Risk Mapping in the Cono Sur Region in Cochabamba, Bolivia

Identifying Potential Risk Areas for Drought, Frost, and Flood: A Case Study of Four Municipalities

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Preface

This project involves a comprehensive analysis of natural phenomena like droughts, floods, and frosts, which significantly impact societal activities and infrastructure (Sun et al. 2020). Droughts, typified by extended periods of water scarcity due to reduced rainfall, are globally acknowledged for their detrimental economic consequences, resulting in widespread agricultural losses and livestock fatalities.

Risk assessment is a pivotal component, originating from the complex interplay between threats and vulnerabilities within a society. Comprehending risk entails considering the likelihood of hazardous events and the susceptibility of the exposed population (U. S. National Committee for the Decade for Natural Disaster Reduction. 1991).

Especially drought-prone nations should establish national drought policies and preparedness plans based on available data. These plans should prioritize risk management over the traditional crisis management approach, which relies heavily on reactive emergency responses. The crisis management method undermines self-reliance and fosters dependence on government and external donors (Belal et al. 2014).

Predicting risks forewarns about potential disasters, signifying the likelihood of future damages and losses caused by external events surpassing a society's capacity to recover. Unmanaged risks culminate in disasters, emphasizing the importance of risk management policies within municipalities and dedicated planning bodies, essential for effective disaster response.

The project emphasizes the creation of threat maps, integrating local and technical perceptions of threats like drought, frosts and flood highlighting the complexity in defining these meteorological events.

In the Andean Region of Cochabamba, stakeholders have identified especially drought and frost as a persistent threat to agriculture and livestock, particularly during the winter months. This has led to the development of the following risk maps, which are essential for planning and mitigating disasters (Saxena et al. 2016).

The project methodology employs a general risk equation in conjunction with multicriteria evaluation techniques, integrating base information from various sources. The objective is to thoroughly assess the risk landscape, zone vulnerable areas, and identify threats such as floods, characterized by sudden increases in water levels causing significant economic and social disruptions (Trovato et al. 2017).

1 Drought Risk

1.1 Frame of Reference

This study was conducted in four areas of Cochabamba's Valle Alto region: Aiquile, Pasorapa, Pojo, and Totoro. These areas are known for their vast farmlands that produce a variety of crops.

Mountain water sources are vital for irrigation in these and other areas. However, there have been disputes over water rights within and between these areas. Changes in climate patterns have led to concerns about water security, causing extended periods of water shortage.

The goal of this study is to develop a method to identify potential weather risks like drought, frost, and flood, Taking into account the distinctive physical and social attributes of the four states within the Bolivian high valley region. The findings are intended to support risk prevention policies in all four areas.

This study uses a cost-effective, scientific, and adaptable approach to different situations. It combines detailed physical aspects, and aims to influencing decisions about land and natural resource management. This method could potentially be used in other regions and nationally.

Drought is a weather event that happens when there's less rainfall than average over a period, causing a significant and long-lasting water shortage that affects human activities. Droughts, which are becoming more common worldwide, are among the most economically damaging natural events, leading to the loss of large areas of crops and the death of many livestock.

Risk is the result of the dynamic relationship between threats and vulnerabilities within a society or its specific components. It's calculated using the following equation: Risk depends on the likelihood of hazardous events happening and the presence of a vulnerable population exposed to the threat. This means that if there's no threat, there's no risk, or if the population isn't vulnerable, the risk is zero.

Risk predicts the probability of future disasters, indicating the potential future damage and losses associated with the impact of an external physical event on a vulnerable society, exceeding the society's ability to recover from such impacts on its own.

Disasters happen because of unmanaged risks. Therefore, it's important for areas to establish risk management policies and create planning bodies like a "Risk Management Unit," equipped

with planning tools and instruments. Risk maps are important tools for land planning that greatly help with risk management.

A group of development workers known as the *Equipo Cono Sur*, from the NGO Agrecol Andes, are focused on helping communities and governments in the Cochabamba's Valle Alto region: including special efforts in Aiquile, Pasorapa, Pojo, and Totoro prepare for future challenges such as droughts, frosts, and floods. They aim to adapt local residents and governments to these risks.

Additionally, they recently conducted a case study on Recharge Zones (called *"Zonas de Recarga Hídrica"* in Spanish) using a similar professional approach as this Multicriteria Analysis Case Study. This Document can been viewed here: Multicriterianalysis Recarga Hídrica (2023).
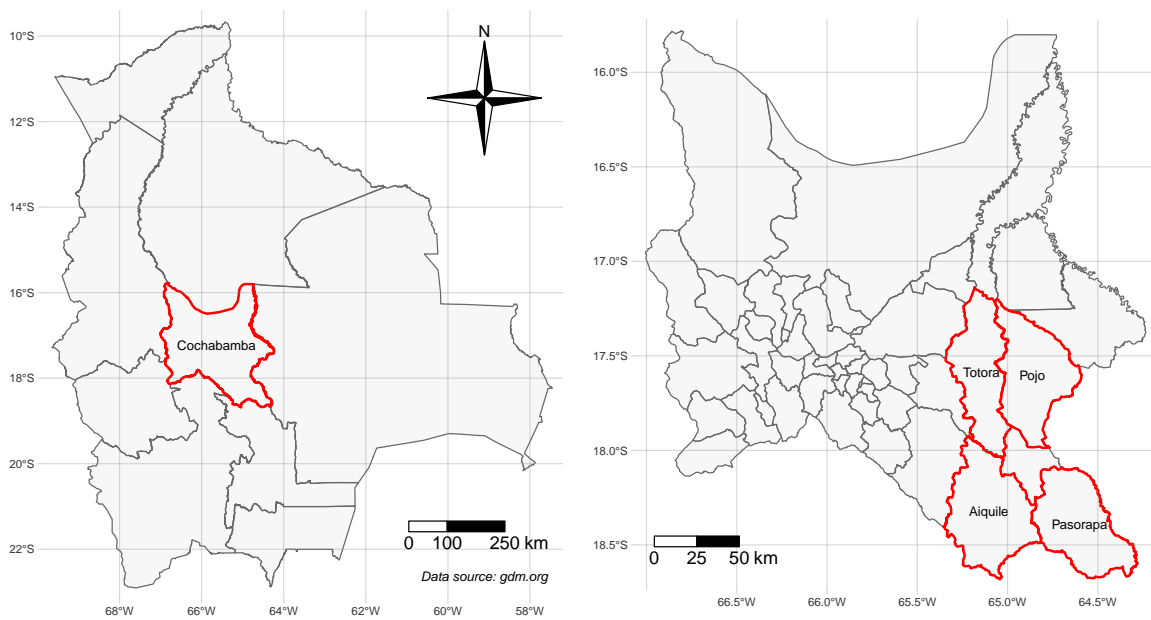
(a) Map of the Plurinational State of Bolivia

(b) Map of Municipalities of Cochabamba and its 4 Municipalities of interest

Figure 1.1: Overview of the frame of Reference Cochabamba and its four Municipalities: Aiquile, Pasorapa, Pojo & Totora

1.2 Methodology of the Case Study

This Multicriteria Analysis employs numerous Raster and Vector Layers, integrating weighted factors. The entire project is conducted within the R-Studio Environment. Key packages utilized in achieving the final results are listed here R-Studio Libraries, delivering essential functions for the conducted calculations.

Table 1.1 shows the data used in order to conduct the multicriteria analysis on the four municipalities in the Cono Sur Region in Cochabamba, Bolivia.

Table 1.2 presents the classification and evaluation of various criteria for drought exposure, illustrating the factors influencing each classification. This table outlines the criteria and their corresponding classifications as follows.

The subsequent sections present the reclassified data for four municipalities in the state of Cochabamba. These sections detail the process of cleaning and further processing the raw data, with relevant code snippets linked to the Appendix for reference.

Table 1.1: Used Data in the Analysis

Data	Types	Source	Period/Year
Riverdata	Vector	Linke et al. (2019)	2013
Political Map	Vector	gadm.org	2024
Precipitation	Raster (30 s)	Fick and Hijmans (2017)	1970-2000
Temperature	Raster (30 s)	Fick and Hijmans (2017)	1970-2000
DEM	Raster (15 s)	Hydrosheds.org	2013

Table 1.2: Classification and evaluation of drought exposure according to factors

Criteria	Very.High	High	Moderate	Low	Very.Low	Weights
River Data	<200	200-700	700-2000	2000-5000	>5000	2.0
Maximum	>30	27-30	25-27		<25	2.0
Temperature						
DEM	>45	20-30	20-30	10-20	<10	1.5
(Inclination)						
DEM	<45°	45-135°	135-225°	225-315°	>315°	1.5
(Perspective)						
Precipitation	<513.8	514-571	571-640	640-1058	>1058	3.0

1.2.1 River Data

The data utilized aimed to estimate the distance to rivers, serving as a proxy for assessing the likelihood of drought occurrences. The underlying assumption was that greater distances from rivers correspond to increased drought probabilities. To calculate distances, the `terra::distance` function was employed on the river shapefiles associated with various municipalities. Detailed processing steps are outlined in the subsequent chapter of the Appendix.

The reclassification has been calculated according to Table 1.2. Defining the classification values Gao et al. (2023) has been using different values in order to classify and evaluate drought exposure, hazard factors, vulnerability, and mitigation capacity.
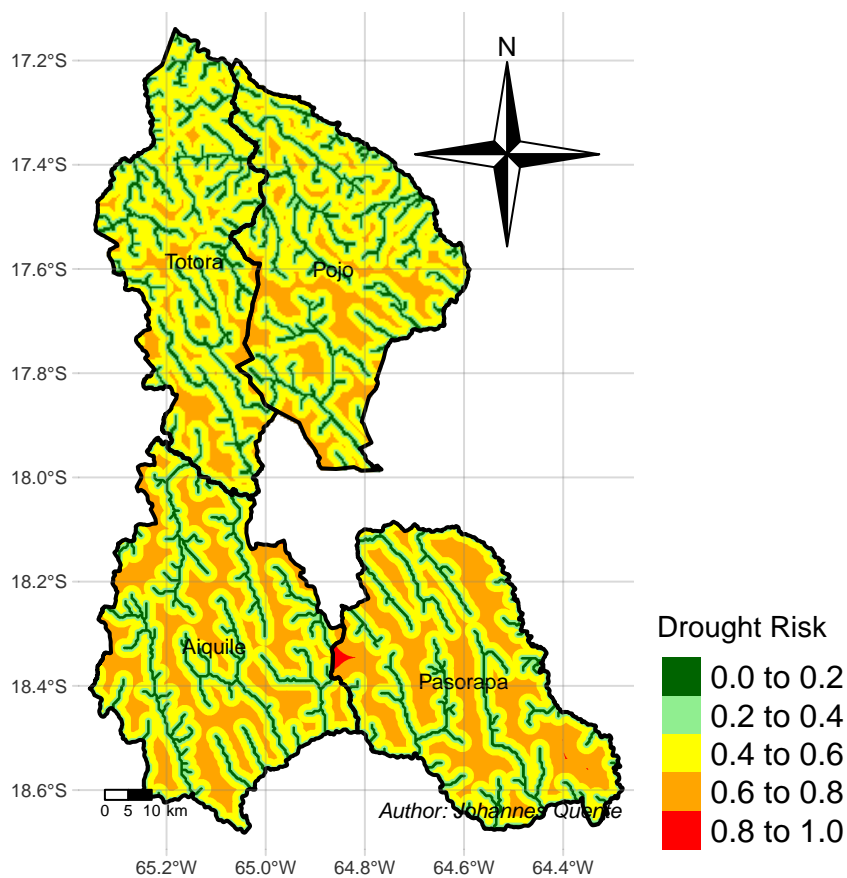

Figure 1.2: River reclassification

1.2.2 Maximum Temperature Data

The Temperature Data from worldclim.org which consists of a variety of global weather data on an 30 Arc Second Accuracy. This data has been used to calculate the highest temperatures over all the available 12 Raster-Layers of the different months. The Result is one Raster-Layer that contains the highest temperatures of the average year from 1970-2000. The reclassification has been calculated according to Table 1.2.

The provided code implements automation to improve the processing of multiple Rasterlayers, consolidating them into a single Rasterlayer containing the minimum values across the dataset. This approach aims to enhance efficiency and simplify the workflow of raster data analysis. The Code used can be seen in the Appendix.
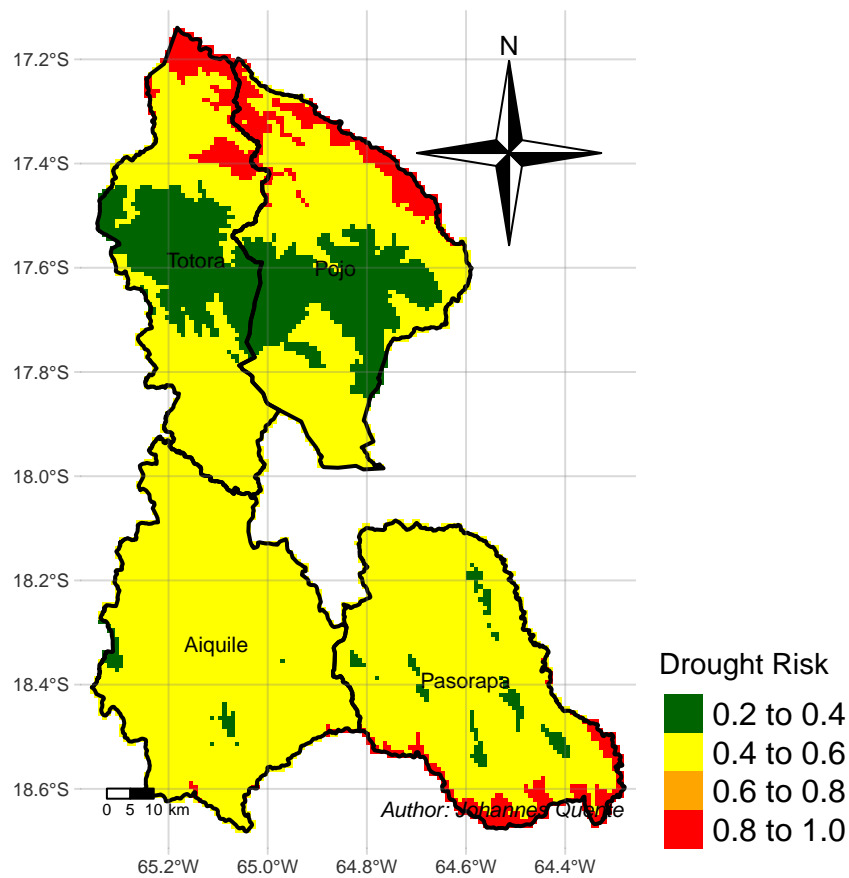

Figure 1.3: Maximum temperature reclassification

1.2.3 DEM (Inclination) Data

The provided Digital Elevation Model (DEM) consists of raster values showcasing variations in altitudes. These altitude values where converted into slope data using the `terra::terrain`-function from the Terra package. The reclassification has been calculated according to Table 1.2.

Subsequently, the slope data was categorized into varying degrees of possibility of drought in percent based on their inclination. For a detailed view of the reclassification code, please refer to the Appendix.
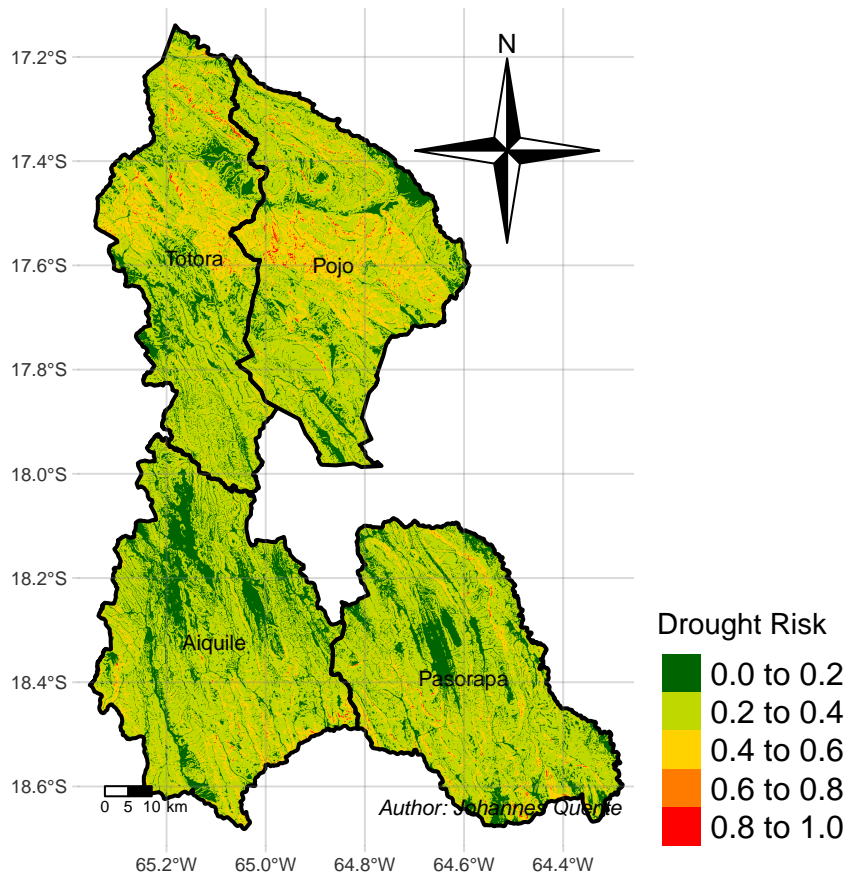

Figure 1.4: DEM derived Inclination reclassification

1.2.4 DEM (Perspective) Data

The provided Digital Elevation Model (DEM) consists of raster values showcasing variations in altitudes. These altitude values where converted into perspective data, therefore each pixel now showing the degree in which the groundstructure faces (0-360 degrees) using the `terra::terrain("aspect")` -function from the Terra package. The reclassification has been calculated according to Table 1.2.

Subsequently the slope data was categorized into varying degrees of possibility of drought (in %) based on their positioning due to facing the sun during the day. For further review of the reclassification code, please refer to the Appendix.
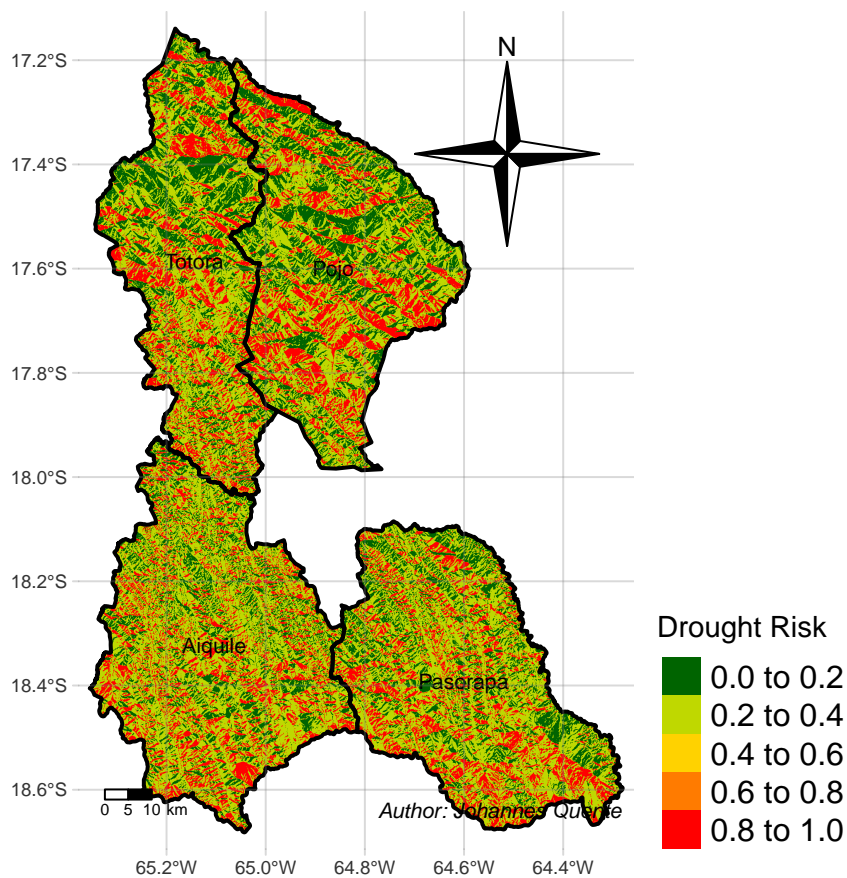

Figure 1.5: DEM derived Perspective reclassification

1.2.5 Precipitation Data

The following Data provided by Fick and Hijmans (2017) resembles Precipitation Data on a 30 Arc Second Accuracy. The format provides one Raster-Layer for each month.

Twelve raster layers have been aggregated to generate a unified raster layer, facilitating subsequent classification. The outcome is a comprehensive raster layer encompassing the total precipitation for the average year spanning from 1970 to 2000. The utilized code is available in the Appendix In the reclassification process, values were partitioned into five equally distributed groups based on frequency, with each group representing 20% of the total data frequency. The distribution and grouping methodology are illustrated in Figure 1.6. The reclassification has been calculated according to Table 1.2.
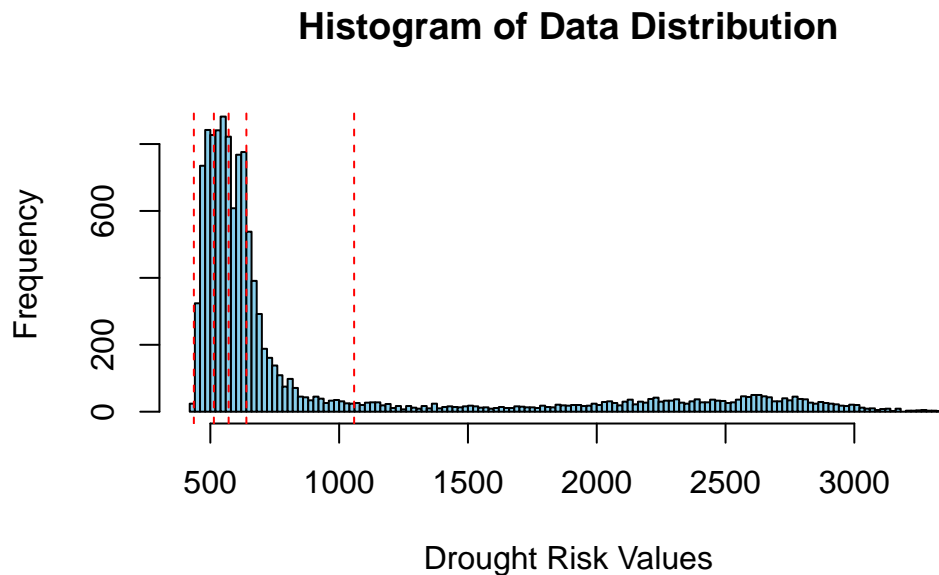
Histogram of Data Distribution

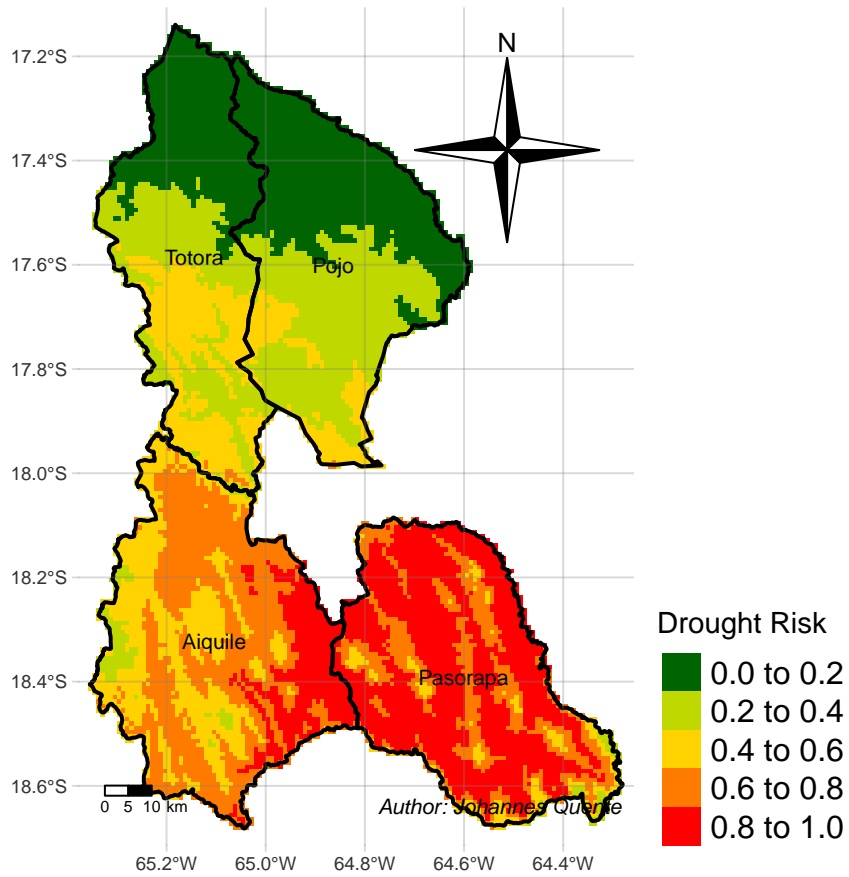Figure 1.6: Distribution of the Precipitation Data

Figure 1.7: Reclassification Result of the Precipitation Data

1.3 Results Drought Risk Modeling

In this chapter the Results of the Drought Risk Modeling are being presented: Figure 1.8 provides a visual representation of the data distribution, offering transparent insight into the significance of the reclassification values.

Further Figure 1.9 showcases the Drought Risk Map results for the four municipalities, aiding in understanding the spatial distribution of drought risk. In Figure 1.10 displays the data values across the four municipalities using Histograms, categorized into five equally distributed classes: "Very Low", "Low", "Moderate", "High", and "Very High".

A ratio scale-based risk mapping has been used to evenly distribute the data produced during the analysis. The Figure 1.11 presents the results with data values equally distributed across the four municipalities, providing a comprehensive overview of drought risk levels.

(a) Distribution of Pojo

(b) Distribution of Pasorapa

(c) Distribution of Aiquile

(d) Distribution of Totora
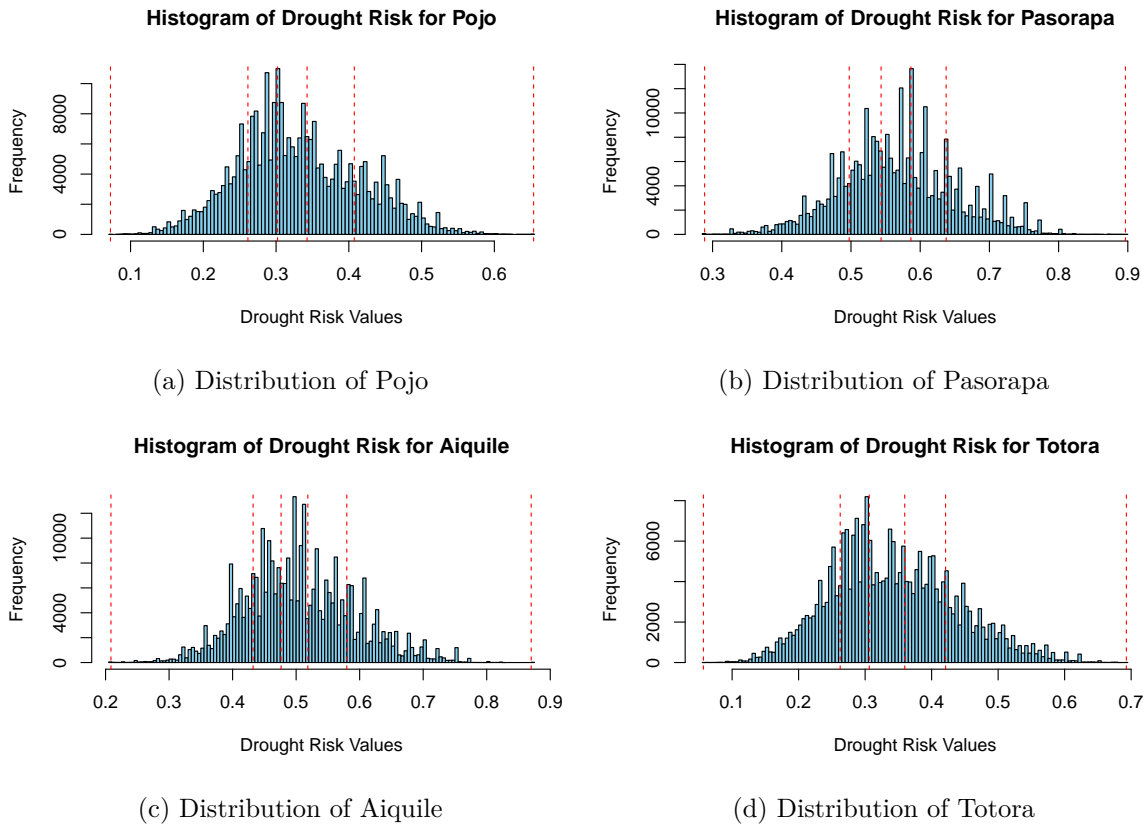
Figure 1.8: Data Distribution of the four Municipalities
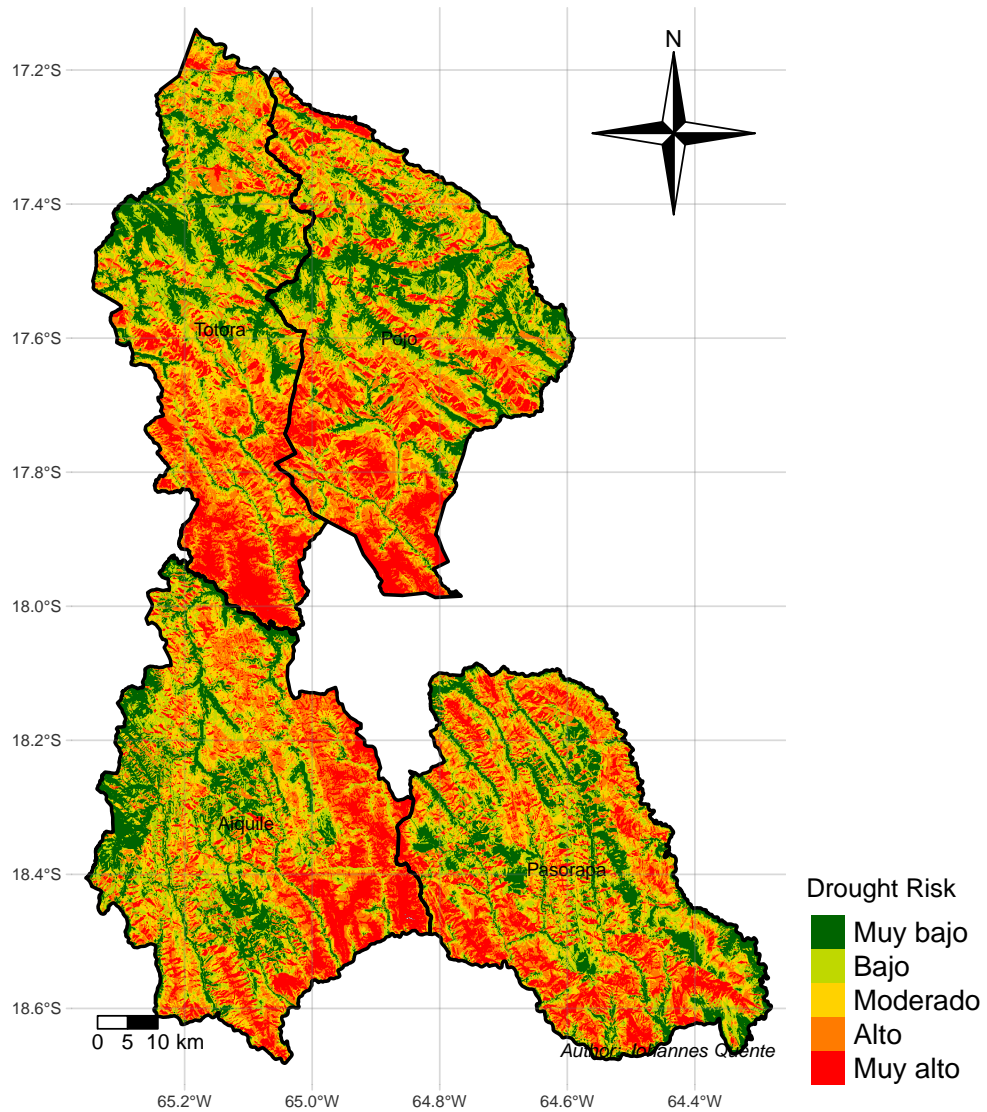
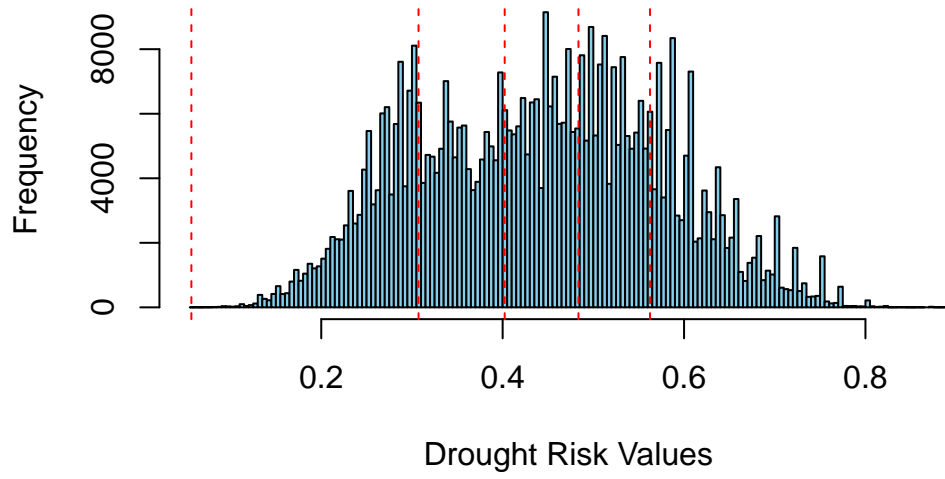Figure 1.9: Result Drought Risk for each Municipality

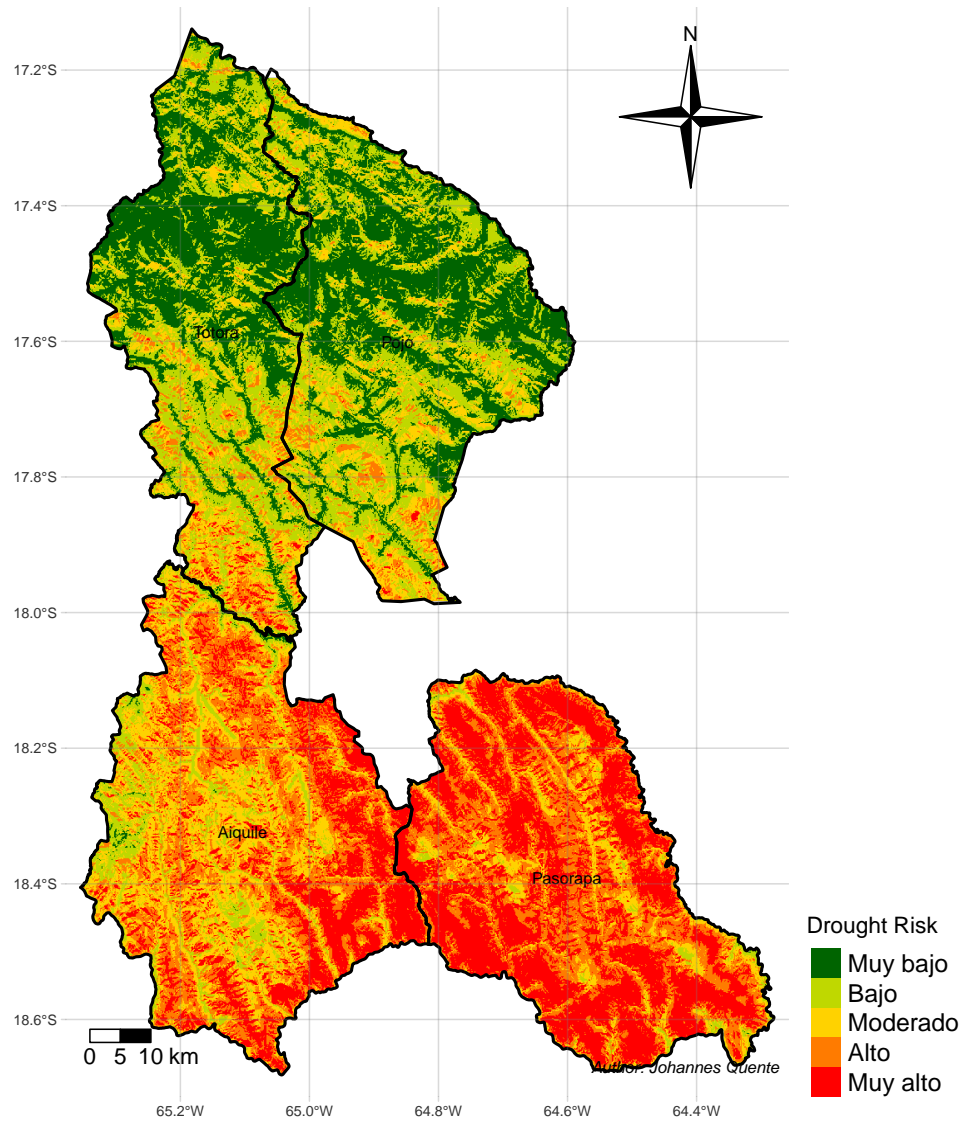Figure 1.10: Distribution of the final Data

Figure 1.11: Result Drought Risk for 4 Municipalities

1.4 Discussion

This study aims to evaluate the risk of drought, flood, and frost and identify potential risk zones in the Valle Alto region of Cochabamba, including Aiquile, Pasorapa, Pojo, and Totoro.

The objective of this study is to provide evidence-based information to enhance the resilience of communities and ecosystems to hazards related to drought, flood, and frost. A ratio scale-based risk mapping has been identified as the most effective method to evenly distribute the data produced during the analysis.

To improve the precision of our models, it is crucial to evaluate this readjustment based on empirical insights and observations from the studied environments. By fine-tuning these weights, we can align our models more closely with the intricate realities of these ecosystems, potentially revealing details that may have been missed in previous analyses.

In proposing these customized weighting and reclassification parameters, my aim is to assist the scientific discourse by introducing a more precise perspective. This method offers a clearer view through which various dynamics of our natural environments can be examined, comprehended, and conveyed.

While temperature is a standard indicator, its impact varies across different plant species, suggesting the need for a more comprehensive consideration of frost impacts beyond freezing temperatures (Condori et al. 2014).

In the future, by leveraging satellite imagery and tapping into local knowledge through field visits and workshops with stakeholders, there is potential to enhance the mapping of historically flood-prone areas significantly. This would involve evaluating the intensity of floods and delineating these zones to gain deeper insights into the frequency and impact of flooding. Such a comprehensive approach is crucial for effectively addressing the multifaceted challenges posed by these natural phenomena (Tanim et al. 2022).

1.5 Conclusion

The objective of this study was to identify areas in the four Municipalities of the Cono Sur area of the State of Cochabamba that are susceptible to droughts, floods, and frosts.

To achieve this, various geospatial datasets were explored, including terrain attributes, geological features, and precipitation records. Each dataset was analyzed using predetermined weights to emphasize their relative importance in the study. During the Multicriteria Analysis, we integrated numerous Raster and Vector Layers using weighted factors.

By utilizing the R-Studio Environment and key packages crucial for these calculations the resultant raster (Figure 1.9 and Figure 1.11) provides a comprehensive representation of the region's environmental aspects.

The methodology aims to identify areas that are at risk of severe impact from certain meteorological conditions. It supports local policymaking by utilizing an adaptable approach.

The risk potential is classified into five categories: 'Very low', 'Low', 'Moderate', 'High', and 'Very High', as shown on the map. To ensure a balanced visualization of the five risk categories, the resulting data has been equally partitioned into five equally distributed groups.
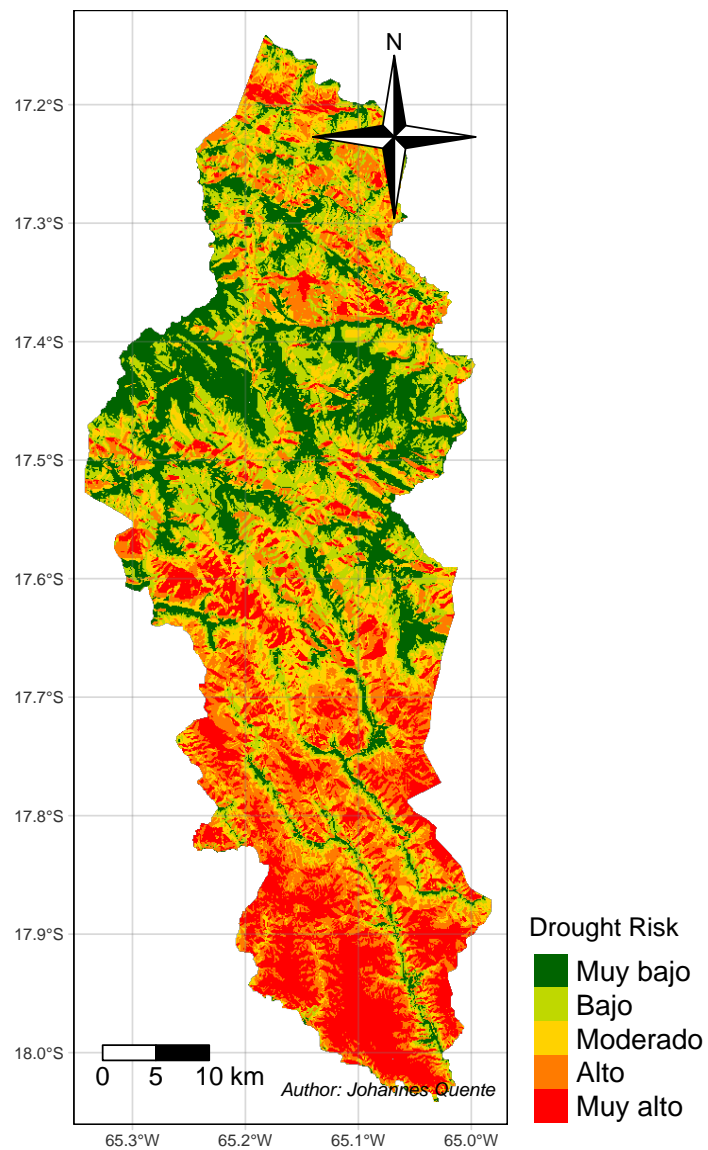
1.6 Appendix Maps

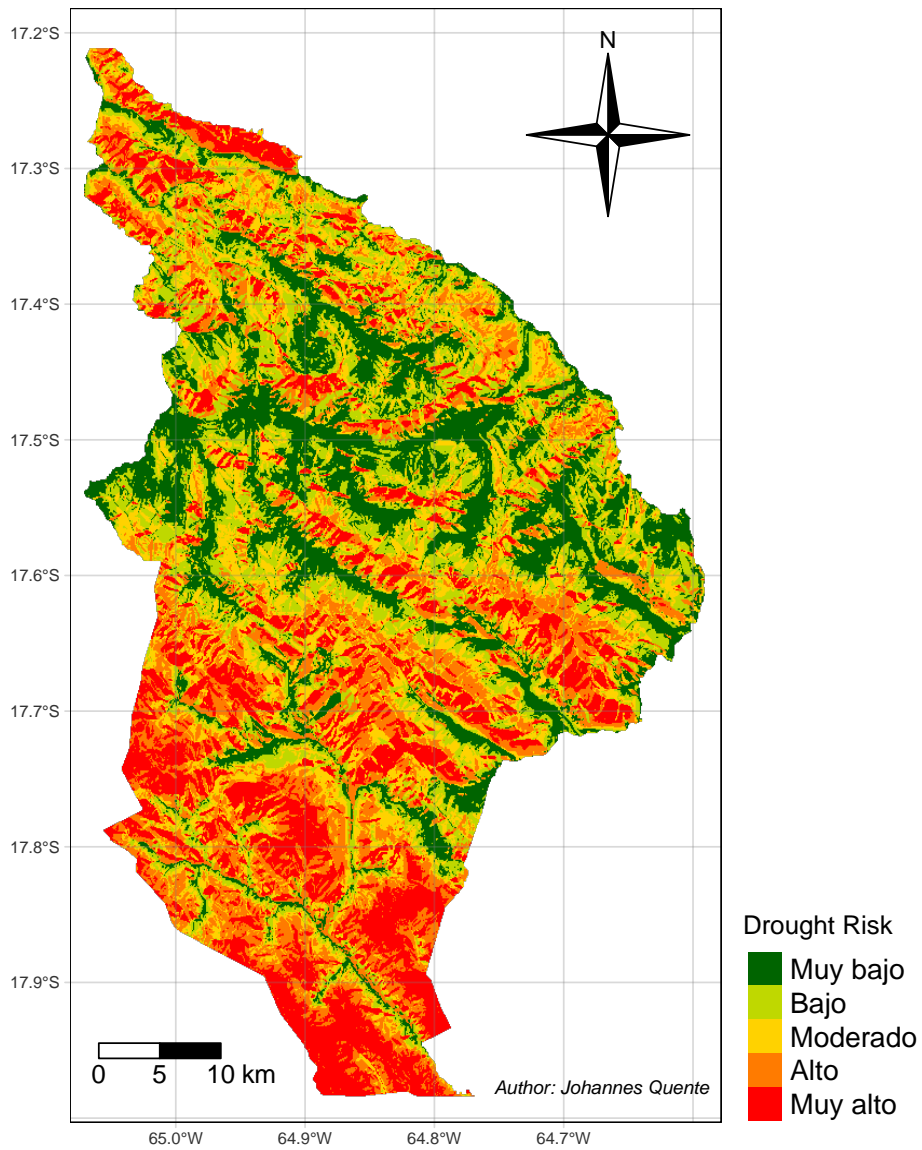Figure 1.12: Reclassified and Weighted Result in Totora

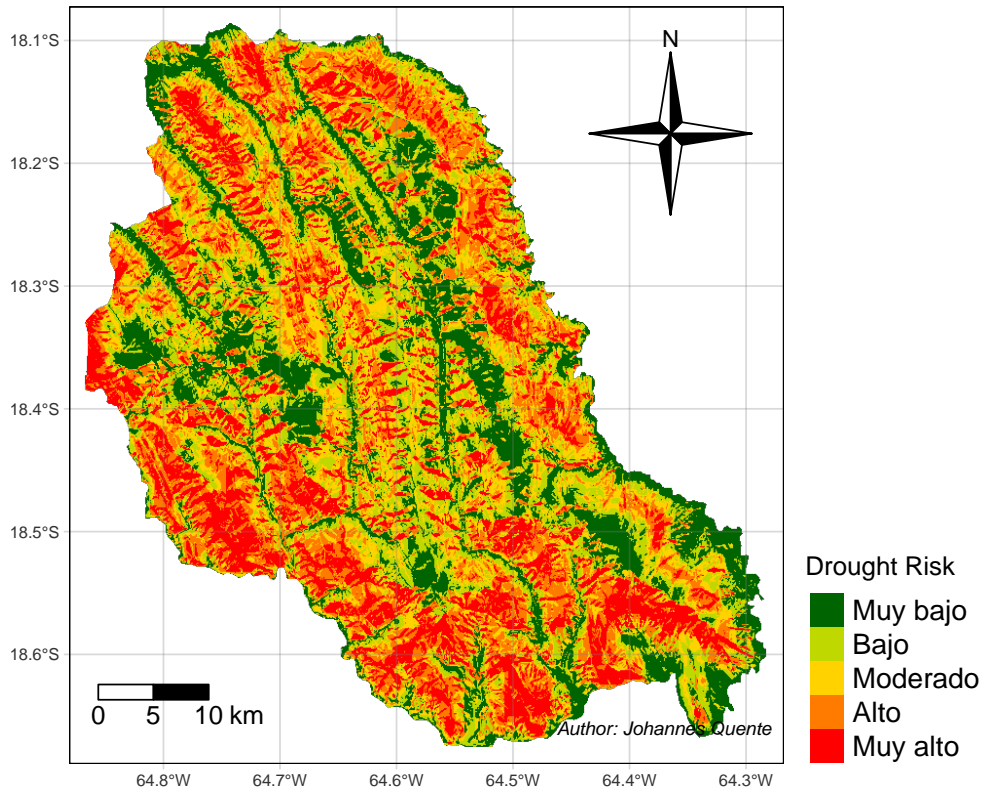Figure 1.13: Reclassified and Weighted Result in Pojo

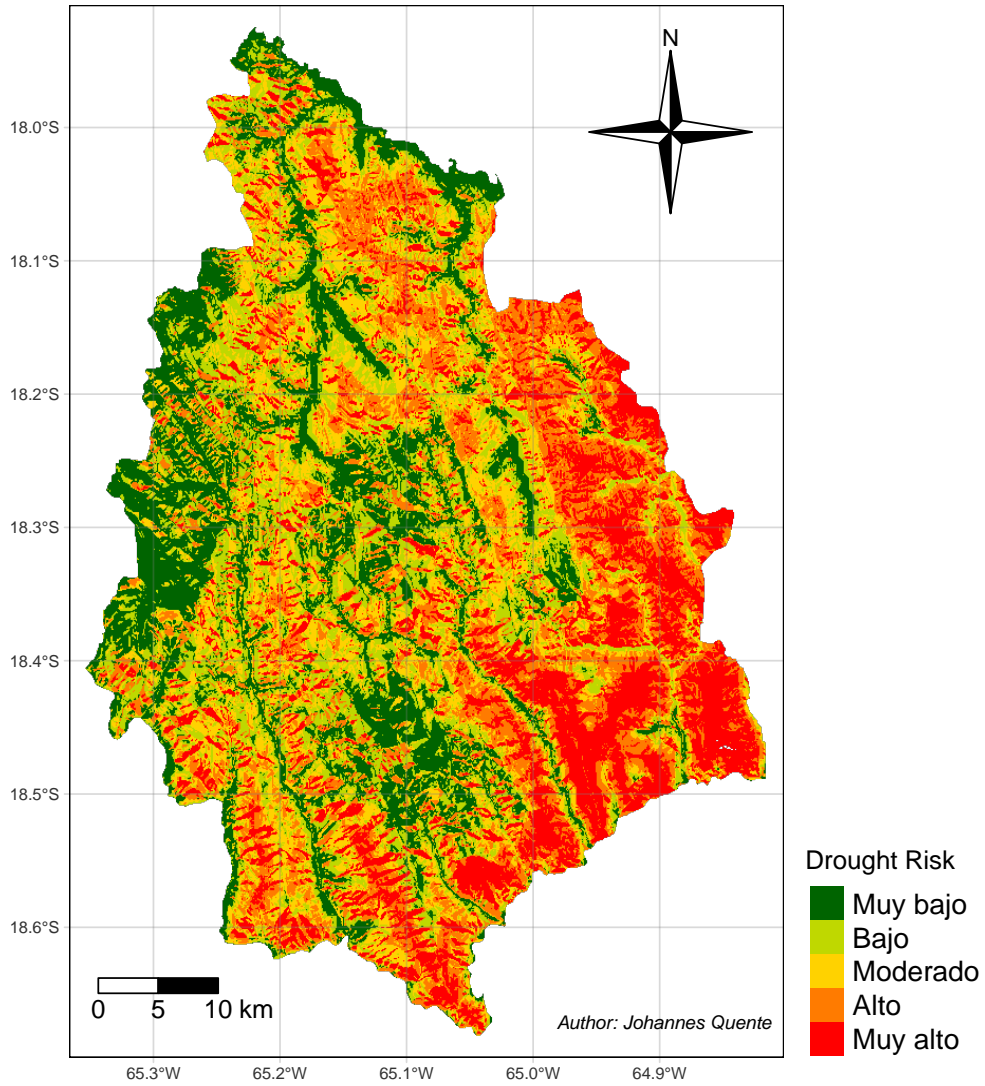Figure 1.14: Reclassified and Weighted Result in Pasorapa

Figure 1.15: Reclassified and Weighted Result in Aiquile

2 Frost Risk

2.1 Frame of Reference

Frost poses a perennial threat to agricultural activities, often resulting in crop damage and substantial economic losses, particularly exacerbated by the lack of comprehensive information on frost occurrences Kotikot and Onywere (2014). This study focuses on mapping potential frost hotspots within Cochabamba's Valle Alto region, encompassing Aiquile, Pasorapa, Pojo, and Totoro.

Assessing frost risk is crucial for agricultural hazard mapping and evaluating crop productivity in the Kenyan highlands. The adverse impacts of frost can be mitigated through systematic assessment of its occurrence probability, providing valuable insights to farmers and agricultural decision-makers.

From an agricultural climatology perspective, frost occurrences are not solely determined by specific temperature thresholds; rather, certain plants are susceptible to damage even at temperatures above freezing point. For instance, tropical crops like coffee and cocoa can be adversely affected by temperatures above zero degrees Celsius.

In the Andean Region of Cochabamba, local stakeholders have identified frost as a persistent threat to crops and livestock, particularly prevalent during the winter season (June - September).

Consequently, the creation of frost risk maps becomes imperative to aid decision-makers in territorial planning and disaster risk mitigation strategies. These maps were developed using a general risk equation approach, integrating factors such as threat and vulnerability through multicriteria evaluation techniques.

Following the risk equation approach, understanding the risk level in different zones requires identifying threats and vulnerabilities. Thus, the initial phase involved crafting maps related to threats and vulnerabilities. These maps identified zones susceptible to frost events at various intensity levels, derived from public available data surces (see Table 2.1).

2.2 Methodology of the Case Study

This Multicriteria Analysis employs numerous Raster and Vector Layers, integrating weighted factors. The entire project is conducted within the R-Studio Environment. Key packages utilized in achieving the final results are listed here R-Studio Libraries, delivering essential functions for the conducted calculations.

Table 2.1 shows the data used in order to conduct the multicriteria analysis on the four municipalities in the Cono Sur Region in Cochabamba, Bolivia.

Table 2.2 presents the classification and evaluation of various criteria for drought exposure, illustrating the factors influencing each classification. This table outlines the criteria and their corresponding classifications as follows.

The subsequent sections present the reclassified data for four municipalities in the state of Cochabamba. These sections detail the process of cleaning and further processing the raw data, with relevant code snippets linked to the Appendix for reference.

Table 2.1: Used Data in the Analysis

Data	Types	Source	Period/Year
Political Map	Vector	gadm.org	2024
Min. Temperature	Raster (30 s)	Fick and Hijmans (2017)	1970-2000
DEM (Perspective)	Raster (15 s)	Hydrosheds.org	2013

Table 2.2: Classification and evaluation of drought exposure according to factors

Criteria	Very.High	High	Moderate	Low	Very.Low	Weights
Minimum Temperature	<5	5-7	7-10		>10	7.5
DEM (Perspective)	<45°	45-135°	135-225°	225-315°	>315°	2.5

2.2.1 Minimum Temperature

The temperature dataset, provided by Fick and Hijmans (2017) encompasses a comprehensive collection of global weather data with a spatial resolution of 30 arc seconds. This dataset serves as the basis for computing the minimum temperatures across 12 raster layers corresponding to different months. The resultant output is a single raster layer representing the lowest temperatures averaged over the period from 1970 to 2000. Reclassification was performed according to a predefined scheme outlined in Table 2.2.

The following code exemplifies the automation of processing procedures across four municipalities. Refer to the Appendix for the specific code implementation: Appendix.

Figure 2.1 illustrates the distribution of minimum temperature data through a histogram. This visualization supports the rationale behind reclassification into five equally distributed groups, each representing 20% of the total data frequency.

Histogram of Data Distribution
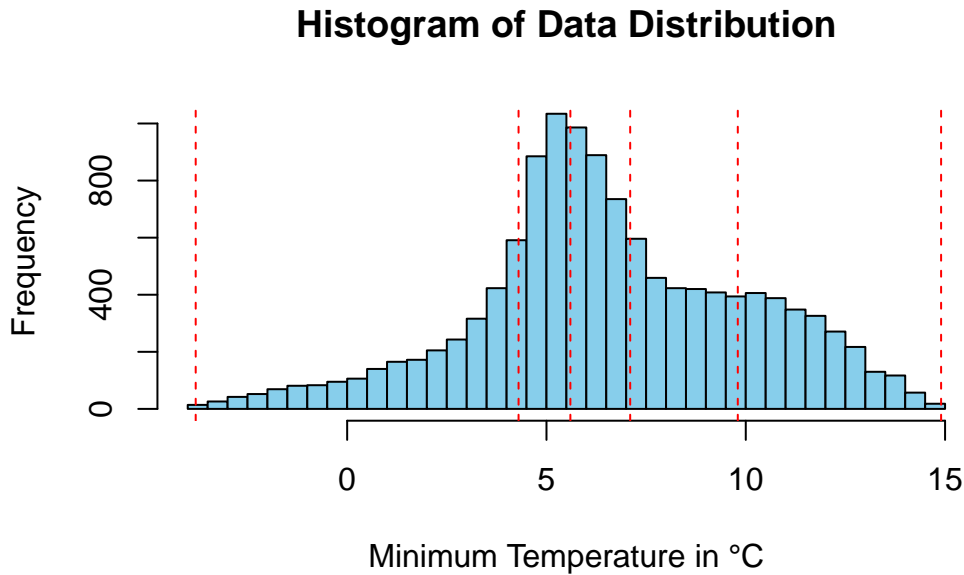
Figure 2.1: Distribution of the Minimum Temperature Data
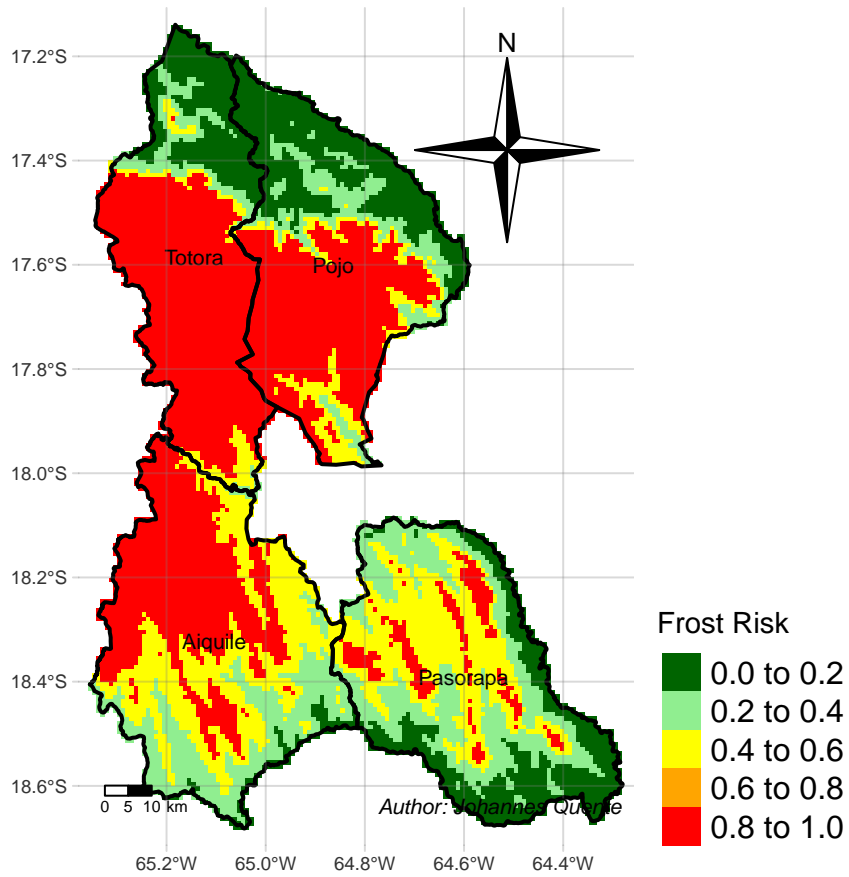
Figure 2.2: Reclassified Minimum Temperature

2.2.2 DEM (Perspective)

The provided Digital Elevation Model (DEM) consists of raster values showcasing variations in altitudes. These altitude values where converted into perspective data, therefore each pixel now showing the degree in which the groundstructure faces (0-360 degrees) using the `terra::terrain("aspect")` -function from the Terra package. The reclassification has been calculated according to Table 2.2.

Subsequently the slope data was categorized into varying degrees of possibility of drought (in %) based on their positioning due to facing the sun during the day. For further review of the reclassification code, please refer to the Appendix.

Figure 2.3: DEM derived Perspective reclassification

2.3 Results Frost Risk

(a) Distribution of Pojo

(b) Distribution of Pasorapa

(c) Distribution of Aiquile

(d) Distribution of Totora

Figure 2.4: Data Distribution of the four Municipalities

Figure 2.5: Result: Frost Risk for each Municipality

3 Flood Risk

3.1 Frame of Reference

This research presents a low-cost and flexible methodology for mapping flood hazard and assessing resulting risk. The methodology is generic and can be customized for freely available data with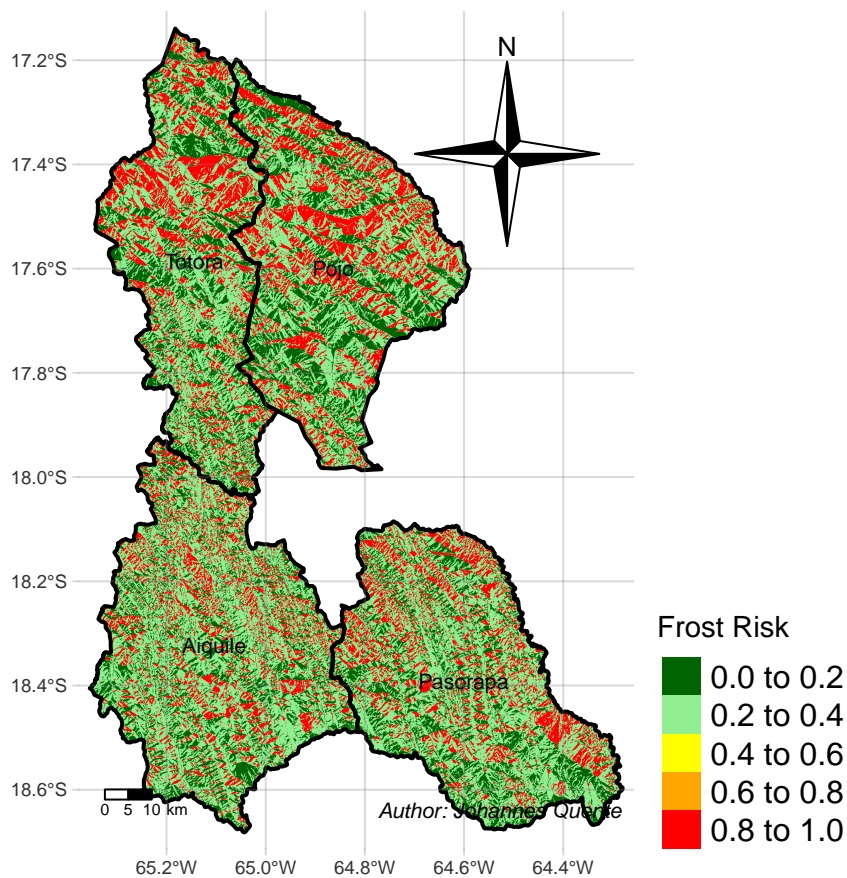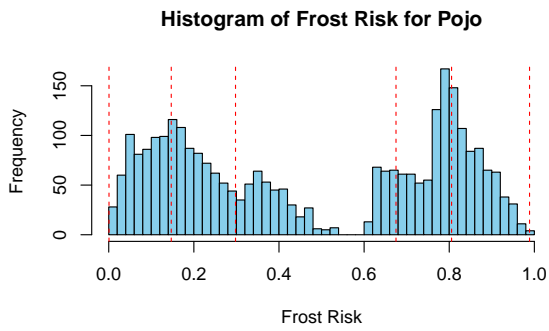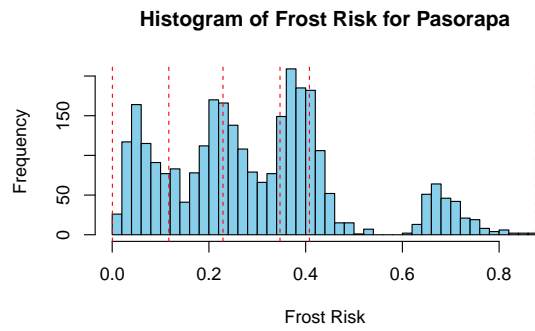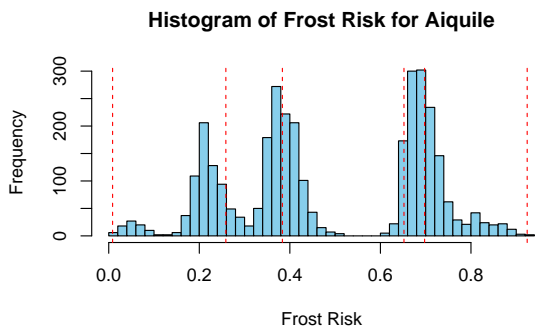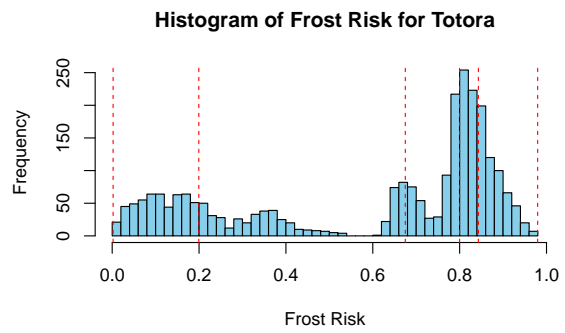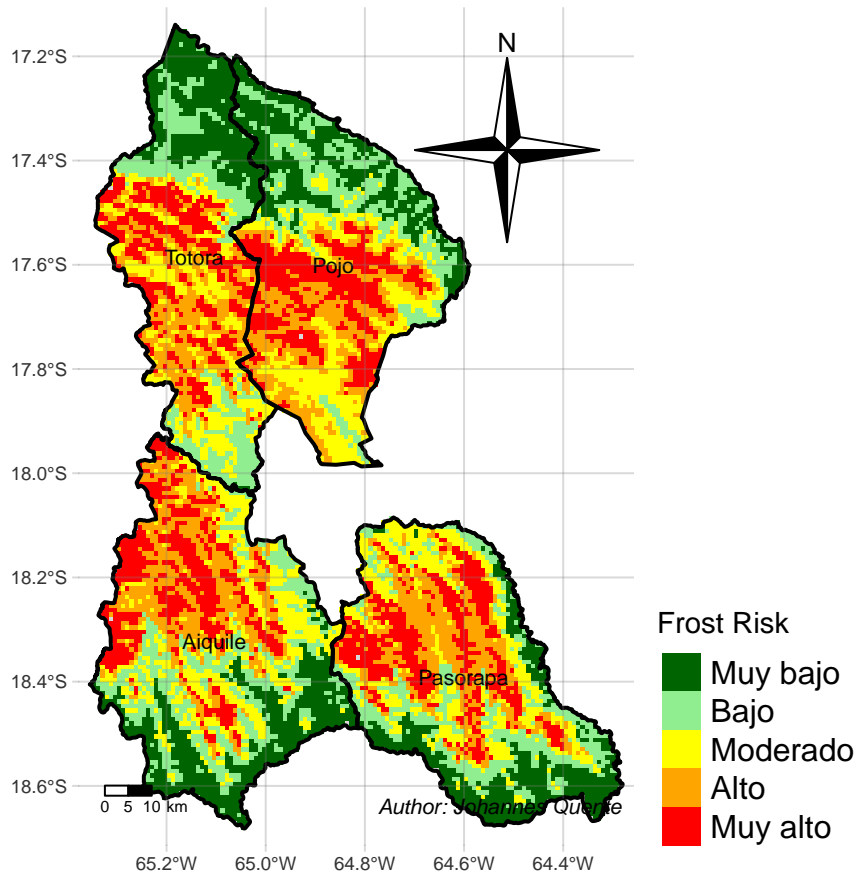 global coverage, allowing for worldwide risk assessment. Region-specific information can be added to the default workflow when available.

Floods are a significant global hazard, posing threats to both human societies and natural ecosystems. The increase in flood occurrences is caused by the interaction between climate variations and changes in land-use patterns. These dynamics put significant stress on river systems, leading to significant changes in river morphology (Hagos et al. 2022).

This study aims to evaluate flood risk and identify inundation zones in the Valle Alto region of Cochabamba, including Aiquile, Pasorapa, Pojo, and Totoro. The genesis of floods is influenced by various factors such as soil properties, terrain slope, elevation, drainage density, and land cover characteristics. In Bolivia, some of these factors were included in the analysis framework due to limited data availability.

The analytic hierarchy process was used to determine the relative weights assigned to each contributing factor, incorporating insights from public institutions and expert consensus. The acquired data was processed in the R-Studio environment to construct a comprehensive flood hazard map.

The aim of this study is to inform evidence-based decision-making processes, ultimately enhancing the resilience of communities and ecosystems to flood-related hazards.

3.2 Methodology of the Case Study

In order to conduct this Multicriteria Analysis, a comparable approach to Hagos et al. (2022) has been undertaken. The analysis employs numerous raster and vector layers, integrating weighted factors. The entire project is conducted within the R-Studio environment. Key packages utilized in achieving the final results are listed in R-Studio Libraries, providing essential functions for the conducted calculations. The following data has been used.

Table 3.1 shows the data used in order to conduct the Multicriteria Analysis on the four municipalities in the Cono Sur Region in Cochabamba, Bolivia.

Table 3.2 presents the classification and evaluation of various criteria for drought exposure, illustrating the factors influencing each classification. This table outlines the criteria and their corresponding classifications as follows.

The subsequent sections present the reclassified data for four municipalities in the state of Cochabamba. These sections detail the process of cleaning and further processing the raw data, with relevant code snippets linked to the Appendix for reference.

Table 3.1: Used Data in the Analysis

Data	Types	Source	Period/Year
Political Map	Vector	gadm.org	2024
River Data	Vector	Linke et al. (2019)	2013
Precipitation	Raster (30 s)	Fick and Hijmans (2017)	1970-2000
DEM (Inclination)	Raster (15 s)	Hydrosheds.org	2013

Table 3.2: Classification and evaluation of drought exposure according to factors

Criteria	Very.High	High	Moderate	Low	Very.Low	Weights
River Data	<200	200-700	700-2000	2000-5000	>5000	2.5
Precipitation	>1058	640-1058	571-640	514-571	<513.8	4.0
DEM (Inclination)	<10	10-20	20-30	30-45	>45	3.5

3.2.1 River Data

The data utilized aimed to estimate the distance to rivers, serving as a proxy for assessing the likelihood of drought occurrences. The underlying assumption was that greater distances from rivers correspond to increased drought probabilities. To calculate distances, the `terra::distance` function was employed on the river shapefiles associated with various municipalities. Detailed processing steps are outlined in the subsequent chapter of the Appendix.

The reclassification has been calculated according to Table 3.2. Defining the classification values Gao et al. (2023) has been using different values in order to classify and evaluate drought exposure, hazard factors, vulnerability, and mitigation capacity.
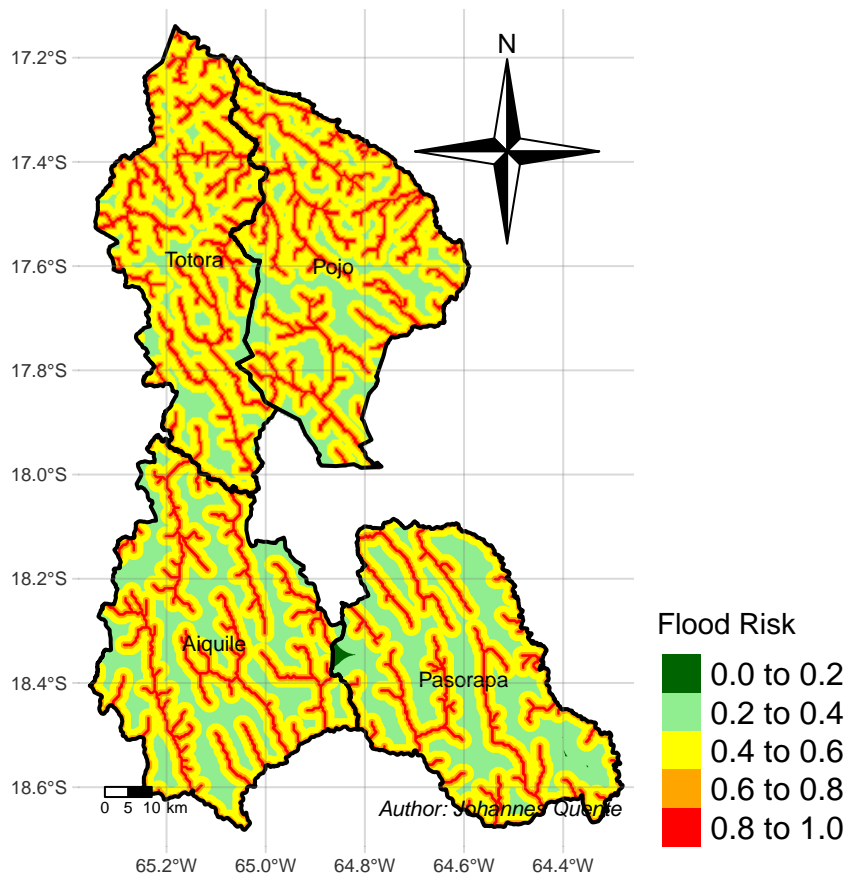
Figure 3.1: Reclassification River Distance

3.2.2 Precipitation Data

The following Data provided by Fick and Hijmans (2017) resembles Precipitation Data on a 30 Arc Second Accuracy. The format provides one Raster-Layer for each month.

Twelve raster layers have been aggregated to generate a unified raster layer, facilitating subsequent classification. The outcome is a comprehensive raster layer encompassing the total precipitation for the average year spanning from 1970 to 2000. The utilized code is available in the Appendix In the reclassification process, values were partitioned into five equally distributed groups based on frequency, with each group representing 20% of the total data frequency. The distribution and grouping methodology are illustrated in Figure 3.2. The reclassification has been calculated according to Table 3.2.

Histogram of Data Distribution
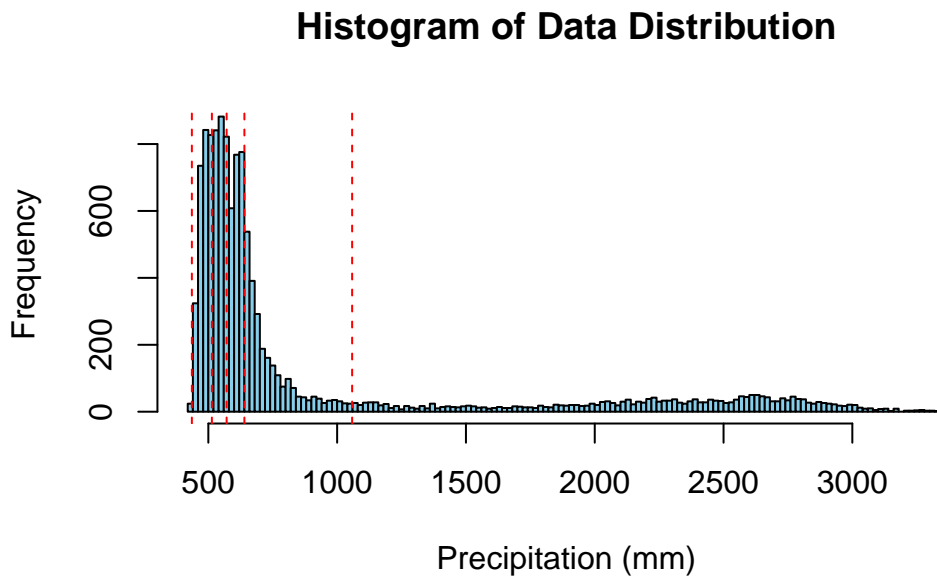
Figure 3.2: Distribution of the Precipitation Data
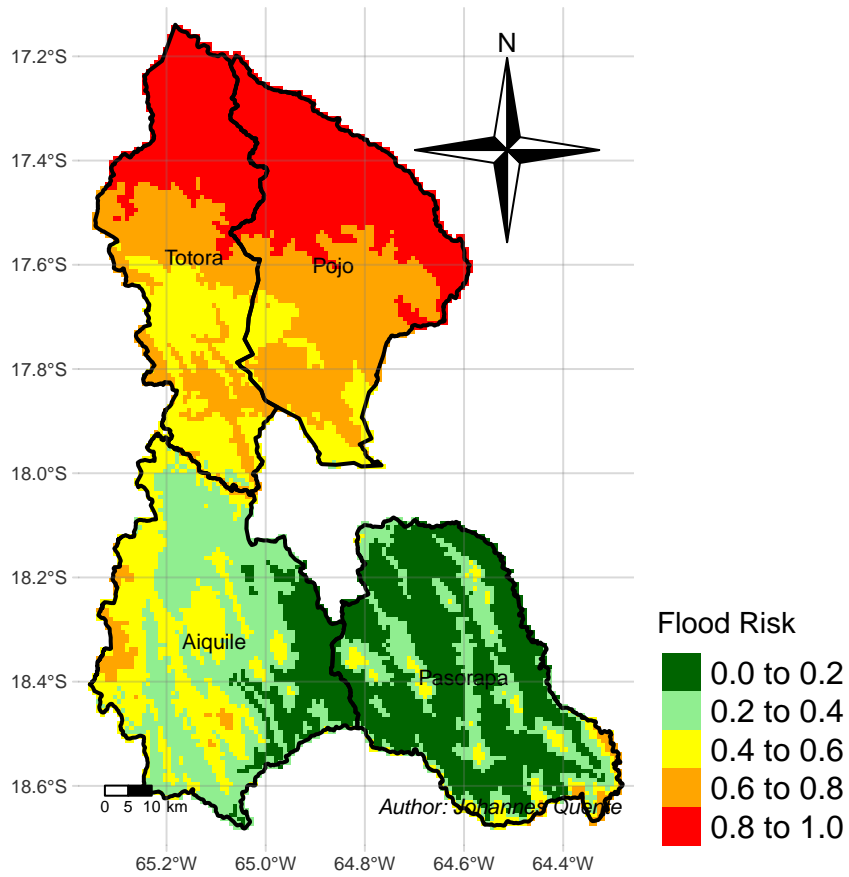
Figure 3.3: Reclassification Result of the Precipitation Data

3.2.3 DEM (Inclination) Data

The provided Digital Elevation Model (DEM) consists of raster values showcasing variations in altitudes. These altitude values where converted into slope data using the `terra::terrain`-function from the Terra package. The reclassification has been calculated according to Table 3.2.

Subsequently, the slope data was categorized into varying degrees of possibility of Flood in percent based on their inclination. For a detailed view of the reclassification code, please refer to the Appendix.
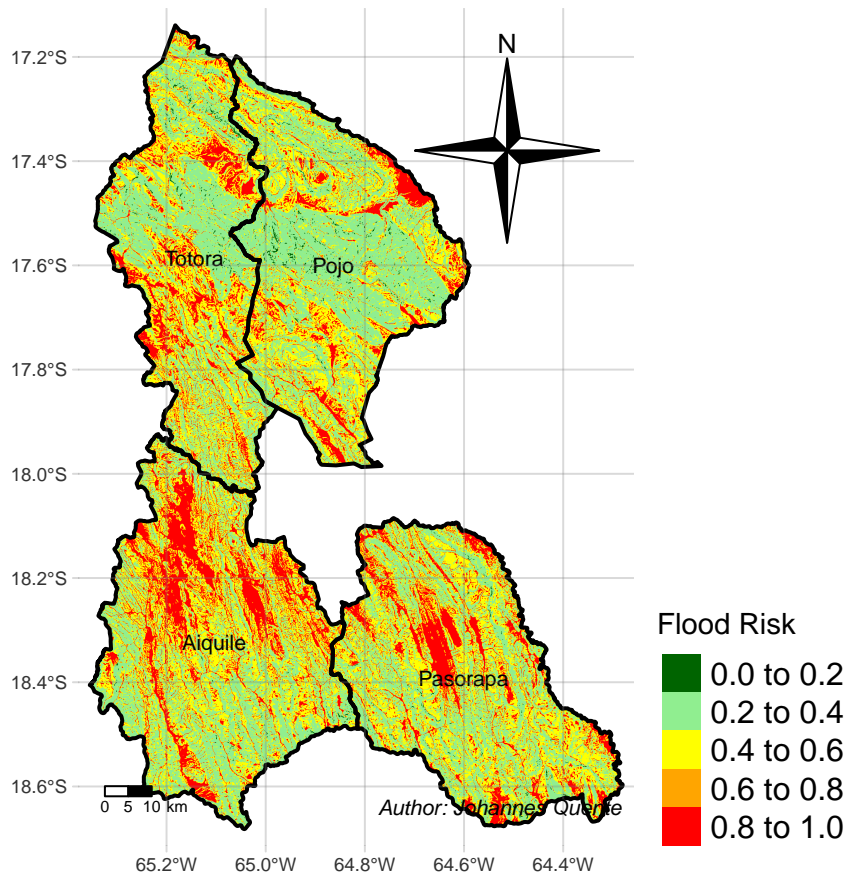
Figure 3.4: Reclassification of DEM derived Inclination

3.3 Results Flood Risk
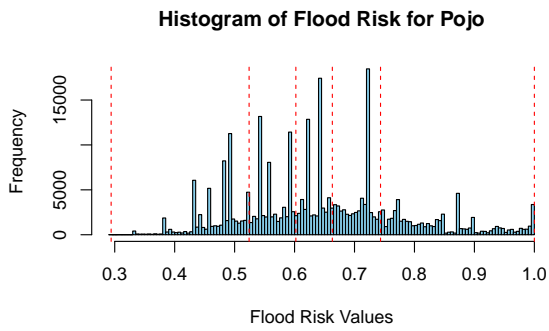
Histogram of Flood Risk for Pojo

(a) Distribution of Pojo

Histogram of Flood Risk for Pasorapa

(b) Distribution of Pasorapa

Histogram of Flood Risk for Aiquile

(c) Distribution of Aiquile

Histogram of Flood Risk for Totora
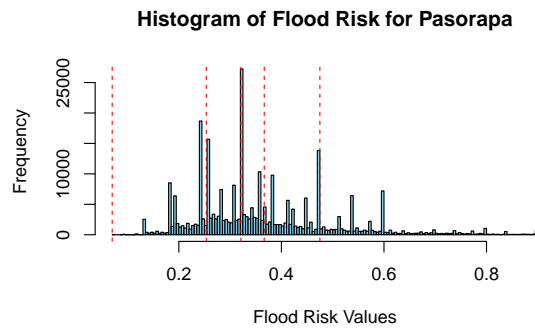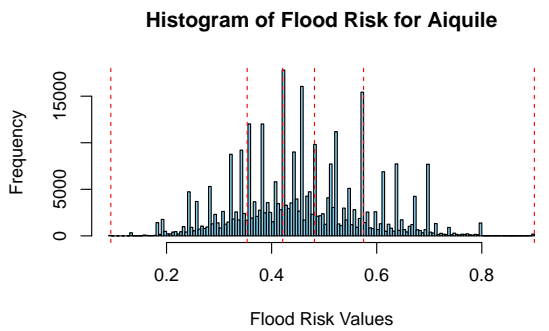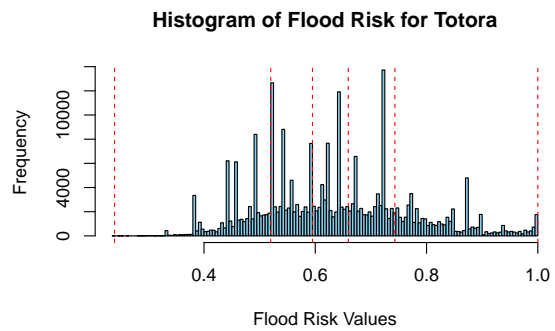
(d) Distribution of Totora

Figure 3.5: Data Distribution of the four Municipalities
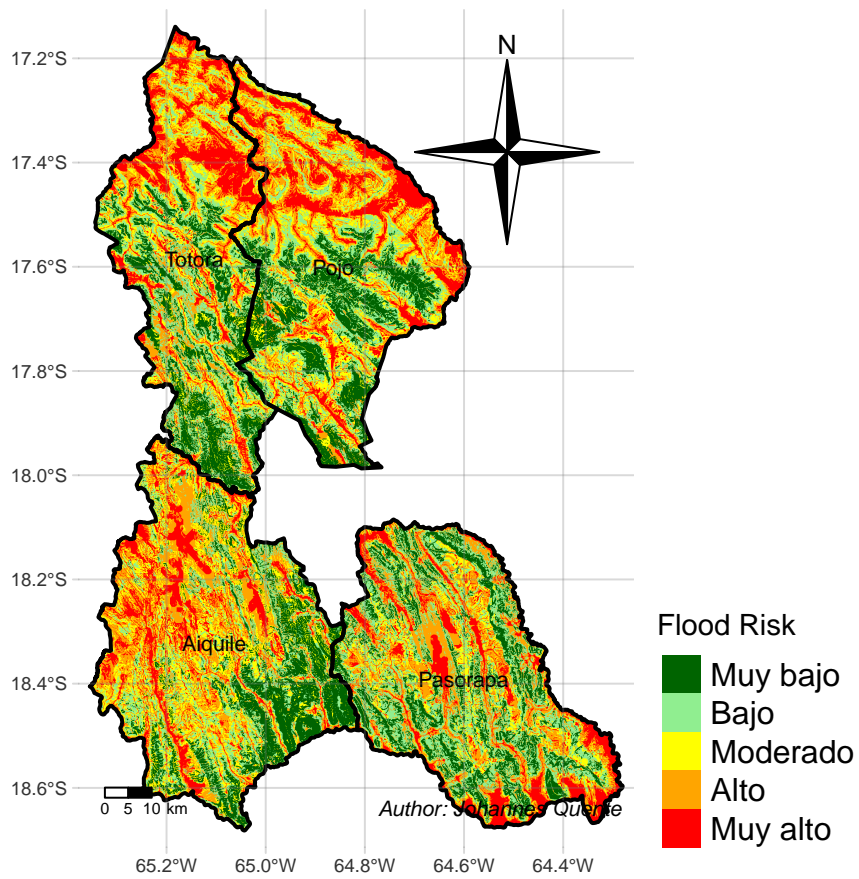
Figure 3.6: Result Flood Risk for each Municipality

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Appendix

R-Studio Libraries

```r
# libraries used
library(raster)
library(terra)
library(ggplot2)
library(tmap)
library(sf)
library(dplyr)
library(tibble)
library(knitr)
library(stringr)
```

Reading Data

```r
bol    <- read_sf("gadm41_BOL_3.shp", crs = 4326) # Pasorapa extent

# river data
river <- read_sf("HydroRIVERS_v10_sa.shp")

## raster
dem    <- rast("s20w070_dem.tif")
```

Data Processing

```r
# select municipalities

cocha <- bol %>% filter(NAME_1 == "Cochabamba")
```

```r
# filter der bol shapes Aiquile
Pasorapa <- cocha %>% filter(NAME_3 == "Pasorapa")
Aiquile  <- cocha %>% filter(NAME_3 == "Aiquile")

# new
totora   <- cocha %>% filter(NAME_3 == "Totora")
pojo     <- cocha %>% filter(NAME_3 == "Pojo")

# read bol_1.shp and Cochabamba.shp
bol_1       <- read_sf("bol_1.shp")
Cochabamba <- read_sf("Cochabamba.shp")
```

Processing River Data

```r
# River Data Calculation with example on Pasorapa
##  200 meters Buffer River data
buffer_river <- sf::st_buffer(Pasorapa, 200)

##  200 meters Buffer River data
buffer_river <- sf::st_buffer(Pasorapa, 200)

river_crop <- read_sf("river_crop.shp")

buffer_river <- st_buffer(river_crop, 100)

# Create an empty raster to rasterize into
empty_raster <- raster(extent(buffer_river), resolution = c(0.0008333333, 0.0008333333))

  # Rasterize
river_raster <- terra::rasterize(buffer_river, empty_raster, field = "CATCH_SKM")

  # calc into %
river_raster <- (river_raster / 100)

# River
##  crop and mask dem
river_crop <- terra::crop(river_raster, Pasorapa)
river_mask <- mask(river_crop, Pasorapa)
```

```r
# Define areas of interest
areas <- list(
  pasorapa = Pasorapa,
  aiquile = Aiquile,
  totora = totora,
  pojo = pojo
)

# Define river distance raster files
river_rasters <- list(
  pasorapa = "dist_to_river_pasorapa.tif",
  aiquile  = "dist_to_river_aiquile.tif",
  totora   = "dist_to_river_totora.tif",
  pojo     = "dist_to_river_pojo.tif"
)

# reclass
# Create a tibble with the reclassification table
reclass_table_river <- tribble(
  ~from, ~to, ~becomes,
  5000,    Inf,  0,
  2000,    5000,  0.25,
  700,     2000,  0.5,
  200,     700,  0.75,
  -Inf,    200,  1
)

# Common CRS for all rasters
common_crs <- "+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0"

# Loop through areas of interest
for (area_name in names(areas)) {
  # Load river distance raster
  dist_to_river <- rast(river_rasters[[area_name]])

  # Assign common CRS
  crs(dist_to_river) <- common_crs
  st_crs(areas[[area_name]]) <- common_crs

  # Crop and mask river distance raster
  river_crop <- crop(dist_to_river, areas[[area_name]])
```

```r
  river_mask <- mask(river_crop, areas[[area_name]])

  # Reclassify the river distance raster
  river_reclassified <- classify(river_mask, reclass_table_river,
                                 include.lowest = TRUE, right = TRUE)

  # Assign to appropriate variable
  assign(paste0("river_reclassified_", area_name), river_reclassified)
}
```

Processing Max. Temperature Data

```r
# read data

# temperatur max
tmax01 <- rast("wc2.1_30s_tmax_01.tif")
tmax02 <- rast("wc2.1_30s_tmax_02.tif")
tmax03 <- rast("wc2.1_30s_tmax_03.tif")
tmax04 <- rast("wc2.1_30s_tmax_04.tif")
tmax05 <- rast("wc2.1_30s_tmax_05.tif")
tmax06 <- rast("wc2.1_30s_tmax_06.tif")
tmax07 <- rast("wc2.1_30s_tmax_07.tif")
tmax08 <- rast("wc2.1_30s_tmax_08.tif")
tmax09 <- rast("wc2.1_30s_tmax_09.tif")
tmax10 <- rast("wc2.1_30s_tmax_10.tif")
tmax11 <- rast("wc2.1_30s_tmax_11.tif")
tmax12 <- rast("wc2.1_30s_tmax_12.tif")
```

```r
### Processing

# LOOP

# Crear una lista con los nombres de los objetos
lista_temp <- paste0("tmax", sprintf("%02d", 1:12))
# Generate names precip01 until precip12

# Inicializar una lista vacía para almacenar los resultados
lista_tmax_mask <- list()
```

```r
# Iterar sobre cada objeto y aplicar las operaciones
for (i in seq_along(lista_temp)) {
  # Acceder al objeto con el nombre correspondiente
  tmax_obj <- get(lista_temp[i])

  # Aplicar las operaciones crop y mask
  tmax_crop <- terra::crop(tmax_obj, Pasorapa)
  tmax_mask <- mask(tmax_crop, Pasorapa)

  # Almacenar el resultado en la lista
  lista_tmax_mask[[i]] <- tmax_mask
}

plot(lista_tmax_mask[[08]])

# Stack the Values and calc the min for everything

# Use rast() to convert the list to a SpatRaster object
stacked_rasters <- terra::rast(lista_tmax_mask)

# Apply the cellStats function to find the minimum value for each pixel across the stack
max_values <- terra::app(stacked_rasters, fun = max, na.rm = TRUE)


### Reclassification of the Temp max Data

max_temp_pasorapa <- readRDS("max_temp_pasorapa.rds")

# reclass
# Create a tibble with the reclassification table
reclass_table_max_temp <- tribble(
  ~from, ~to, ~becomes,
  -Inf, 25, 0.2,
  25, 27, 0.4,
  27, 30, 0.6,
  30, Inf, 1
)

# Reclassify the slope raster based on the reclassification table
max_temp_reclassified_pasorapa <- terra::classify(max_temp_pasorapa,
          reclass_table_max_temp, include.lowest = TRUE, right = TRUE)
```

```r
# read data aiquile
max_temp_aiquile <- readRDS("max_temp_aiquile.rds")

# Reclassify the slope raster based on the reclassification table
max_temp_reclassified_aiquile <- terra::classify(max_temp_aiquile,
        reclass_table_max_temp, include.lowest = TRUE, right = TRUE)

# Totora

max_temp_totora <- readRDS("max_temp_totora.rds")

# Reclassify the slope raster based on the reclassification table
max_temp_reclassified_totora <- terra::classify(max_temp_totora,
        reclass_table_max_temp, include.lowest = TRUE, right = TRUE)

# Pojo

max_temp_pojo <- readRDS("max_temp_pojo.rds")

# Reclassify the slope raster based on the reclassification table
max_temp_reclassified_pojo <- terra::classify(max_temp_pojo,
        reclass_table_max_temp, include.lowest = TRUE, right = TRUE)
```

Processing Min. Temperature Data

```r
# read data

# temperatur max
tmin01 <- rast("wc2.1_30s_tmin_01.tif")
tmin02 <- rast("wc2.1_30s_tmin_02.tif")
tmin03 <- rast("wc2.1_30s_tmin_03.tif")
tmin04 <- rast("wc2.1_30s_tmin_04.tif")
tmin05 <- rast("wc2.1_30s_tmin_05.tif")
tmin06 <- rast("wc2.1_30s_tmin_06.tif")
tmin07 <- rast("wc2.1_30s_tmin_07.tif")
tmin08 <- rast("wc2.1_30s_tmin_08.tif")
tmin09 <- rast("wc2.1_30s_tmin_09.tif")
tmin10 <- rast("wc2.1_30s_tmin_10.tif")
tmin11 <- rast("wc2.1_30s_tmin_11.tif")
```

```r
tmin12 <- rast("wc2.1_30s_tmin_12.tif")


# LOOP

# Crear una lista con los nombres de los objetos
lista_temp <- paste0("tmin", sprintf("%02d", 1:12))
# Generate names precip01 until precip12

# Inicializar una lista vacía para almacenar los resultados
lista_tmin_mask <- list()

# Iterar sobre cada objeto y aplicar las operaciones
for (i in seq_along(lista_temp)) {
  # Acceder al objeto con el nombre correspondiente
  tmin_obj <- get(lista_temp[i])

  # Aplicar las operaciones crop y mask
  tmin_crop <- terra::crop(tmin_obj, Aiquile)
  tmin_mask <- mask(tmin_crop, Aiquile)

  # Almacenar el resultado en la lista
  lista_tmin_mask[[i]] <- tmin_mask
}

# Stack the Values and calc the min for every values in the Rasterstack

# Use rast() to convert the list to a SpatRaster object
stacked_rasters <- terra::rast(lista_tmin_mask)

# Apply the cellStats function to find the minimum value for each pixel across the stack
min_values <- terra::app(stacked_rasters, fun = min, na.rm = TRUE)


min_temp_pasorapa <- readRDS("min_temp_pasorapa.rds")
min_temp_pojo     <- readRDS("min_temp_pojo.rds")
min_temp_aiquile  <- readRDS("min_temp_aiquile.rds")
min_temp_totora   <- readRDS("min_temp_totora.rds")

# Create a list of the SpatRaster objects
raster_list <- merge(min_temp_pasorapa, min_temp_pojo, min_temp_aiquile, min_temp_totora)
```

```r
# Specify the number of breaks (bins)
num_breaks <- 5

break_values <- quantile(values(raster_list, na.rm = TRUE),
            probs = seq(0, 1, length.out = num_breaks + 1))

# Extract numeric values
numeric_breaks <- as.numeric(as.character(break_values))

# Create the histogram with equal-frequency breaks
hist(values(raster_list), breaks = "FD", main = "Histogram of Data Distribution",
  xlab = "Drought Risk Values", col = "skyblue", border = "black", plot = TRUE)

# Add vertical lines to represent the breaks
abline(v = quantile(values(raster_list, na.rm = TRUE),
      probs = seq(0, 1, length.out = num_breaks + 1)), col = "red", lty = 2)


# Temperature breaks for all municipalities

# Define file names
file_names <- c("min_temp_pasorapa.rds", "min_temp_pojo.rds",
              "min_temp_aiquile.rds", "min_temp_totora.rds")

# Initialize an empty list to store numeric breaks for each municipality
numeric_breaks_list <- list()

# Loop over each file name
for (file_name in file_names) {
  # Read the raster file
  raster_data <- readRDS(file_name)

  # Calculate the numeric breaks
  break_values <- quantile(values(raster_data, na.rm = TRUE),
            probs = seq(0, 1, length.out = num_breaks + 1))

  # extract breaks as.numeric
  numeric_breaks <- as.numeric(as.character(break_values))

  # Extract the municipality name from the file name
  municipality <- gsub(".rds", "", file_name)
```

```r
  # Store the numeric breaks in the list with the municipality name as the key
  numeric_breaks_list[[municipality]] <- numeric_breaks
}

# Print the numeric breaks for each municipality
print(numeric_breaks_list)


### Reclass
# Create a tibble with the reclassification table

#   0%  20%  40%  60%  80% 100%
# -3.8  4.3  5.6  7.1  9.8 14.9

reclass_table_min_temp <- tribble(
  ~from, ~to, ~becomes,
  -3.8, 4.3, 1,
   4.3, 5.6, 0.8,
   5.6, 7.1, 0.4,
   7.1, 9.8, 0.2,
   9.8, 14.9, 0
)

# Reclassify the slope raster based on the reclassification table
min_temp_pasorapa_reclassified <- terra::classify(min_temp_pasorapa,
        reclass_table_min_temp, include.lowest = TRUE, right = TRUE)

min_temp_pojo_reclassified     <- terra::classify(min_temp_pojo,
        reclass_table_min_temp, include.lowest = TRUE, right = TRUE)

min_temp_aiquile_reclassified  <- terra::classify(min_temp_aiquile,
        reclass_table_min_temp, include.lowest = TRUE, right = TRUE)

min_temp_totora_reclassified   <- terra::classify(min_temp_totora,
        reclass_table_min_temp, include.lowest = TRUE, right = TRUE)
```

Processing DEM derived Inclination Data

```r
# Define areas of interest
areas <- list(
  pasorapa = Pasorapa,
  aiquile = Aiquile,
  totora = totora,
  pojo = pojo
)


# Flood Risk Calculation
# Create a tibble with the reclassification table
reclass_table_dem <- tribble(
  ~from, ~to, ~becomes,
  0, 10, 1,              # 0-10: Plano
  10, 20, 0.56,         # 10-20: Mod. inclinado
  20, 30, 0.34,         # 20-30: Inclinado
  30, 45, 0.2,          # 30-45: Mod. empinado
  45, Inf,0.09          # 45 and above: Fuert. empinado
)


# Drought Risk Calculation
## Create a tibble with the reclassification table
reclass_table_dem <- tribble(
  ~from, ~to, ~becomes,
  0, 10, 0.09,             # 0-10: Plano
  10, 20, 0.2,             # 10-20: Mod. inclinado
  20, 30, 0.34,            # 20-30: Inclinado
  30, 45, 0.56,            # 30-45: Mod. empinado
  45, Inf, 1               # 45 and above: Fuert. empinado
)



# Loop through areas of interest
for (area_name in names(areas)) {
  # Crop and mask dem
  dem_crop <- crop(dem, areas[[area_name]])
  dem_mask <- mask(dem_crop, areas[[area_name]])

  # Calculate terrain
  terrain <- terrain(dem_mask)
```

```r
  # Reclassify DEM
  dem_reclassified <- classify(terrain, reclass_table_dem,
                               include.lowest = TRUE, right = TRUE)

  # Assign to appropriate variable
  assign(paste0("dem_reclassified_", area_name), dem_reclassified)
}
```

Processing DEM derived Aspect Data

```r
# Reclassification of the Aspect Data

### terrain::aspect Pasorapa & Aiquile
aspect_pasorapa <- terrain(dem_mask_pasorapa, "aspect")
aspect_aiquile  <- terrain(dem_mask_aiquile, "aspect")

# reclass
# Create a tibble with the reclassification table
reclass_table_aspect <- tribble(
  ~from, ~to, ~becomes,
  -Inf, 45, 0,
  45, 135, 0.25,
  135, 225, 1,
  225, 315, 0.25,
  315, Inf, 0
)

# Pasorapa: Reclassify the slope raster based on the reclassification table
aspect_reclassified_aiquile <- terra::classify(aspect_aiquile,
      reclass_table_aspect, include.lowest = TRUE, right = TRUE)

# Aiquile: Reclassify the slope raster based on the reclassification table
aspect_reclassified_pasorapa <- terra::classify(aspect_pasorapa,
      reclass_table_aspect, include.lowest = TRUE, right = TRUE)

# read other data
aspect_reclassified_pojo <- readRDS("aspect_reclassified_pojo.rds")

aspect_reclassified_totora <- readRDS("aspect_reclassified_totora.rds")
```

Processing Precipitation

```r
# LOOP
# Crear una lista con los nombres de los objetos
lista_precip <- paste0("precip", sprintf("%02d", 1:12))
# Genera los nombres de precip01 a precip12

# Inicializar una lista vacía para almacenar los resultados
lista_precip_mask <- list()

# Iterar sobre cada objeto y aplicar las operaciones
for (i in seq_along(lista_precip)) {
  # Acceder al objeto con el nombre correspondiente
  precip_obj <- get(lista_precip[i])

  # Aplicar las operaciones crop y mask
  precip_crop <- terra::crop(precip_obj, aiquile)
  precip_mask <- mask(precip_crop, aiquile)

  # Almacenar el resultado en la lista
  lista_precip_mask[[i]] <- precip_mask
}

# Use the first raster as a base for the sum
sum_raster <- lista_precip_mask[[1]]

# Loop through the remaining rasters and add their values to the sum_raster
for (i in 2:length(lista_precip_mask)) {
  sum_raster <- sum_raster + lista_precip_mask[[i]]
}

# Reclassification of the Precipitation Data

precip_pasorapa <- rast("sum_raster_pasorapa.tif")
precip_aiquile  <- rast("sum_raster.tif")

precip_pojo     <- rast("precip_pojo.tif")
precip_totora   <- rast("precip_totora.tif")

precip_todos    <- rast("precip_todos.tif")
```

```
# Reclass
# Create a tibble with the reclassification table
reclass_table_precip <- tribble(
  ~from, ~to, ~becomes,
  1058.2, Inf,     0,
  640,     1058.2, 0.25,
  571,     640,     0.5,
  513.8,  571,     0.75,
  -Inf,    513.8,   1
)


# Reclassify the slope raster based on the reclassification table
precip_reclassified_pasorapa <- terra::classify(precip_pasorapa,
          reclass_table_precip, include.lowest = TRUE, right = TRUE)

precip_reclassified_aiquile <- terra::classify(precip_aiquile,
          reclass_table_precip, include.lowest = TRUE, right = TRUE)

precip_reclassified_pojo <- terra::classify(precip_pojo,
          reclass_table_precip, include.lowest = TRUE, right = TRUE)

precip_reclassified_totora <- terra::classify(precip_totora,
          reclass_table_precip, include.lowest = TRUE, right = TRUE)

# All together
precip_reclassified_todos <- terra::classify(precip_todos,
          reclass_table_precip, include.lowest = TRUE, right = TRUE)
```

Final Raster Calculation and Weighting

```
# Final Weightings for the Reclassification example: Totora

# Align resolutions
river_reclassified <- resample(river_totora, dem_reclassified_totora)

aspect_reclassified <- resample(aspect_reclassified_totora, river_reclassified)

max_temp_reclassified <- resample(max_temp_reclassified_totora, aspect_reclassified)
```

```r
precip_reclassified <- resample(precip_reclassified_totora, max_temp_reclassified)

dem_reclassified <- resample(dem_reclassified_totora, precip_reclassified)

# Adjusted weights
weight_temp_max    <- 0.2
weight_perspektive <- 0.15
weight_dem         <- 0.15
weight_river_dist  <- 0.2
weight_precip      <- 0.3

# Perform the adjusted weighted combination
final_raster <- weight_temp_max     * max_temp_reclassified +
                weight_perspektive  * aspect_reclassified +
                weight_dem          * dem_reclassified +
                weight_river_dist   * river_reclassified +
                weight_precip       * precip_reclassified

final_raster_totora <- final_raster
# plot(final_raster)

# Define the weights and data
weights <- c(0.2, 0.1, 0.1, 0.1, 0.2, 0.3)
data_names <- c("Max temp", "Perspektive", "Land Use", "DEM",
                "River Data", "Precipitation")

# Create the table
table_data <- data.frame(Weight = weights, Data = data_names)


# Define the municipalities
municipalities <- c("pojo", "pasorapa", "aiquile", "totora")

# Set the number of breaks (bins)
num_breaks <- 5

# Loop over each municipality
for (municipality in municipalities) {
  # Get the final raster data for the current municipality
  final_raster <- switch(municipality,
                         pojo = final_raster_pojo,
                         pasorapa = final_raster_pasorapa,
```

```r
                        aiquile = final_raster_aiquile,
                        totora = final_raster_totora)

    # Check if final_raster is NULL
  # if (is.null(final_raster)) {
  #   cat("Error: Final raster data is NULL for", municipality, "\n")
  # } else {

    # Compute the break values
    break_values <- quantile(values(final_raster, na.rm = TRUE),
              probs = seq(0, 1, length.out = num_breaks + 1))

    # Capitalize the first letter of the municipality name
    capitalized_municipality <- str_to_title(municipality)

    # Create the histogram with equal-frequency breaks
  hist(values(final_raster), breaks = "FD", main = paste("Histogram of Drought Risk for",
    capitalized_municipality), xlab = "Drought Risk Values",
    col = "skyblue", border = "black", plot = TRUE)

    # Add vertical lines to represent the breaks
    abline(v = break_values, col = "red", lty = 2)
}
```

Final Mapping Results

```r
# Define breaks and labels for the reclassification
breaks <- numeric_breaks
labels <- c("Muy bajo", "Bajo", "Moderado", "Alto", "Muy alto")

# Cut the raster values into categorical factors
factor_raster <- cut(values(final_raster), breaks = breaks,
                labels = labels, include.lowest = TRUE)

# change name
names(final_raster) <- "Drought Risk"

# Create a new raster with categorized values
r_categorized          <- final_raster
```

```r
values(r_categorized) <- as.factor(factor_raster)

if (knitr::is_html_output()) {

# view
tmap_mode("view")

tm_shape(r_categorized, labels = "New Legend Label") +
  tm_raster(palette = colors) +
  tm_shape(all_municipalities) +
    tm_borders(lwd = 2, col = "black") +
    tm_layout(frame = FALSE) +
  tm_text("NAME_3", size = 0.7)

} else if (knitr::is_latex_output()) {

 # view
tmap_mode("plot")

tm_shape(r_categorized, labels = "New Legend Label") +
  tm_raster(palette = colors) +
  tm_shape(all_municipalities) +
    tm_borders(lwd = 2, col = "black") +
    tm_layout(frame = FALSE) +
  tm_text("NAME_3", size = 0.7) +
    tm_scale_bar(breaks = c(0, 5, 10), text.size = 0.9, position = c("left")) +
  tm_compass(type = "4star", size = 6, position = c("right", "top")) +
  tm_credits("Author: Johannes Quente", fontface = "italic", align = "right") +
  tm_graticules(alpha = 0.3) +
  tm_layout(
    legend.text.size = 1,
    legend.position = c("left", "bottom"),
    legend.outside = TRUE
  )
}
```