Spatial Analysis of Oil and Gas Pipeline Accidents in Texas

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May, 2024

1. Introduction

Pipelines serve as the fundamental means of transporting natural gas, crude oil and petroleum products (Mahjoob, Noorollahi and Naghavi, 2024). They are often considered as an economical and safer alternative for the transportation of hazardous materials compared to other mode of transportation such as railway, road and ship (Cozzani et al., 2018; Belvederesi et al., 2018; Zardasti et al., 2017). Despite their numerous advantages, pipelines are associated with risks due to potential pipeline accidents as a result of equipment failures, natural hazards (e.g., earthquakes), human induced hazards (e.g., vandalism), and other factors leading to severe consequences, including fatalities, injuries, environmental degradation, and substantial economic losses (Girgin and Krausmann, 2016; Naik and Kiran, 2018; Woldesellasse and Tesfamariam, 2023).

In the United States, considerable frequency of pipeline accidents has occurred in the past leading to severe consequences for the exposed population and for the surrounding environment (Liu and Liang, 2021). Between 1986 and 2013, pipeline accidents resulted in an average annual spillage of 76,000 barrels. Over this period, nearly 8,000 incidents occurred, averaging about 300 per year. These accidents led to more than 500 fatalities, over 2,300 injuries, and approximately $7 billion in damages (Stover, 2014). The numerous severe incidents in the U.S. highlight the significant risks associated with pipeline accidents, making it impossible to ignore their occurrence. Major accidents include, the spill of 20,000 barrels of oil into the Kalamazoo River (National Transportation Safety Board, 2012), the flooding of the Texas San Jacinto River, in October 1994 which caused several pipelines to rupture, resulting in the release of 34,500 barrels of crude oil and petroleum products into the river. The spill ignited, leading to significant environmental damage and causing 547 individuals to suffer from inhalation problems and burns (Girgin and Krausmann, 2016). These accidents are most common in states with a long history of oil and gas development, such as Texas and California, but they have caused damage to people, property, and the environment across all 48 contiguous states in the U.S. (Stover, 2014).

The analysis of historical accident data is crucial for identifying the primary causes, impacts, and patters associated with pipeline accidents (Girgin and Krausmann, 2016). Spatial analysis, serves as a powerful tool for studying environmental phenomena (Mahjoob, Noorollahi and Naghavi, 2024). This method allows for the detailed examination of the spatial relationships and patterns that emerge from the data, providing a clearer understanding of how these accidents impact different regions over time (Mahjoob, Noorollahi and Naghavi, 2024). Utilizing spatial analysis techniques, we can effectively map and analyze the risk landscape, identify hotspots, and assess the potential exposure of human and environmental variables to pipeline accidents (Obida et al., 2018). For example, Obida et al. (2018) used advanced geostatistical techniques to analyze the spatial distribution of oil pollution in the Niger Delta region. By leveraging spatial analysis techniques, they were able to quantify the exposure of both human populations and the environment to oil contamination, offering valuable insights into the extent and impact of the pollution. Therefore, the aim of this study is to conduct a comprehensive spatial analysis of historical accident data, enabling an evaluation of the potential human and environmental exposure within Texas. The specific objectives of this study include, (i) to examine pipeline accidents and characterize potential clusters of incidents; (ii) to assess the exposure of the human population and the environment to pipeline accidents.

This study will provide valuable insights into the spatial patterns of pipeline accidents and their potential impact on communities and ecosystems in Texas. This information can inform decision-making processes, risk mitigation strategies, and policy interventions aimed at enhancing safety measures for pipeline infrastructure and protecting human health and the environment.

2. Methods

2.1. Pipeline accident data

The analysis presented in this report is based on data supplied by the U.S. Department of Transportation Pipeline and Hazardous Materials Safety Administration on pipeline accidents involving gas or oil from 1986 to 2017 for the entire USA and compiled by Dr. Richard Stover (Stover, 2014). The database covers 8,890 pipeline incidents from 1986 to 2017, providing detailed information about each incident, including fatalities, injuries, monetary property damage, accident location, accident type, and a narrative about the accident. 2.2. Population and river data Population data at the block level for Texas was acquired from the U.S. Census Bureau through the tidycensus package in R.

This data provides detailed information on population counts at the block level for Texas. River data was sourced from the Texas Water Development Board (https://www.twdb.texas.gov/mapping/gisdata.asp), which contains a shapefile of the major rivers in Texas. Boundary data was obtained using the tigris library in R, which provides shapefiles for the boundaries of Texas counties.

2.2. Data pre-processing

The preliminary pre-processing of the pipeline accident data involved filtering the dataset to include only incidents that occurred in Texas. The study only considered pipeline accidents with reported latitude and longitude coordinates to accurately map and analyze the spatial distribution of the accidents, ensuring the accuracy and relevance of the spatial analysis. Additionally, the boundary shapefile for Texas was downloaded from the tigris library to provide a precise geographical context. Initially, the geographical Coordinate Reference System (CRS) for the pipeline data was set to OGC:CRS84. Subsequently, both the pipeline data and boundary data were reprojected to a suitable CRS to ensure compatibility and accuracy in the spatial analysis. Finally, a spatial intersection operation was performed to remove any points that were outside the state's boundary, thereby producing a dataset that contains only those pipeline accident points that fall within the geographic boundaries of Texas. This step ensures that subsequent analyses focus exclusively on accidents within the state, thereby improving the accuracy and relevance of the findings.

```r
library(tidyverse)  # general set of useful R libraries
library(tigris) # For boundary data
library(tidycensus) # Access US Census data
library(crsuggest) # help select a projected CRS
library(mapsf)    # useful map making library
library(sf) # Handle spatial data with Simple Features
library(sfdep)  # For spatial dependency
require(remotes)
install_version("mapsf",version='0.7.1')

# Read in the pipeline data
pipeline <- "data/pipeline.csv" %>%
  read_csv()

# Rename the column name
pipeline <- pipeline %>%
  rename(Recorded_Long_Lat = 14) %>%
  # Filter the data to include only incidents with recorded lat/long
coordinates
  dplyr::filter(Recorded_Long_Lat == "YES")


# Subset for Texas
tx_pipeline <- pipeline %>%
  dplyr::filter(State == "TX" )

# Create an sf object and set the CRS
tx_pipeline_sf <- tx_pipeline %>%
  st_as_sf(coords = c("Longitude", "Latitude")) %>%
  st_set_crs("OGC:CRS84")

# Retrieve boundary data for Texas: https://github.com/walkerke/tigris
tx_boundary_sf <- counties(cb = TRUE) %>%
  dplyr::filter(STUSPS == "TX")

# list some candidate projections for Texas
tx_boundary_sf %>%
  suggest_crs()

# Transform pipeline data and boundary data to the projected CRS
tx_boundary_sf <- tx_boundary_sf %>%
  st_transform(6579)


tx_pipeline_sf <- tx_pipeline_sf  %>%
  st_transform(6579)

# Perform spatial intersection to remove points outside the boundary
tx_pipeline_clipped <- st_intersection(tx_pipeline_sf, tx_boundary_sf)
```

2.3. Spatial analysis of pipeline accidents

2.3.1. Mapping pipeline accidents

The locations of past pipeline accidents were visualized on a map of Texas using the mapsf library. This provides an initial overview of the spatial distribution of pipeline accidents across Texas.

```
# Define the names of counties to label
counties_to_label <- c("Dallas", "Houston", "Jefferson", "Chambers",
"Galveston", "El Paso", "Midland", "Potter", "Lubbock", "Travis", "Bexar",
"Harris", "Cameron")

# Subset county data for the specified counties
counties_subset <- tx_boundary_sf[tx_boundary_sf$NAME %in% counties_to_label,
]

# Modified from https://riatelab.github.io/mapsf/reference/index.html

# Export the map
mf_export(tx_boundary_sf, file = "pipeline_point.png", width = 10, height =
8, units = "in", res = 300)

# Plot the boundary
tx_boundary_sf %>%
  mf_map(type = "base",
         col = "white")

# Plot the pipeline accidents in Texas
tx_pipeline_clipped %>%
  mf_map(pch = 16,
         col = "red",
         cex = 1,
         leg_pos = "topright",
         leg_adj = c(0, 1),
         leg_title = "Incidents",
         add= TRUE)

# Add labels
counties_subset %>% mf_label(
  var = "NAME",
  col = "black",
  cex = 0.7,
  font = 4,
  halo = TRUE,
  bg = "white",
  r = 0.1,
  overlap = FALSE,
  lines = FALSE
)
```

```r
# Add a title
mf_title("Pipeline Accidents in Texas", 'center', bg = "white", fg = "black",
cex = 1.5, tab = FALSE)

# Add a North arrow
mf_arrow()

# Add a scale bar
mf_scale()

# Add a credit line
mf_credits("Data Source: US Department of Transportation Pipeline and
Hazardous Materials Safety Administration", cex = 0.7, pos = "bottomleft")

# Count the number of point in polygon
https://gis.stackexchange.com/questions/323698/counting-points-in-polygons-
with-sf-package-of-r
tx_boundary_sf$pipe_count <- tx_boundary_sf %>%
  st_intersects(tx_pipeline_clipped) %>%
  lengths()

# Ensure that counties with no accidents are shown as zero
tx_boundary_sf$pipe_count[is.na(tx_boundary_sf$pipe_count)] <- 0

# Modified from https://riatelab.github.io/mapsf/reference/index.html

# Export the map
mf_export(tx_boundary_sf, file = "pipeline_map.png", width = 10, height = 8,
units = "in", res = 300)

# plot the results
tx_boundary_sf %>%
  mf_map(type = "choro",
         var = "pipe_count",
         pal = "Oranges",
         nbreaks  = 4,
         breaks = 'jenks',
         leg_title = "Number of Incidents",
         leg_val_rnd = -1)

counties_subset %>% mf_label(
  var = "NAME",
  col = "black",
  cex = 0.7,
  font = 4,
  halo = TRUE,
  bg = "white",
  r = 0.1,
  overlap = FALSE,
```

```
  lines = FALSE
)

# Add a title
mf_title("Pipeline Accidents in Texas",
         'center',
         bg = "white",
         fg = "black",
         cex = 1.5,
         tab = FALSE)

# Add a North arrow
mf_arrow(pos = "topright")

# Add a scale bar
mf_scale(pos = "bottomleft")

# Add a credit line
mf_credits("
     Data Source: US Department of Transportation Pipeline and Hazardous
Materials Safety Administration",
           cex = 0.7,
           pos = "bottomright",)
```

2.3.2. Hotspot Analysis

To identify clusters of pipeline accidents within Texas, a hotspot analysis using Local Moran's I was conducted. This statistical technique is widely used for measuring spatial autocorrelation by assessing the similarity of values between neighbouring features (Moran, 1948; O'Sullivan and Unwin, 2010). Unlike global statistics, such as the global Moran's I, which provide an overall measure of spatial autocorrelation for an entire study area, local spatial statistics like local Moran's I are more effective at identifying and examining localized clusters or hotspots of events (O'Sullivan and Unwin, 2010). In the context of this study, local Moran's I is applied to pinpoint areas with statistically significant high-density clusters of pipeline accidents, as well as areas with low-density clusters. This approach is similar to the one used by Xie and Yan (2013) to estimate traffic accident hotspots, demonstrating its effectiveness in detecting significant clusters of incidents. Utilizing the sfdep library, the first step involved constructing a neighbours list using the Queen's case. From this list, row-standardized weights are generated. Subsequently, Local Moran's I is calculated to assess the spatial autocorrelation of pipeline accidents at a local level. Finally, the results of the Local Moran's I analysis are plotted to visualize the spatial distribution of significant clusters of pipeline accidents within Texas.

```
# Construct the neighbours list using the Queen's case
pp_q_nb <- tx_boundary_sf %>%
  st_contiguity(queen= TRUE)

# Create the row-standarized weights
```

```r
pp_q.lw <- pp_q_nb %>%
 st_weights(style = "W")

# local moran calculation
pp_lmi <- tx_boundary_sf$pipe_count %>%
  local_moran(pp_q_nb, pp_q.lw, na.action = na.exclude)

pp_lmi <- pp_lmi %>%
  # create a new colour variable based on the significance value and quadrant
  mutate (
    colour = ifelse(p_ii < 0.05 & mean == "High-High","red",
                    ifelse(p_ii < 0.05 & mean == "Low-Low","blue",
                           ifelse(p_ii < 0.05 & mean == "High-Low","pink",
                                  ifelse(p_ii < 0.05 & mean == "Low-
High","lightblue","grey"))))
  )

# Export the map
mf_export(tx_boundary_sf, file = "local_morans.png", width = 10, height = 8,
units = "in", res = 300)

# Plot out the zones in colour
tx_boundary_sf %>%
  mf_map(type = "base",
         col = pp_lmi$colour,
         border = "black",
         lwd=0.2)

# Add a title
mf_title("Local Moran's I Significance - Pipeline Accidents by County",
         'center',
         bg = "white",
         fg = "black",
         cex = 1.0,
         tab = FALSE)

# Add a legend
mf_legend(type = "typo",
          pos  = "topleft",
          val = c("High-High",
                  "High-Low",
                  "Low-High",
                  "Low-Low",
                  "Not Significant"),
          pal = c("red", "pink", "lightblue", "blue", "grey78", "black"),
          title = "    Legend")

# Add a North arrow
mf_arrow(pos = "topright")
```

```r
# Add a scale bar
mf_scale()

# Add a credit line
mf_credits("Data Source: US Department of Transportation Pipeline and Hazardous Materials Safety Administration",
           cex = 0.7,
           pos = "bottomleft")
```

2.4. Potential human and environmental exposure to pipeline accidents

To evaluate potential human and environmental exposure to pipeline accidents, a buffer of 2.5 km which is the maximum known impact radius of a pipeline spill (Obida et al., 2018), was created around each accident location. This buffer was used to analyze the proximity to population and environmental features. This approach aimed to assess the extent of potential exposure, acknowledging that the impact radius can vary depending on factors such as the type of pipeline, the volume of the substance transported, the nature of the surrounding environment, and emergency response times (Obida et al., 2018). To estimate the population potentially at risk, the total population count within the buffer zones was calculated before and after overlaying these zones on the population data. Additionally, to evaluate potential environmental exposure, the proximity of rivers to the pipeline accident sites was analyzed by intersecting the buffer zones with river data, thereby identifying rivers within the impact areas.

```r
# https://cloud.r-project.org/web/packages/tidycensus/index.html
# Download population data for Texas at the block level
tx_pop_sf <- get_decennial(
  geography = "block",
  variables = "P001001",
  state = "TX",
  year = 2010,
  geometry = TRUE,
  output = "wide"
)

# Transform the population data to match the CRS of the pipeline and boundary data
tx_pop_sf <- tx_pop_sf %>%
  st_transform(6579)

# Get the total population
pop_total1 <- tx_pop_sf %>%
  summarize(total_population = sum(P001001, na.rm = TRUE))

# Print the total population
print(pop_total1)

# create a buffer of 2.5 km around the pipeline accidents
pipe_buf_sf <- tx_pipeline_clipped %>%
st_buffer(2500)
```

```r
# Export the map
mf_export(tx_boundary_sf, file = "buffers_map.png", width = 10, height = 8,
units = "in", res = 300)

# plot the buffers
tx_boundary_sf %>%
  mf_map(type = "base",
         col = "white",
         border = "darkgrey",
         lty = 1)

pipe_buf_sf %>%
  mf_map(type = "base",
         col = "yellow",
         border = "black",
         lty = 1,
         add = TRUE)

# Add title
mf_title("Pipeline Accident + Buffers - Texas", 'center',
         bg = "white",
         fg = "black",
         cex = 1.5,
         tab = FALSE)

# Add a North arrow
mf_arrow()

# Add a scale bar
mf_scale(pos = "bottomleft")

# Add a credit line
mf_credits("Data Source: US Department of Transportation Pipeline and
Hazardous Materials Safety Administration",
           cex = 0.7,
           pos = "bottomright")

# Perform spatial intersection to get the affected population
pop_pp_sf <- pipe_buf_sf %>%
  st_intersection (tx_pop_sf)

# Get the total population after creating the buffer(affected population)
pop_total2 <- pop_pp_sf %>%
  summarize(total_pop = sum(P001001, na.rm = TRUE))

# Print the total population
print(pop_total2)

# https://www.twdb.texas.gov/mapping/gisdata.asp
# Load water bodies data and transform to the same projected CRS
```

```r
tx_r_sf <-
st_read("/home/rtd7/GY7707_PRACTICALS/Pipeline/data/MajorRivers_dd83.shp")
%>%
  st_transform(crs = 6579)

# Export the map
mf_export(tx_boundary_sf, file = "rivers_map.png", width = 10, height = 8,
units = "in", res = 300)

# plot the rivers
tx_boundary_sf %>%
  mf_map(type = "base",
         col = "white",
         border = "darkgrey",
         lty = 1)

tx_r_sf %>%
  mf_map(type = "base",
         col = "blue",
         pch = 16,
         cex = 1,
         add = TRUE)

# Add title
mf_title("Major Rivers in Texas", 'center',
         bg = "white",
         fg = "black",
         cex = 1.5,
         tab = FALSE)

# Add a North arrow
mf_arrow()

# Add a scale bar
mf_scale(pos = "bottomleft")

# Add a credit line
mf_credits("Data Source: Texas Water Development Board",
           cex = 0.7,
           pos = "bottomright")

# Export the map
mf_export(tx_boundary_sf, file = "riversbuf.png", width = 10, height = 8,
units = "in", res = 300)

# plot the buffers
tx_boundary_sf %>%
  mf_map(type = "base",
         col = "white",
         border = "darkgrey",
```

```
        lty = 1)

tx_r_sf %>%
  mf_map(type = "base",
         col = "blue",
         pch = 16,
         cex = 1,
         add = TRUE)

pipe_buf_sf %>%
  mf_map(type = "base",
         col = "yellow",
         border = "black",
         lty = 1,
         add = TRUE)

# Add title
mf_title("Rivers + Buffers - Texas", 'center',
         bg = "white",
         fg = "black",
         cex = 1.5,
         tab = FALSE)

# Add a North arrow
mf_arrow()

# Add a scale bar
mf_scale(pos = "bottomleft")

# Add a credit line
mf_credits("Data Source: Texas Water Development Board",
           cex = 0.7,
           pos = "bottomright")
```

3. Results

3.1. Spatial analysis of pipeline accidents

The spatial distribution of pipeline accidents in Texas over the study period are illustrated in Figures 1and 2. The data indicate that pipeline accidents are more prevalent in specific counties, particularly in the southeastern part of the state. Some counties, such as Harris, Jefferson, and Midland, have consistently experienced pipeline incidents throughout the study period. Overall, the areas with the greatest number of pipeline accidents include Harris, Midland, Jefferson, Chambers and Galveston counties with Harris clearly showing the highest number of accidents, indication potential hotspot (Figure 2). The spatial distribution of the accidents is influenced by the configuration of the pipeline network in the city as shown in Figure 3. In addition, there is a noticeable clustering and high concentration of accidents in regions with a dense network of pipelines. Apart from outliers in counties such as Potter in the north and Cameron in the south, the majority of accidents occur in central and southeastern Texas. This pattern can be partly explained by the concentration of oil and gas infrastructure in these regions.

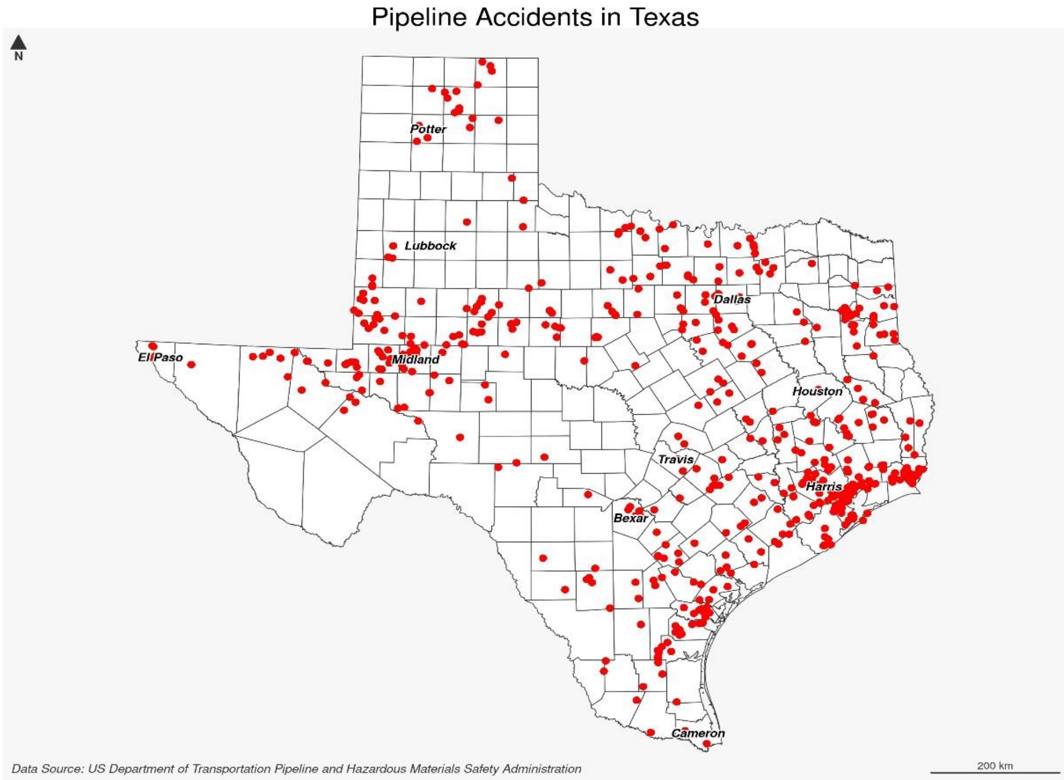

Figure 1. Spatial distribution of oil and gas pipeline accidents in Texas. Each point represents a recorded pipeline incident.

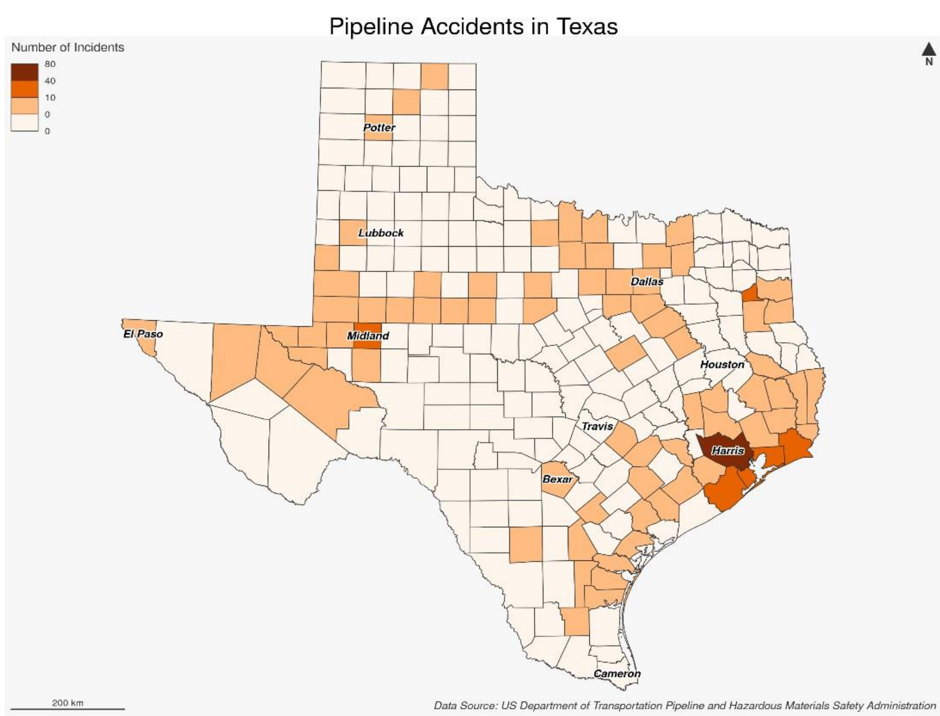

Figure 2. Choropleth map illustrating the distribution of oil and gas pipeline accidents across counties in Texas.

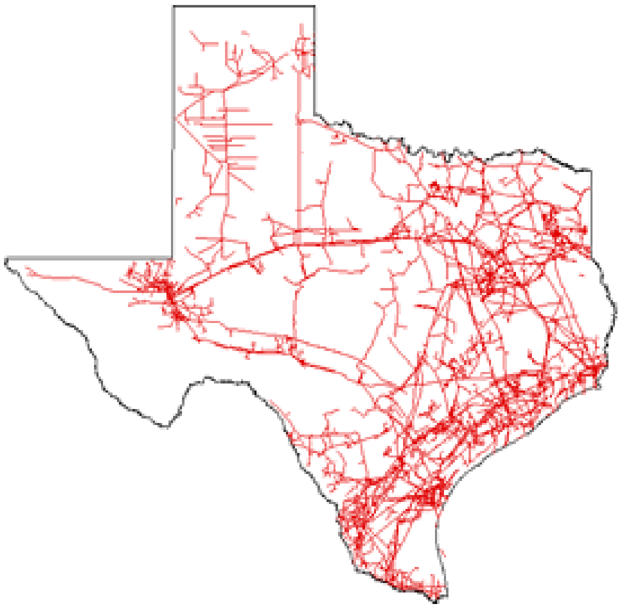

Figure 3. Texas pipeline network map. (Source, U.S. Energy Information Administration.)

The results of the hotspot analysis, using Local Moran's I, identify significant clusters of pipeline accidents across Texas (Figure 4). According to the results, areas of high-high clusters particularly around Harris County and Midland County, exhibit high accident rates surrounded by other high-rate areas, indicating significant hotspots, with low-low Clusters found some part of the southeastern part of Texas, indicating low accident rates surrounded by other low-rate areas and the majority of Texas counties, showing no significant clustering of pipeline accidents.

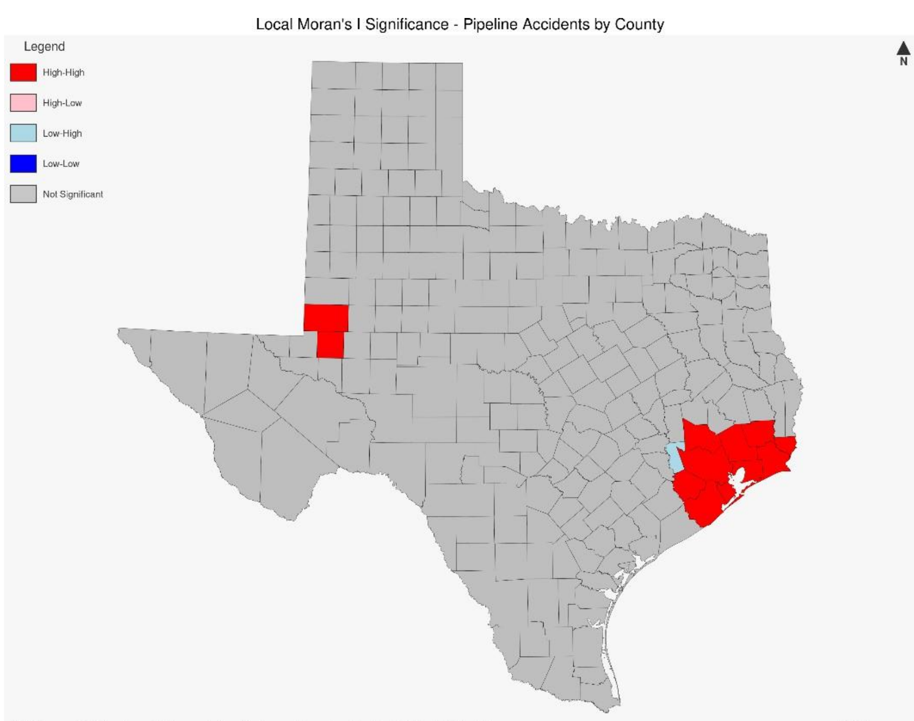

Figure 4. Pipeline accident hotspots in Texas based Local Moran's I

3.2. Potential human and environmental exposure to pipeline accidents To understand the potential extent of human exposure to pipeline accidents, a proximity analysis was conducted using a 2.5 km buffer around pipeline accident sites (Figure 5). The initial population count before applying the buffer zones was 25,145,561. After overlaying the buffer zones, a total of 2,812,906 people were found to be within the buffer zones, indicating the population potentially at risk. These buffer zones were created to identify areas that are in close proximity to the pipeline accidents. The analysis reveals that a significant portion of the population that resides particularly within the hotspots are potentially at risk.

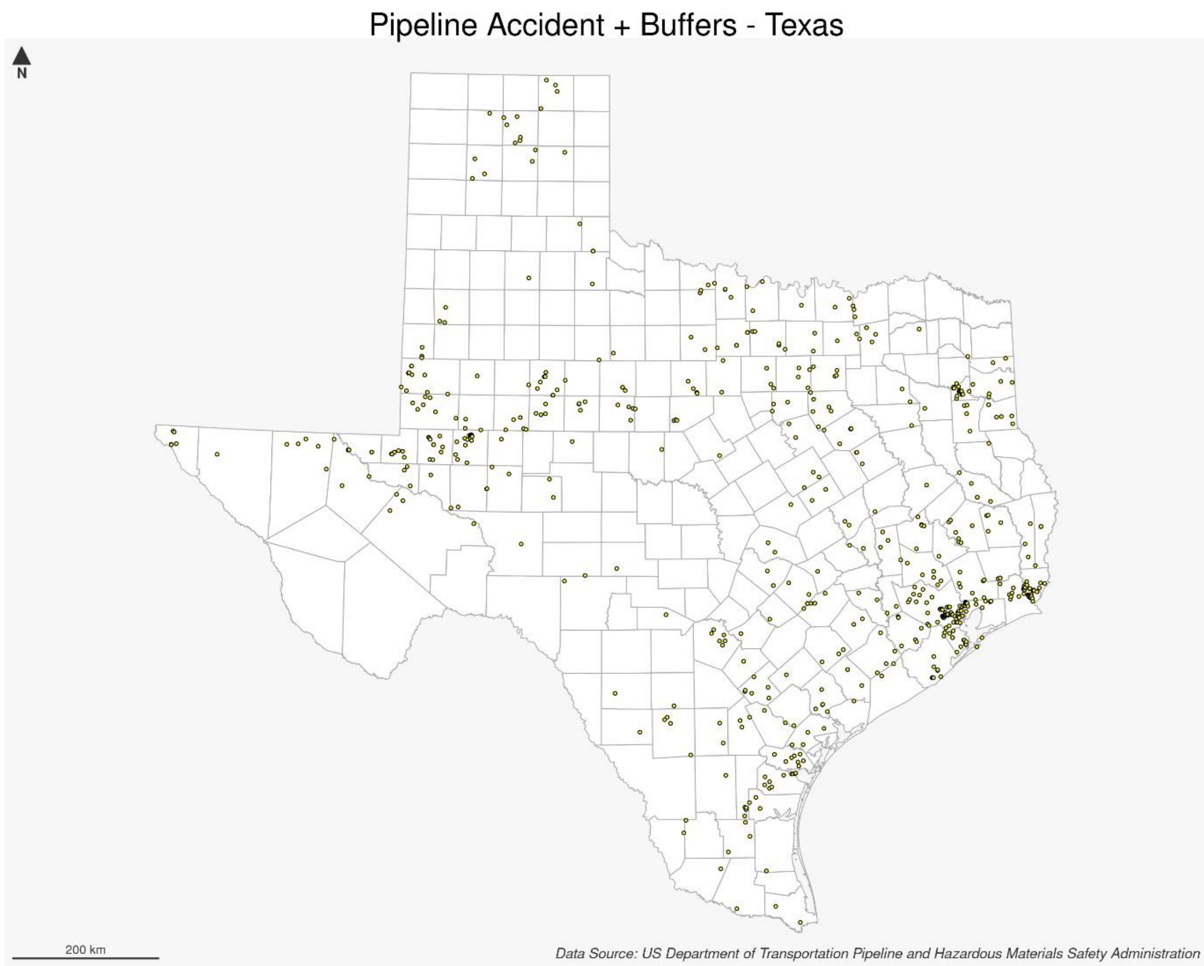

Figure 5. Buffer zones of 2.5 km around pipeline accident locations.

In addition, the impact of pipeline accidents on the major rivers in Texas was assessed (Figure 6). Rivers within the buffer zones indicate potential environmental risks in the event of pipeline accidents (Figure 7). There is a moderate to high exposure risks, particularly in areas with significant overlap between buffer zones and rivers. This pattern can be influenced by the configuration of the pipeline networks close to the rivers.

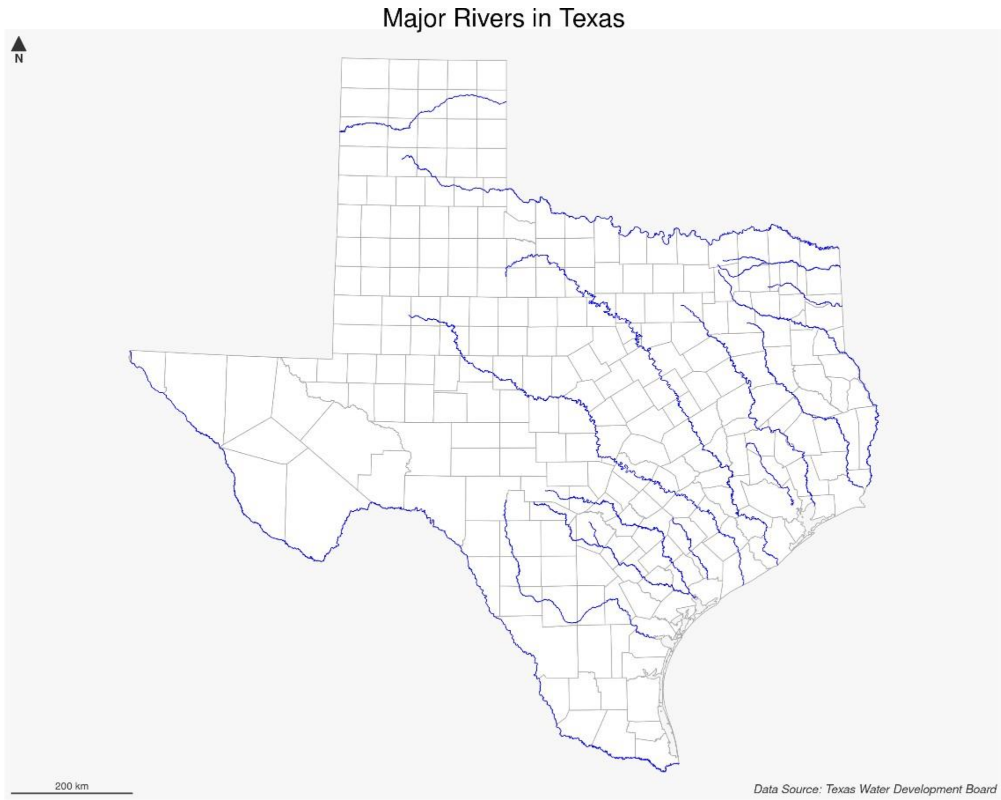

Figure 6. Major rivers of Texas

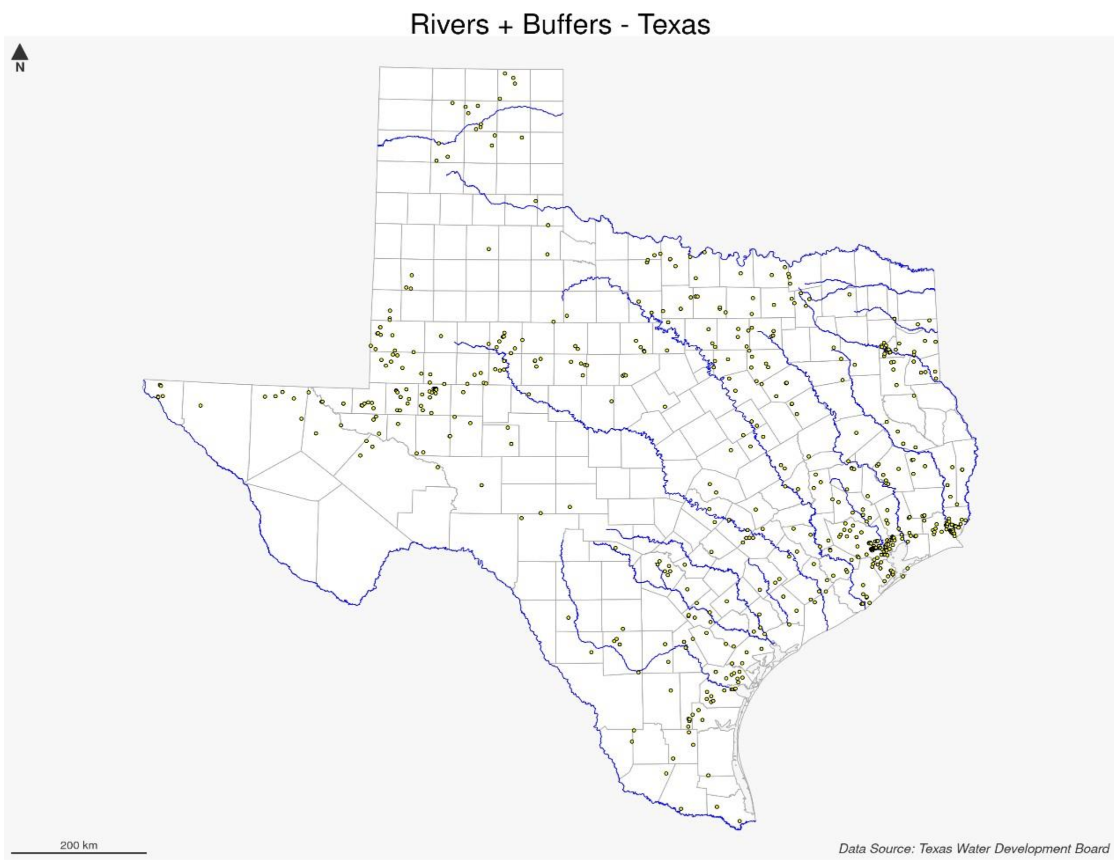

Figure 7. Buffer zones of 2.5 km around rivers.

4. Discussion and Conclusion

Pipeline accidents poses significant threats the exposed population and the surrounding environment. A comprehensive assessment of the spatial distribution of pipeline accident and the potential human and environmental exposure is crucial. This study aimed to evaluate the spatial distribution of pipeline accidents in Texas and assess the potential human and environmental exposure. Local Moran's I have been often used for detecting spatial patters of accidents (Truong and Somenahalli, 2011; Xie and Yan, 2013), and the result of the analysis show the effectiveness of such approach. The analysis revealed several key findings and provided insights into areas of particular concern. The southeastern region of Texas, particularly counties like Harris, Jefferson, Midland, Chambers, and Galveston, exhibits a higher concentration of pipeline accidents, which may be attributed to the dense network of oil and gas infrastructure in these areas. This clustering of accidents suggests a heightened risk to the local population and environment in these areas.

Additionally, the human and environmental exposures were assessed based on the outcomes of proximity analysis. The results indicated that approximately 2.8 million people live within the buffer zones around pipeline accident sites, underscoring the significant exposure risk. In terms of environmental exposure, the analysis showed that several major rivers intersect with the buffer zones around pipeline accidents. This intersection indicates that rivers are also at significant risk of contamination in the event of a pipeline failure. The proximity of rivers to these accident sites highlights the potential for widespread environmental impact, affecting water quality.

Overall, this study demonstrates the effectiveness of using R and spatial analysis in addressing real-world problems. R provides extensive libraries such as sf, tidyverse, and mapsf for efficiently analyzing spatial data, enabling detailed and accurate assessments. Spatial analysis techniques, such as proximity and hotspot analysis, combined with the integration of several spatial data types, provide a comprehensive understanding of geographic patterns and risks, as illustrated in this study. Further research is warranted to understand and mitigate the risks associated with pipeline infrastructure by incorporating additional spatial analysis techniques and environmental factors to refine risk assessments and inform targeted interventions.

References

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