi	14480.3	1375	0.174708
7	Polygon	Ohangwena	10703.2	1375	0.174708
13	Polygon	Kavango East	48455.2	1375	0.174708
6	Polygon	Kunene	115273.9	1281.457761	0

Figure 8: Outputs after joining the region to the fire and evapotranspiration respectively.

After the joins have been created, we can then visualize the connection between the fire and evapotranspiration layers and the regions. This will allow us to see the degree to which the regions are affected by the fire and the evapotranspiration respectively.

## Regions affected by fire and evapotranspiration

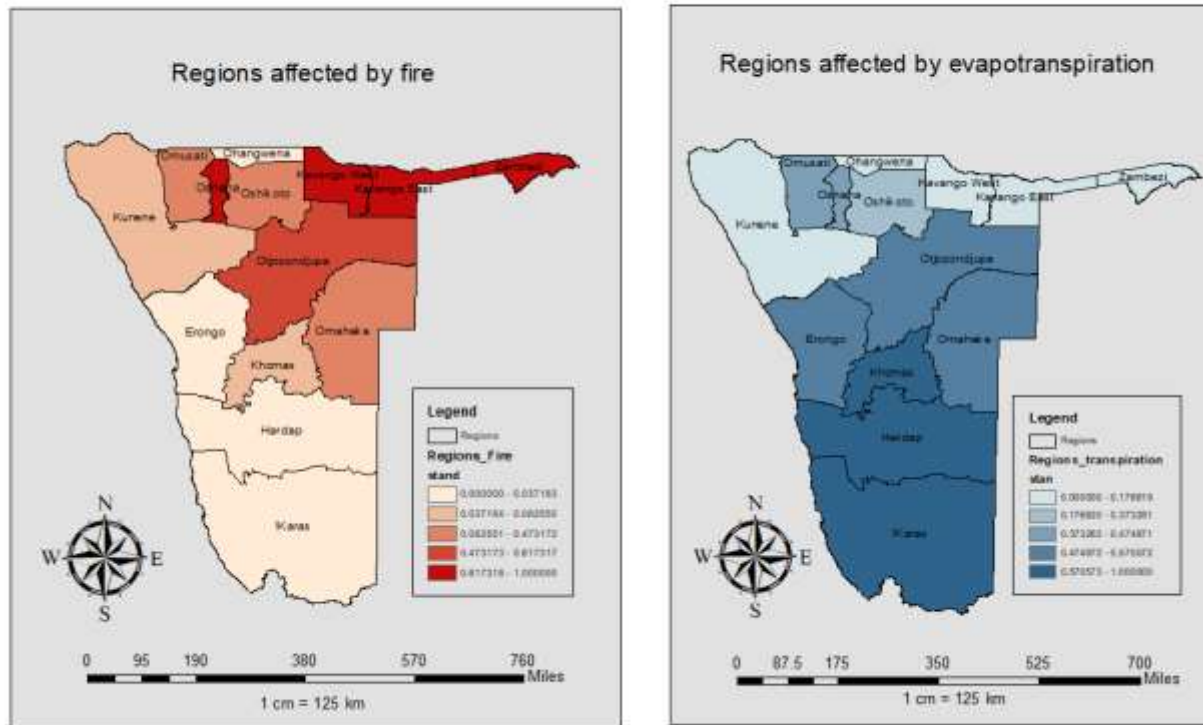


Figure 9: Regions affected by fire and evapotranspiration

### Risk levels

Risk levels refer to the classification of potential risks or threats into different categories based on their severity, likelihood, or impact. As this study is focused on finding which regions in Namibia are at most risk of being affected by natural shocks, it is more meaningful to represent the data in categorical terms (Low, Medium, High) rather than as continuous values. This simplifies the interpretation and communication of results. Reclassification is the process of reassigning one or more values in a raster dataset to new output values (Esri, 2020). The Reclassify tool is available in the Spatial Analyst extension in ArcMap.

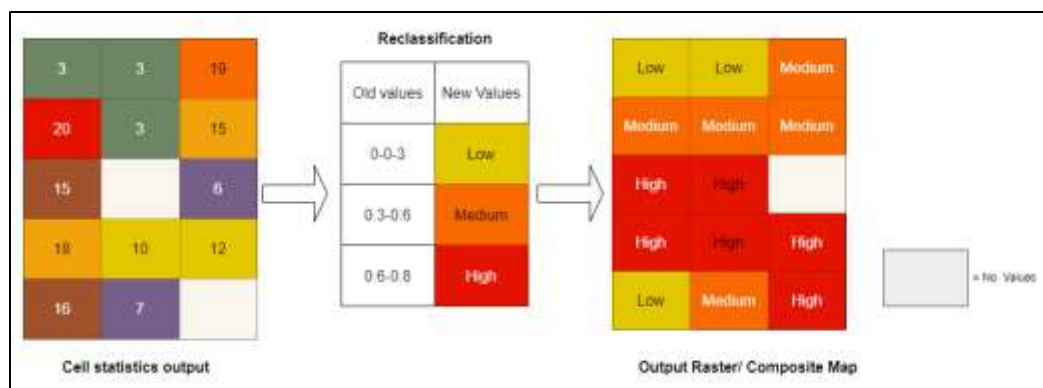


Figure 10. Illustration: Reclassification tool

To visualize the risk levels of the regions the reclassify tool is used, a map is created showing the risk levels for both the fire and evapotranspiration layers is found below:

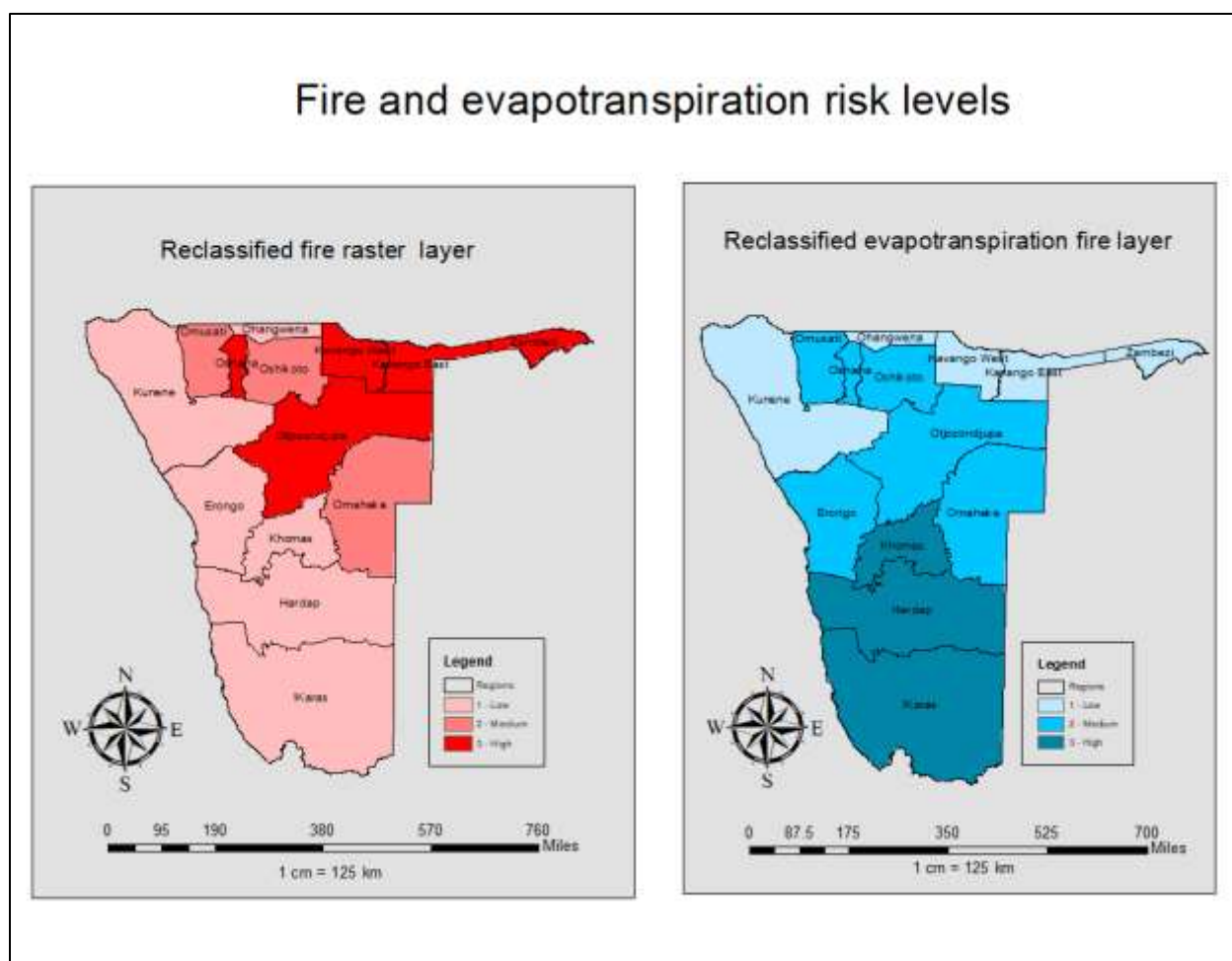


Figure 11: Fire and evapotranspiration risk levels

The fire map shows us that regions found in the north and northeast of Namibia are at highest risk of being affected by wild fires. The rest of the regions have a medium to low risk of being affected by wild fires. The evapotranspiration map shows that the Kunene, Ohangwena, Kavango East, Kavango West and Zambezi regions are lowest risk of being impacted by evapotranspiration. However, the risk starts to increase as we move south towards the central and southern parts of Namibia. We see the evapotranspiration risk increase to medium and then high. Regions in southern part of Namibia are at the highest risk of being affected by evapotranspiration.

### Composite map creation

The next step is to create a composite natural shock map. A composite map allows the integration and visualization of multiple natural shocks simultaneously. This provides understanding of the combined effects of different factors on a specific region and assist in assessing the overall risk profile of the regions. The "Cell Statistics" tool found in Spatial Analyst toolbar allows the execution of analysis on multiple raster datasets. An illustration on how the tool operates is shown below:

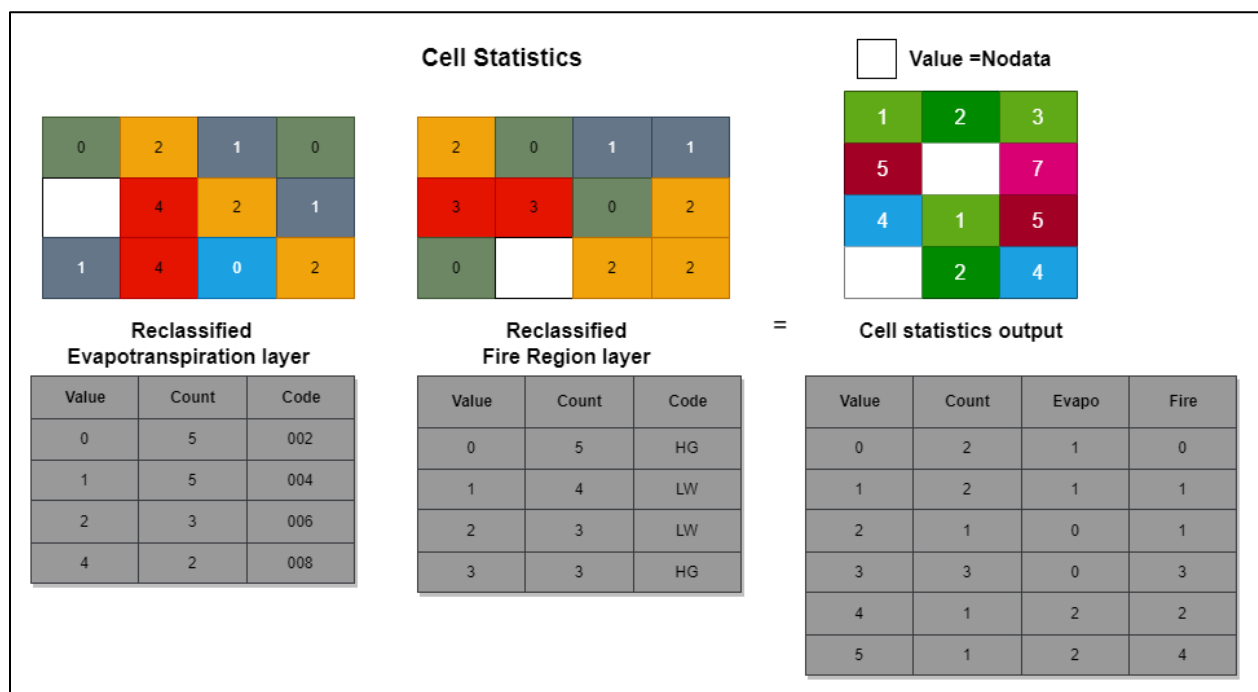


Figure 12. Illustration: Cell Statistics output process.

The two rasters shown above (Reclassified Evapotranspiration layer and the Reclassified Fire Region layer) used as input rasters in the Cell Statistics tool to generate the output. The output is shown below:

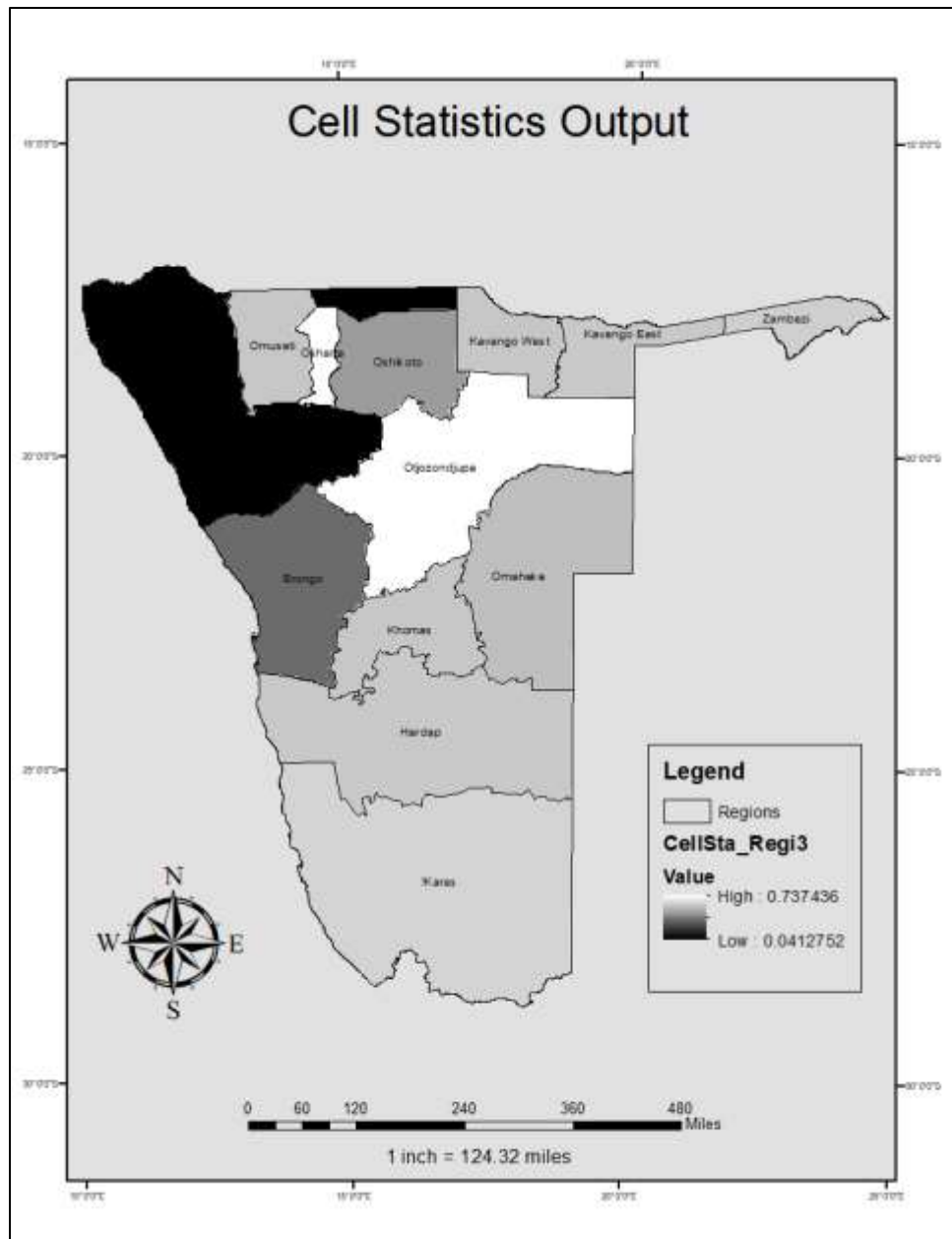


Figure 13: Cell statistics output

The Cell Statistics output is then used to create a composite natural shock map that shows the combined impact of the drought and evapotranspiration on the Namibian regions. This is done by reclassifying the output into three categories low, medium and high using the reclassify tool. Reclassification is the process of reassigning one or more values in a raster dataset to new output values. The output and illustration of the tool is shown below:





## Technical Review

The combined natural shock map shows that the Otjozondjupa and Oshana regions are at most risk to suffer from natural shocks. The Kunene and Ohangwena regions are at the least risk of being affected by natural shocks, the rest of the country has a medium chance of being affected by natural shocks.

## ICA Categories

Exposure to natural shocks	Recurrence of Food Insecurity		
	LOW	MEDIUM	HIGH
LOW	<b>CATEGORY 5</b> Programming that enhances <b>disaster preparedness</b> to reduce risks and build resilience to natural shocks and other stressor	<b>CATEGORY 3</b> Long-term programming to address underlying (chronic) causes of food insecurity <b>likely to be caused by non-climatic factors</b> (eg poverty, protracted conflict, etc.) aimed at improving food security and building resilience – for example by building human and social capital and removing specific barriers to human development.	
MEDIUM	<b>CATEGORY 4</b> Programming that enhances <b>early warning and disaster preparedness</b> (considering trends in environmental degradation) to reduce risk and build resilience to natural shocks and other sources of stress	<b>CATEGORY 2</b> Programming to address <b>seasonal food insecurity and / or support post-shock rehabilitation</b> , aimed at reducing risk and build resilience to natural shocks and other sources of stress.	<b>CATEGORY 1</b> Long-term programming to respond to situations of <b>protracted crises and frequent natural shocks</b> that impede recovery and rehabilitation, aim to improve food security, reduce risks and build resilience to natural shocks and other sources of stress.
HIGH			

Figure 15: ICA Categories. Source: World Food Programme (World Food Programme Part 1: Integrated Context Analysis)

The ICA categorizes the country's regions into Categories 1 to 5 based on their levels of recurring food insecurity and exposure to natural shocks. This is done by overlaying the outcomes of the food security and natural hazards analysis to get a map that categorizes each region from category one to category five. The final map is shown below:



## Technical Review

As already mentioned, The ICA categorizes the country's regions into Categories one to five based on their levels of recurring food insecurity and exposure to natural shocks. The map above shows the !Karas, Khomas and Omusati regions fall in category 2 of the ICA which means they have a medium chance of suffering from a recurrence of food insecurity. The Kunene and Ohangwena regions fall under category 3, which means these regions, have a medium to high chance of suffering from a recurrence food security. The Oshana region, which is category 4, has the lowest chance of suffering from recurrence of food security. The remaining regions are all in category 1 of the ICA meaning they have a high chance of being affected by the recurrence of food insecurity.

### Methods, Techniques, and Tools:

Spatial Join: Used to combine fire and transpiration data with Namibian regions.

Cell Statistics: Perform cell-by-cell analysis on multiple raster datasets.

Reclassify tool: Reclassifies the values in a raster dataset into new values based on specified criteria.

Zonal Statistics as Table: Calculates statistics for cells in a raster dataset that correspond to zones defined by a set of polygons.

ArcMap: Employed for spatial analysis and map creation.

### Challenges Encountered:

Throughout the project cycle, several challenges were encountered; including data inconsistencies, technical difficulties in spatial analysis and limited data for the natural shocks was available. Each challenge was addressed through a systematic problem-solving approach, contributing to the overall learning experience.

## 5. Conclusion

In conclusion, this Integrated Context Analysis (ICA) has successfully shown the intricate relationship between natural shocks, specifically wildfires and evapotranspiration, and their impact on food security in Namibia. This project has, to the student's best ability, effectively addressed the challenges presented in the introduction, showing the relationship between natural shocks and food security in Namibia. The

findings contribute to a better understanding of how environmental events such as fire and evapotranspiration can impact agricultural productivity and, consequently, food availability.

The practical possibilities of this research extend beyond Namibia. By discovering and implementing sustainable methods, the findings can be used to assist communities in other African countries against the adverse effects of natural disasters, creating resilience against environmental challenges. This can be used to create accurate seasonal livelihood calendars that capture common practices, shocks and stressors to inform specific activities and interventions at sub-nation/ District level. SLPs can then suggest participatory discussions with specific communities and local authorities to help refine local development plans (WFP, Integrated Context Analysis (ICA) ZIMBABWE, 2021).

For organizations like the World Food Program (WFP) and Namibian ministries responsible for agriculture, water, forestry, environment, and tourism, this project offers a strategic advantage. The identified regions susceptible to natural disasters and food insecurity can guide resource allocation, policy enhancement, and informed decision-making. Sharing these findings across disciplines, including conservation, mining, and farming, can foster collaboration and strengthen comprehensive approaches to sustainable development..

Looking ahead, if given another six months, an expansion of the analysis to include additional variables could deepen our understanding of food security dynamics. Exploring categories such as flooding, drought, access to markets, human and animal diseases, and poverty would provide a more comprehensive view. This expanded dataset could enable insights that are more refined and increase the accuracy of ICA and seasonal livelihood calendars.

Reflecting on my personal growth throughout this project, I have not only gained proficiency in GIS tools but also developed essential social skills such as teamwork, hard work, and adaptability. The experience has further proven the immediate impact GIS can have on communities today and its potential to shape a sustainable future for generations to come.

As we progress, this pilot project can act as a contributing force for continued investigation, collaboration, and the application of sustainable strategies to preserve the livelihoods of communities and safeguard food security in Namibia.

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