Double-click (or enter) to edit

Tanzania Water Wells

Business Understanding

Overview

Boosting food production and reducing reliance on aid are key goals in developing countries. International aid groups (NGOs) often tackle these challenges by building water systems. However, a crucial step is being missed. Many NGOs launch new projects without utilizing existing data, leading to inefficient use of resources and donor funding.

Tanzania, as a developing country, has encountered this issue prominently. Here, poorly planned water projects have resulted in wasted funds and, even worse, lives lost due to insufficient access to clean water.

Problem Statement

Maji Safi Global, an NGO dedicated to improving water distribution in developing nations, relies on donor funding to support its community outreach efforts. Collaborating with the Tanzanian government through the Visima Vyema initiative, Maji Safi aims to enhance existing infrastructure by repairing dysfunctional wells and analyzing patterns in non-operational wells.

In my role as a data scientist, I am tasked with identifying wells in need of repair and conducting an in-depth analysis to forecast patterns in non-functional wells. This analysis will provide valuable insights for Maji Safi Global and the Tanzanian government, guiding strategic investments for the future.

Data Understanding

1 Features description

I will use the features in this dataset to predict the wells' operating condition and the features are as follows:

amount_tsh - Total static head (amount water available to waterpoint)

date_recorded - The date the row was entered

funder - Who funded the well

gps_height - Altitude of the well

installer - Organization that installed the well

longitude - GPS coordinate

latitude - GPS coordinate

wpt_name - Name of the waterpoint if there is one

num_private -basin - Geographic water basin

subvillage - Geographic location

region - Geographic location

region_code - Geographic location (coded)

district_code - Geographic location (coded)

lga - Geographic location

ward - Geographic location

population - Population around the well

public_meeting - True/False

recorded_by - Group entering this row of data

scheme_management - Who operates the waterpoint

scheme_name - Who operates the waterpoint

permit - If the waterpoint is permitted

construction_year - Year the waterpoint was constructed

extraction_type - The kind of extraction the waterpoint uses

extraction_type_group - The kind of extraction the waterpoint uses

extraction_type_class - The kind of extraction the waterpoint uses

management - How the waterpoint is managed

management_group - How the waterpoint is managed

payment - What the water costs

payment_type - What the water costs

water_quality - The quality of the water

quality_group - The quality of the water

quantity - The quantity of water

quantity_group - The quantity of water

source - The source of the water

source_type - The source of the water

source_class - The source of the water

waterpoint_type - The kind of waterpoint

waterpoint_type_group - The kind of waterpoint

Load Libraries

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix, classification_report, roc_curve,
from sklearn.metrics import confusion_matrix

from sklearn.tree import DecisionTreeClassifier

from sklearn.neighbors import KNeighborsClassifier

from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.preprocessing import FunctionTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.impute import SimpleImputer

from sklearn.compose import ColumnTransformer

from sklearn.pipeline import Pipeline

from imblearn.over_sampling import SMOTE
from imblearn.combine import SMOTEENN

from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
from sklearn.ensemble import VotingClassifier
!pip install xgboost
from xgboost import XGBClassifier

from sklearn.feature_selection import RFECV
from sklearn.linear_model import LogisticRegression
```

```
Requirement already satisfied: xgboost in c:\users\hp 430\anaconda3\lib\site-packages (2.0.3)
Requirement already satisfied: numpy in c:\users\hp 430\anaconda3\lib\site-packages (from xgboost) (1.26.3)
Requirement already satisfied: scipy in c:\users\hp 430\anaconda3\lib\site-packages (from xgboost) (1.11.4)
```

```
#importing training data
df1 = pd.read_csv('Downloads/Training Set Values.csv')
df2 = pd.read_csv('Downloads/Training_set_labels.csv')
```

```
#Merging df1 & df2
df=pd.merge(df1, df2, on='id', how='outer')
#Viewing the first five rows of the combined dataframe
df.head()
```

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	lati
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825

5 rows × 41 columns

```
#Viewing the last 5 rows
df.tail()
```

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	
59395	60739	10.0	2013-05-03	Germany Republi	1210	CES	37.169807	-
59396	27263	4700.0	2011-05-07	Cefa-njombe	1212	Cefa	35.249991	-
59397	37057	0.0	2011-04-11	NaN	0	NaN	34.017087	-
59398	31282	0.0	2011-03-08	Malec	0	Musa	35.861315	-
59399	26348	0.0	2011-03-23	World Bank	191	World	38.104048	-

5 rows × 41 columns

```
#Checking for number of rows and columns
df.shape
```

```
(59400, 41)
```

This dataset has 59,400 rows and 41 columns

```
# Getting the basic information about the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     59400 non-null  int64
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object
 3   funder                 55763 non-null  object
 4   gps_height             59400 non-null  int64
 5   installer              55745 non-null  object
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59398 non-null  object
 9   num_private            59400 non-null  int64
 10  basin                  59400 non-null  object
 11  subvillage             59029 non-null  object
 12  region                 59400 non-null  object
```

```
 13  region_code            59400 non-null  int64
 14  district_code          59400 non-null  int64
 15  lga                    59400 non-null  object
 16  ward                   59400 non-null  object
 17  population             59400 non-null  int64
 18  public_meeting         56066 non-null  object
 19  recorded_by            59400 non-null  object
 20  scheme_management      55522 non-null  object
 21  scheme_name            30590 non-null  object
 22  permit                 56344 non-null  object
 23  construction_year      59400 non-null  int64
 24  extraction_type        59400 non-null  object
 25  extraction_type_group  59400 non-null  object
 26  extraction_type_class  59400 non-null  object
 27  management             59400 non-null  object
 28  management_group       59400 non-null  object
 29  payment                59400 non-null  object
 30  payment_type           59400 non-null  object
 31  water_quality          59400 non-null  object
 32  quality_group          59400 non-null  object
 33  quantity               59400 non-null  object
 34  quantity_group         59400 non-null  object
 35  source                 59400 non-null  object
 36  source_type            59400 non-null  object
 37  source_class           59400 non-null  object
 38  waterpoint_type        59400 non-null  object
 39  waterpoint_type_group  59400 non-null  object
 40  status_group           59400 non-null  object
dtypes: float64(3), int64(7), object(31)
memory usage: 18.6+ MB
```

Of the 41 columns in our dataset, 10 are numerical and 31 have categorical data.

```
#Getting the statistical summary of numerical columns
df.describe()
```

	id	amount_tsh	gps_height	longitude	latitude	num_pri
count	59400.000000	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.00
mean	37115.131768	317.650385	668.297239	34.077427	-5.706033e+00	0.47
std	21453.128371	2997.574558	693.116350	6.567432	2.946019e+00	12.23
min	0.000000	0.000000	-90.000000	0.000000	-1.164944e+01	0.00
25%	18519.750000	0.000000	0.000000	33.090347	-8.540621e+00	0.00
50%	37061.500000	0.000000	369.000000	34.908743	-5.021597e+00	0.00
75%	55656.500000	20.000000	1319.250000	37.178387	-3.326156e+00	0.00
max	74247.000000	350000.000000	2770.000000	40.345193	-2.000000e-08	1776.00

Data Cleaning

1. Duplicates

```
#Checking for duplicate rows number
duplicate_rows_count = df.duplicated().sum()
duplicate_rows_count
```

```
0
```

Good News! No duplicates were found in our dataset.

2. Missing value

```
#Checking for missing values
df.isnull().sum()
```

```
id                          0
amount_tsh                  0
date_recorded               0
funder                   3637
gps_height                  0
installer                3655
longitude                   0
latitude                    0
```

```
wpt_name                    2
num_private                 0
basin                       0
subvillage                371
region                      0
region_code                 0
district_code               0
lga                         0
ward                        0
population                  0
public_meeting           3334
recorded_by                 0
scheme_management        3878
scheme_name             28810
permit                   3056
construction_year           0
extraction_type             0
extraction_type_group       0
extraction_type_class       0
management                  0
management_group            0
payment                     0
payment_type                0
water_quality               0
quality_group               0
quantity                    0
quantity_group              0
source                      0
source_type                 0
source_class                0
waterpoint_type             0
waterpoint_type_group       0
status_group                0
dtype: int64
```

```
#Calculating the percentage of the missing value per column
missing_percentage_per_column = (df.isnull().sum() / len(df)) * 100

# Filtering to only print non-zero columns
non_zero_missing_percentage_columns = missing_percentage_per_column[missing_percentage_per_column > 0]

# Convert the series to a DataFrame to use the style method
non_zero_missing_percentage_df = non_zero_missing_percentage_columns.to_frame(name='Missing Percentage')

# Display the DataFrame with a gradient background
styled_df = non_zero_missing_percentage_df.style.background_gradient(cmap='coolwarm')
styled_df
```

	Missing Percentage
funder	6.122896
installer	6.153199
wpt_name	0.003367
subvillage	0.624579
public_meeting	5.612795
scheme_management	6.528620
scheme_name	48.501684
permit	5.144781

Funder

The government may examine whether there's a correlation between faulty wells and their funding sources. If a pattern emerges, they could investigate the reasons behind it and identify contributing factors. Therefore, we shall only drop the rows with missing values in this column since its only 5.86%.

```
#dropping the missing values in the funder column
df.dropna(subset=['funder'], inplace=True)
```

Installer

Both the government and Maji Safi Global are interested in determining if there's a correlation between the installer and the occurrence of faulty wells. A specific installer may be responsible for substandard work. In this case we only drop the 5.91% rows with the missing values in this column.

```
df.dropna(subset=['installer'], inplace=True)
```

Subvillage

This column gives us the location of the wells which we can get from longitude and latitude so we drop this column.

```
# We drop the subvillage column
df.drop(columns=['subvillage'], inplace=True)
```

Public_meeting

The purpose of the column, pertaining to the type of meeting, is ambiguous, therefore we drop it.

```
# We drop the public_meeting column
df.drop(columns=['public_meeting'], inplace=True)
```

Permit

Maji Safi Global aims to avoid investing in unpermitted wells, making this column valuable for our assignment. Therefore, we will only eliminate rows with missing values.

```
df.dropna(subset=['permit'], inplace=True)
```

Scheme_name and Scheme_management

The "scheme_name" column has 48.78% of its values missing, while "scheme_management" has 6.53% missing values. Since both columns provide information about the entity operating the water point, we need to explore whether the operator affects the pump's functionality. Consequently, we decide to drop the "scheme_name" column due to its high percentage of missing values and remove the missing rows from the "scheme_management" column.

```
# We drop the scheme_name column
df.drop(columns=['scheme_name'], inplace=True)

#Then drop the missing values in the scheme_management column
df.dropna(subset=['scheme_management'], inplace=True)
```

wpt_name

This column provides the name of the waterpoint, which is not significant for our objective. We have other features that capture the geographical location of the well so we just drop the column entirely.

```
#dropping the wpt_name column
df.drop(columns=['wpt_name'], inplace=True)
```

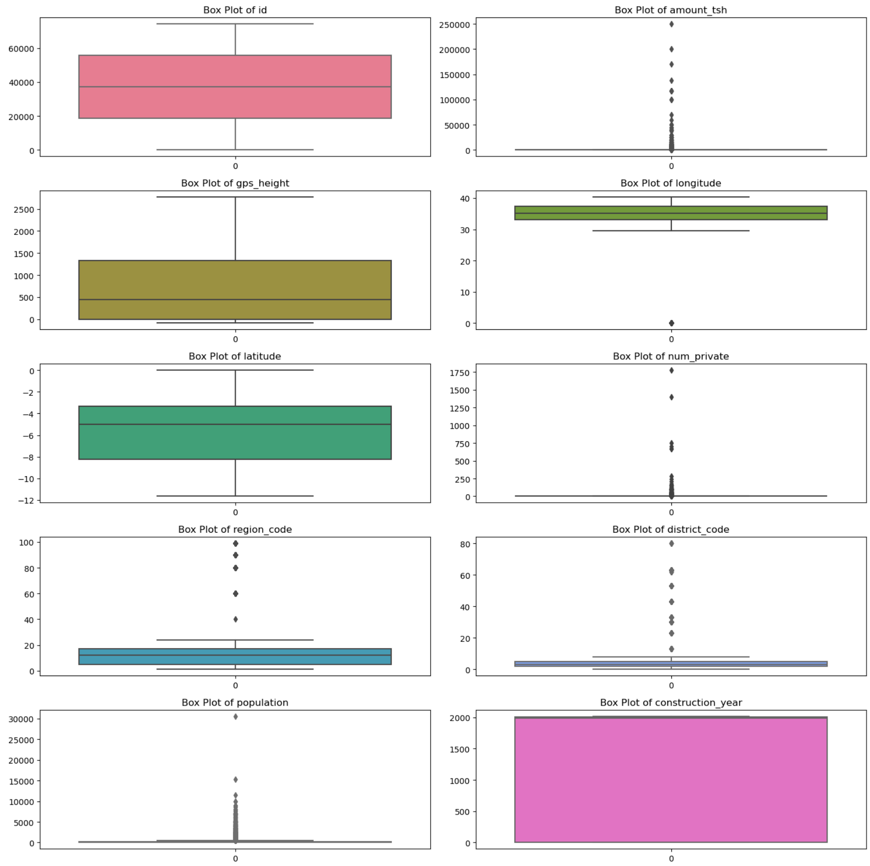
```
#Counter checking Missing Values
df.isnull().sum().sum()
```

```
0
```

Great! Our dataset does not have any missing values.

3. Outliers

```
# Selecting numerical columns
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns

# To do a layout of two columns
num_columns = 2

# Calculating the number of rows needed
num_rows = len(numerical_columns) // num_columns + (len(numerical_columns) % num_columns > 0)

# Create a figure and set the size
fig, axes = plt.subplots(num_rows, num_columns, figsize=(15, num_rows * 3))

# Flatten the axes array for easy iteration
axes = axes.flatten()

# Define a colormap
colors = sns.color_palette("husl", len(numerical_columns))

# Loop through each numerical column and create a box plot
for i, column in enumerate(numerical_columns):
    sns.boxplot(data=df[column], ax=axes[i], color=colors[i])
    axes[i].set_title('Box Plot of {}'.format(column))

# Remove any unused subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

# Adjust the layout
plt.tight_layout()
plt.show()
```



From the visualization, we can see that amount_tsh, longitude, num_private, region_code, district_code, and population contain outliers. Since longitude, region_code, and district_code correspond to actual geographical locations, we will leave these values unchanged. Furthermore, amount_tsh, num_private, and population are meaningful indicators, and we will perform exploratory data analysis (EDA) to examine their distributions in more detail.

4. Dropping of Columns

```
#Previewing the columns we have
df.columns
```

```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'num_private', 'basin', 'region',
```

```
            'region_code', 'district_code', 'lga', 'ward', 'population',
            'recorded_by', 'scheme_management', 'permit', 'construction_year',
            'extraction_type', 'extraction_type_group', 'extraction_type_class',
            'management', 'management_group', 'payment', 'payment_type',
            'water_quality', 'quality_group', 'quantity', 'quantity_group',
            'source', 'source_type', 'source_class', 'waterpoint_type',
            'waterpoint_type_group', 'status_group'],
           dtype='object')
```

Given our business objective to identify wells requiring repair and to detect patterns in non-functional wells, not all columns will be relevant to this task. Consequently, we will drop the following columns:

1. date_recorded
2. num_private
3. region_code
4. discrict_code
5. ward
6. extraction_type_group
7. extraction_type_class
8. management_group
9. payment_type
10. quality_group
11. quantity_group
12. source_type
13. waterpoint_type_group
14. recorded_by

date_recorded

We will drop this column because, in relation to our objective, the date is not significant. Our primary focus is on the functionality of the well

```
#dropping the date_recorded column
df.drop(columns=['date_recorded'], inplace=True)
```

num_private

```
# Calculate value counts as percentages
num_private_percentage = df["num_private"].value_counts(normalize=True) * 100

# Display the percentages
print(num_private_percentage)
```

```
num_private
0       98.539392
6        0.157956
1        0.140406
5        0.089704
8        0.089704
           ...
35       0.001950
141      0.001950
213      0.001950
698      0.001950
1402     0.001950
Name: proportion, Length: 61, dtype: float64
```

The data in this column is unclear, and since 98% of its values are zeros, we will drop it.

```
#Dropping the num_private column
df.drop(columns=['num_private'], inplace=True)
```

region_code & district_code

Since these columns provide geographical location details already captured by the 'region' column, we will drop them.

```
#Dropping the two columns
df.drop(columns=['region_code', 'district_code'], inplace=True)
```

ward

This column provides geographical location details, but the information in the 'region' and 'lga' columns is sufficient for our objective, so we will drop it.

```
#dropping the ward column
df.drop(columns=['ward'], inplace=True)
```

extraction_type_group & extraction_type_class

Since these columns provide the same details already captured by the 'extraction_type' column, we will drop them.

```
df["extraction_type"] == df['extraction_type_group']
```

```
0        True
1        True
2        True
3        True
5        True
         ...
59394    True
59395    True
59396    True
59398    True
59399    True
Length: 51280, dtype: bool
```

```
#Dropping the two columns
df.drop(['extraction_type_group', 'extraction_type_class'], axis=1, inplace=True)
```

management_group

This column provides details similar to those in the 'management' column, so we will drop it and use the information from the 'management' column instead.

```
#dropping the management_group column
df.drop(columns=['management_group'], inplace=True)
```

payment_type

This column provides details similar to those in the 'payment' column, so we will drop it and use the information from the 'payment' column instead.

```
#dropping the payment_type column
df.drop(columns=['payment'], inplace=True)
```

quality_group

This column provides details similar to those in the 'water_quality' column, so we will drop it and use the information from the 'water_quality' column instead.

```
#Dropping the quality_group column
df.drop(columns=['quality_group'], inplace=True)
```

quantity_group

As above, this column provides details similar to those in the 'quantity' column, so we will drop it and use the information from the 'quantity' column instead.

```
#Dropping the quantity_group column
df.drop(columns=['quantity_group'], inplace=True)
```

source_type

This columns provide details similar to those in the 'source' column, so we will drop it and rely on the information in the 'source' column.

```
#Dropping the two columns
df.drop(columns=['source_type', 'source_class'], inplace=True)
```

waterpoint_type_group

This column provides details similar to those in the 'waterpoint_type' column, so we will drop it and use the information from the 'waterpoint_type' column instead.

```
#Dropping the waterpoint_type_group column
df.drop(columns=['waterpoint_type_group'], inplace=True)
```

recorded_by

Since all the values were recorded by the same consulting firm, dropping this collun will not affect our objective

```
df.drop(columns=['recorded_by'], inplace=True)
```

```
df.shape
```

```
(51280, 22)
```

```
(df["funder"]).value_counts()
```

```
funder
Government Of Tanzania    8510
Danida                    3107
Hesawa                    1560
Kkkt                      1265
World Bank                1239
                          ...
Rwi                          1
Muwasa                       1
Msigw                        1
Overland High School         1
Brown                        1
Name: count, Length: 1681, dtype: int64
```

```
#Saving a copy of my clean data
df.to_csv('cleaned_df.csv', index=False)
```

Exploratory Data Analysis

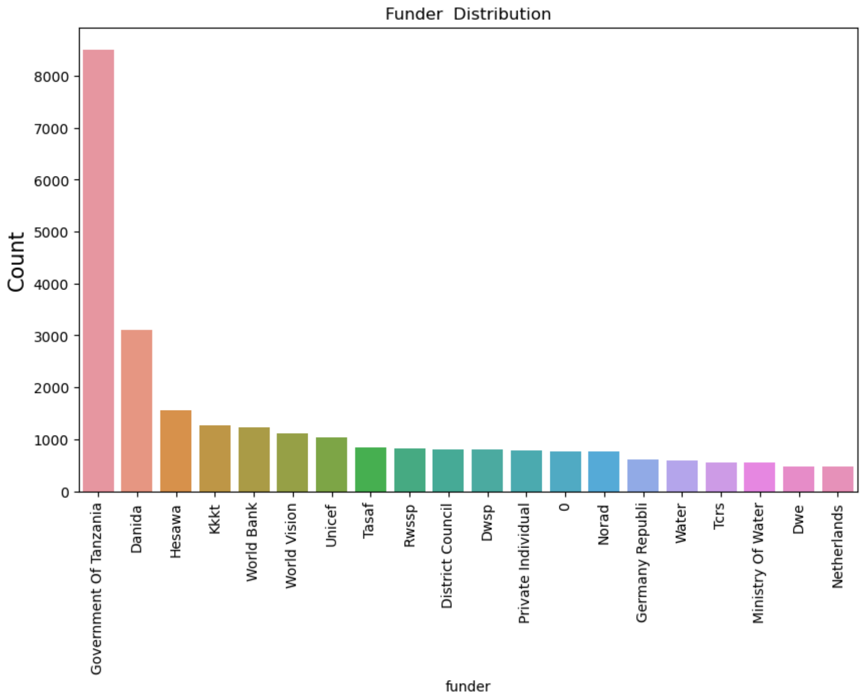
Univariate Analysis

```
# Select columns
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns
categorical_columns = df.select_dtypes(include=['object']).columns
```

```
# Function to plot distribution of a specified column
def plot_data(df, column, title):
    fig, ax = plt.subplots(figsize=(10, 6))

    # Getting the value counts for the  column
    counts = df[column].value_counts()

    # Plotting the top 20 most frequent values
    sns.barplot(x=counts.head(20).index, y=counts.head(20).values, ax=ax)

    # Setting the title and labels
    ax.set_title(title)
    ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
    ax.set_ylabel('Count', fontsize=15)

    # Show the plot
    plt.show()
```

Funder Distribution

```
plot_data(df, 'funder', 'Funder  Distribution')
```

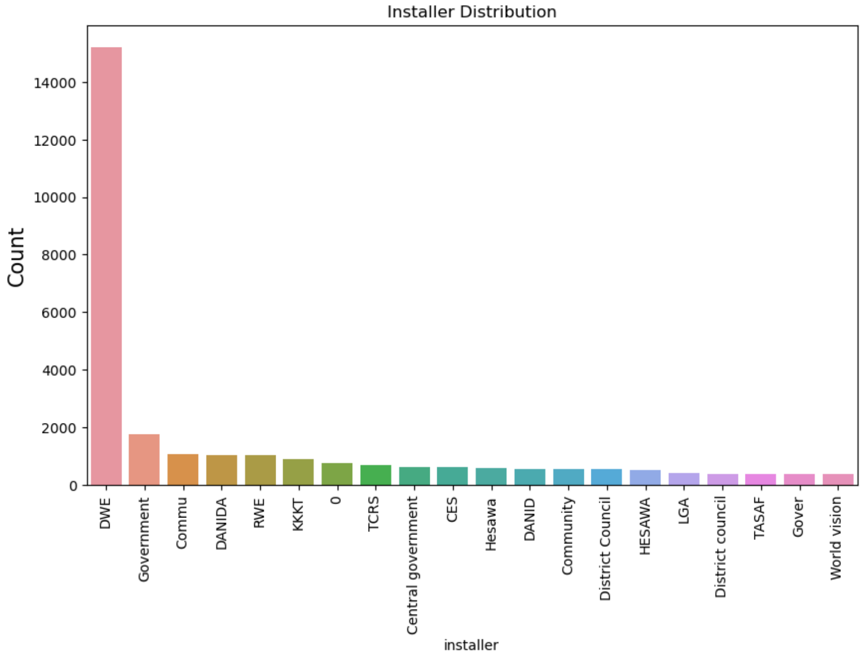


From the above, Tanzanian Goverment is the greatest funder. Also from the distribution we have a funder "0" which we shall treat as unknown.

```
# Replacing 0 with unknown
df['funder'].replace({np.nan: 'Unknown', '0': 'Unknown'}, inplace=True)
```

Installer Distribution

```
plot_data(df, 'installer', 'Installer Distribution')
```

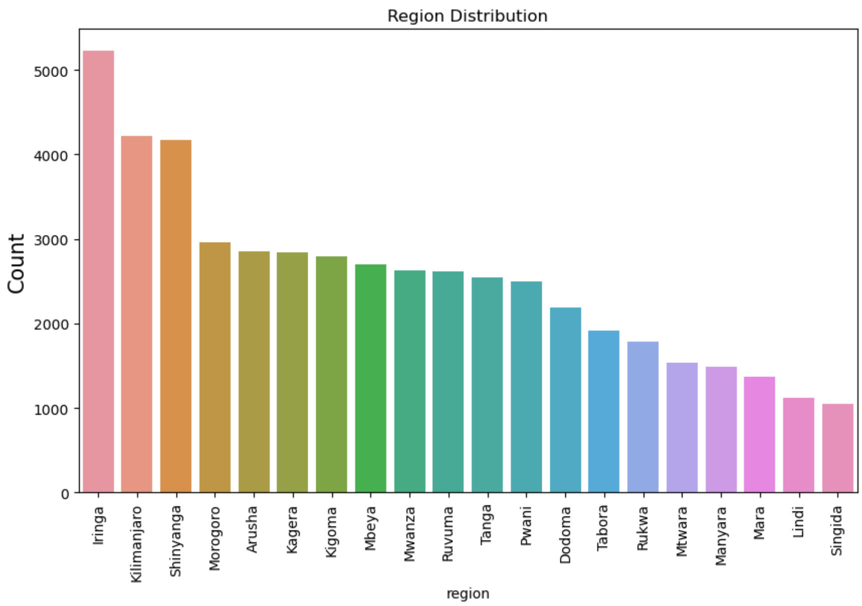


DWE has done the most installation. We also can see there is a in staller called '0' which we shall treat as unknown

```
# Replacing 0 with unknown
df['installer'].replace({np.nan: 'Unknown', '0': 'Unknown'}, inplace=True)
```

Region Distribution

```
plot_data(df, 'region', 'Region Distribution')
```



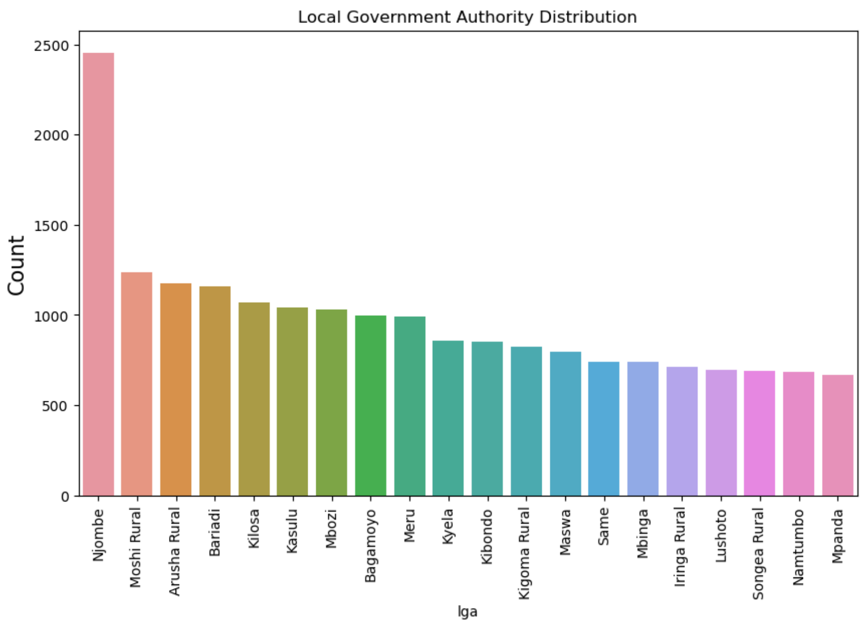
Most wells are in the iringa region.

```
df.columns
```

```
Index(['id', 'amount_tsh', 'funder', 'gps_height', 'installer', 'longitude',
       'latitude', 'basin', 'region', 'lga', 'population', 'scheme_management',
       'permit', 'construction_year', 'extraction_type', 'management',
       'payment_type', 'water_quality', 'quantity', 'source',
       'waterpoint_type', 'status_group'],
      dtype='object')
```

Local Government Authority Distribution

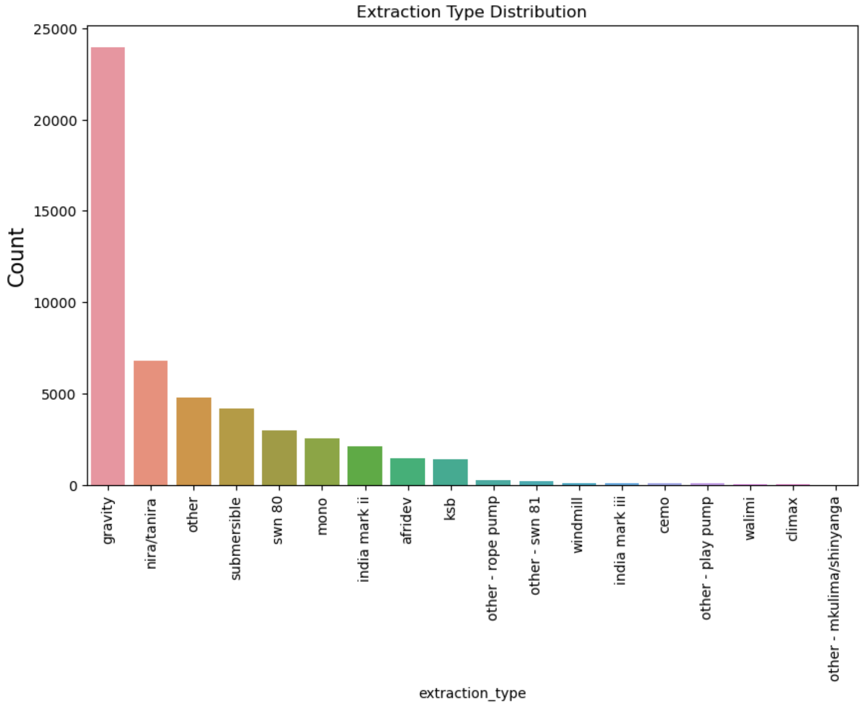
```
plot_data(df,'lga', 'Local Government Authority Distribution')
```



Most Wells are within Njombe Area.

Extraction Type Distribution

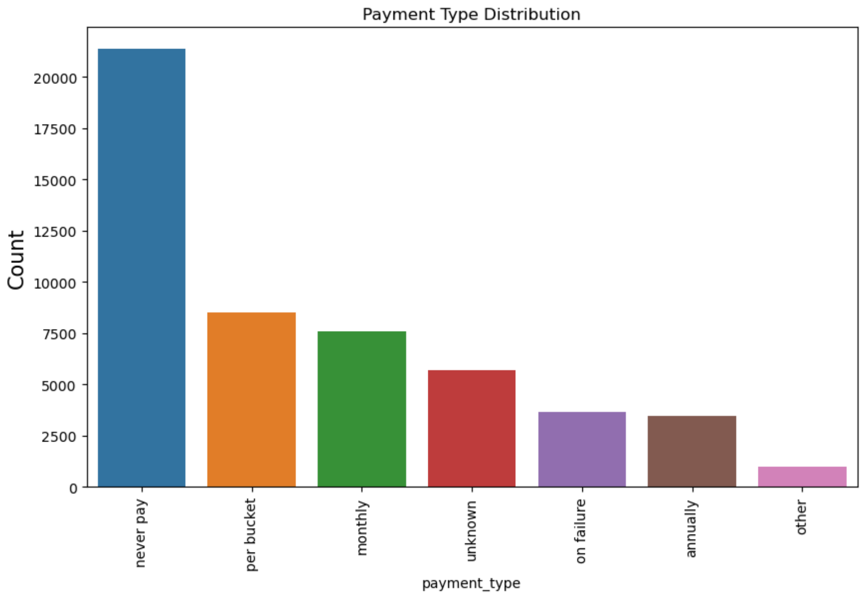
```
plot_data(df, 'extraction_type', 'Extraction Type Distribution')
```



Gravity is the most common extraction type according to the distribution.

Payment Type Distribution

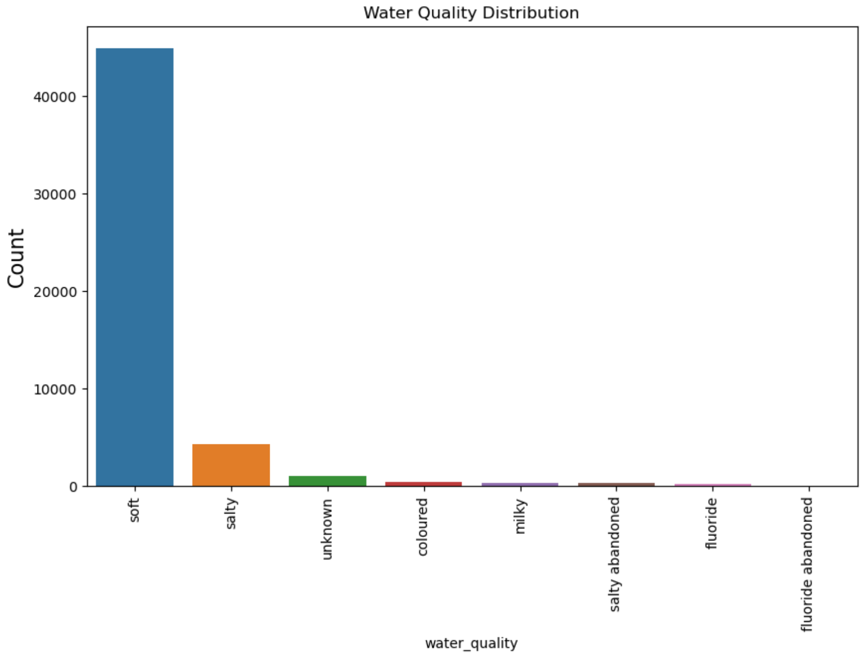
```
plot_data(df, 'payment_type', 'Payment Type Distribution')
```



Most of the wells do not require payment to access water.

Water Quality Distribution

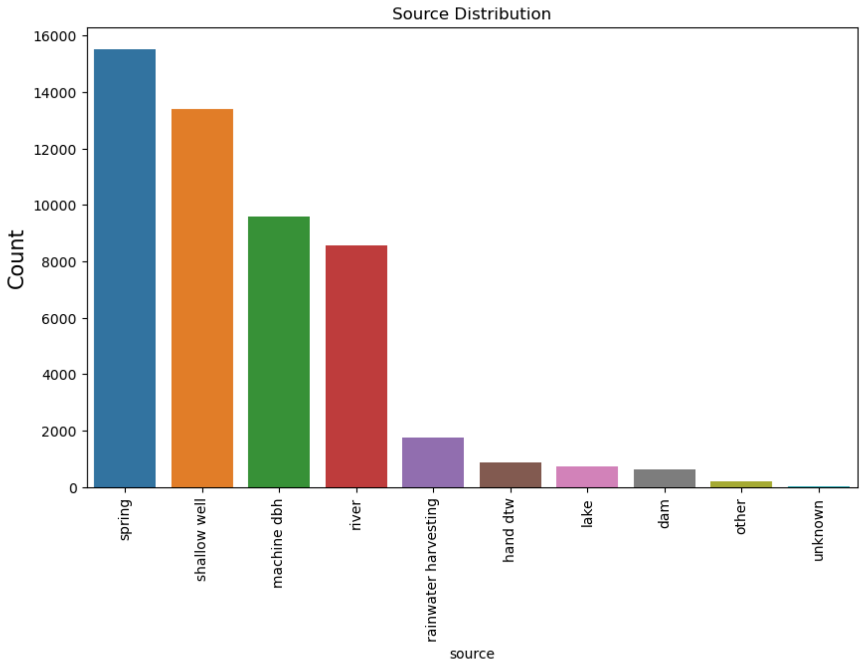
```
plot_data(df, 'water_quality', 'Water Quality Distribution')
```



Most Wells have soft water.

Source Distribution

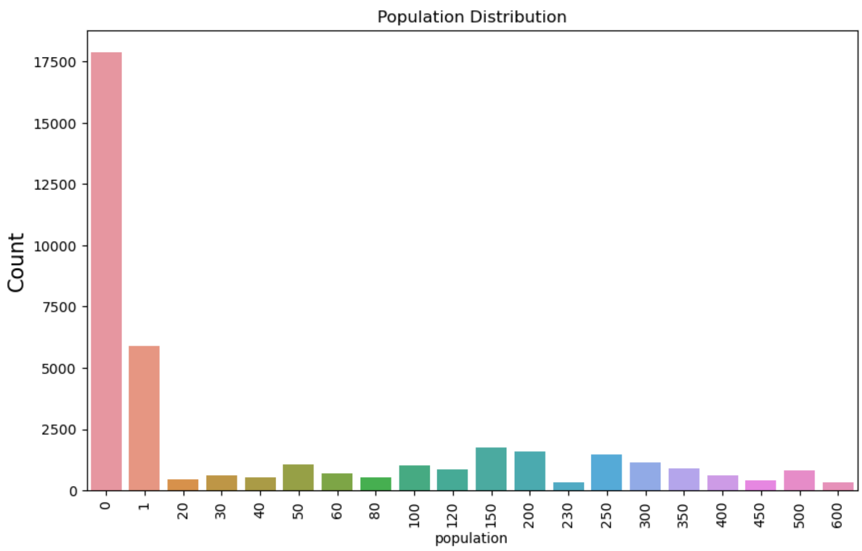
```
plot_data(df,'source', 'Source Distribution')
```



Most Water sources are springs

Population Distribution

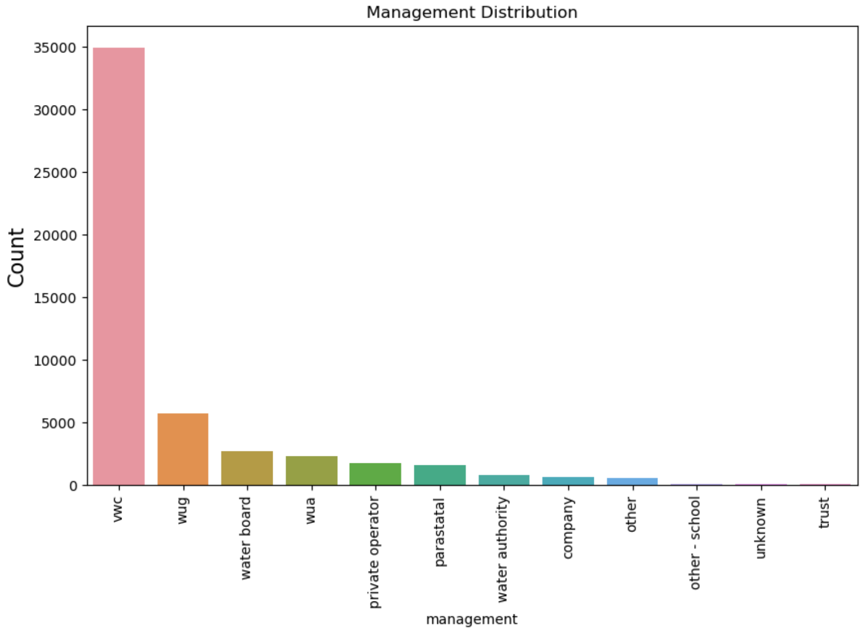
```
plot_data(df,'population', 'Population Distribution')
```



From the distribution above, it is evident that most wells have no people around them. This indicates that the majority of people obtain water through other means rather than directly from the well.

Management Distribution

```
plot_data(df,'management', 'Management Distribution')
```

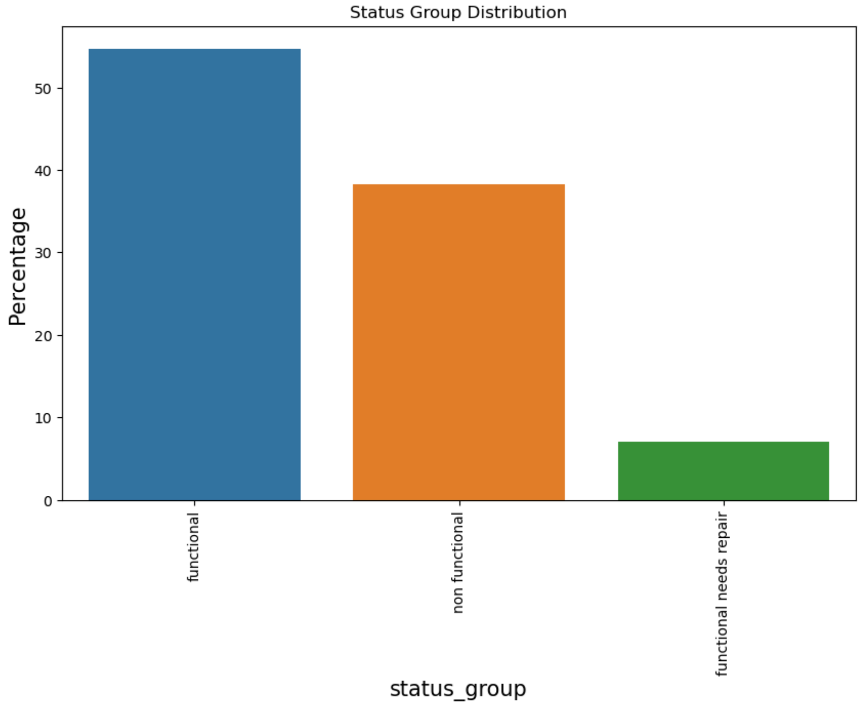


The distribution above indicates that vwc manages most waterpoints.

Status Group Distribution

```
def plot_data(df, column, title):
    fig, ax = plt.subplots(figsize=(10, 6))

    # Getting the value counts and convert them to percentages
    counts = df[column].value_counts(normalize=True) * 100

    # Plot the top 20 most frequent values as percentages
    sns.barplot(x=counts.head(20).index, y=counts.head(20).values, ax=ax)

    # Set the title and labels
    ax.set_title(title)
    ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
    ax.set_ylabel('Percentage', fontsize=15)
    ax.set_xlabel(column, fontsize=15)

    # Show the plot
    plt.show()
```

```
plot_data(df,'status_group', 'Status Group Distribution')
```

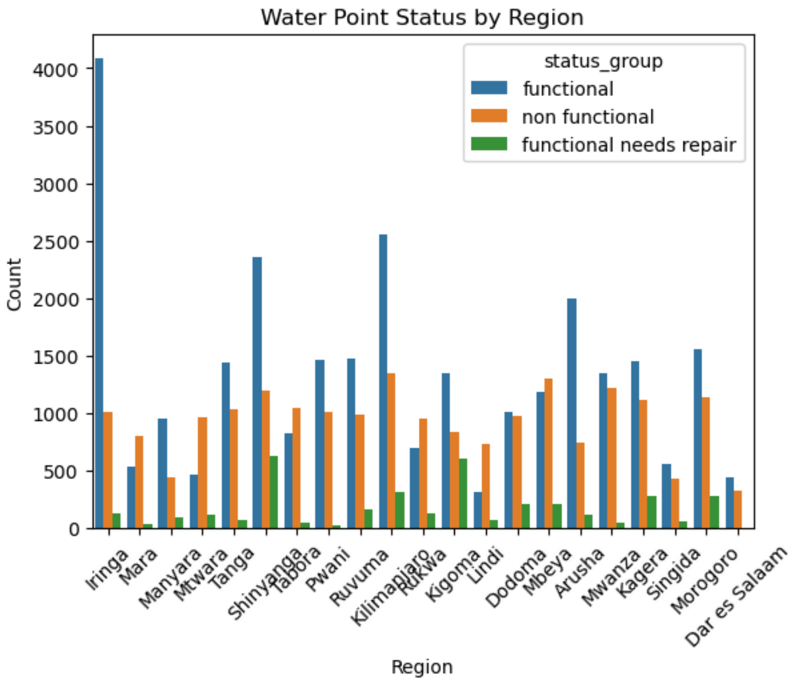


Based on the distribution, about 55% of the water points are functional, 38% are non-functional, and 7% are functional but require repairs.

Bivariate Analysis

Water Point Status by Region

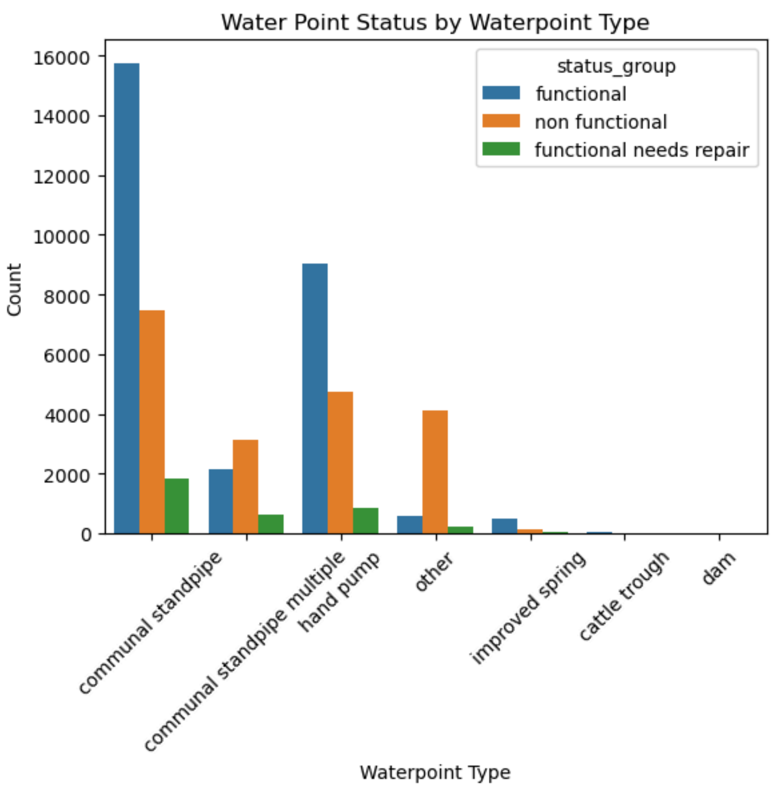
```
# Visualization
sns.countplot(data=df, x='region', hue='status_group')
plt.title('Water Point Status by Region')
plt.xlabel('Region')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



Based on the distribution, Iringa has the highest number of functional water points, Ruvuma has the most non-functional water points, and Tanga has the most water points that need repair.

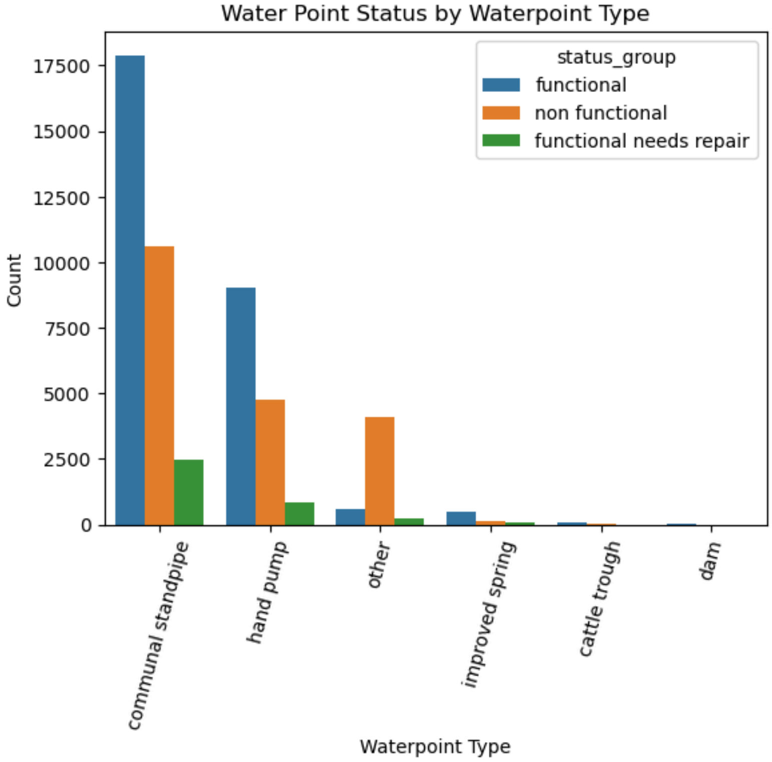
'Water Point Status by Waterpoint Type

```
# Visualization
sns.countplot(data=df, x='waterpoint_type', hue='status_group')
plt.title('Water Point Status by Waterpoint Type')
plt.xlabel('Waterpoint Type')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



From the distribution, there is communal standpipe and communal standpipe multiple, for the sake of this analysis We shall treat this as the same and plot the distribution again

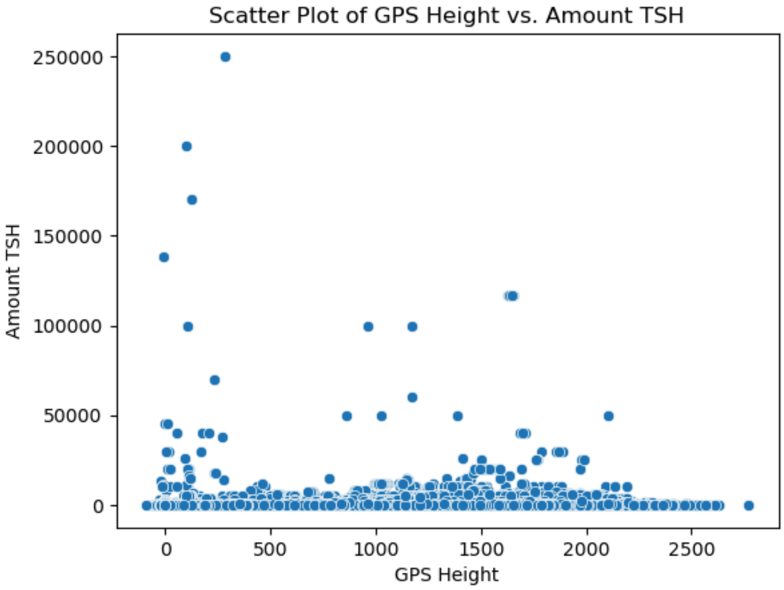
```
df['waterpoint_type'].replace('communal standpipe multiple', 'communal standpipe', inplace=True)


sns.countplot(data=df, x='waterpoint_type', hue='status_group')
plt.title('Water Point Status by Waterpoint Type')
plt.xlabel('Waterpoint Type')
plt.ylabel('Count')
plt.xticks(rotation=75)
plt.show()
```



GPS Height vs. Amount TSH

```
correlation = df['gps_height'].corr(df['amount_tsh'])
print(f"Pearson correlation: {correlation}")

# Visualization
sns.scatterplot(data=df, x='gps_height', y='amount_tsh')
plt.title('Scatter Plot of GPS Height vs. Amount TSH')
plt.xlabel('GPS Height')
plt.ylabel('Amount TSH')
plt.show()
```

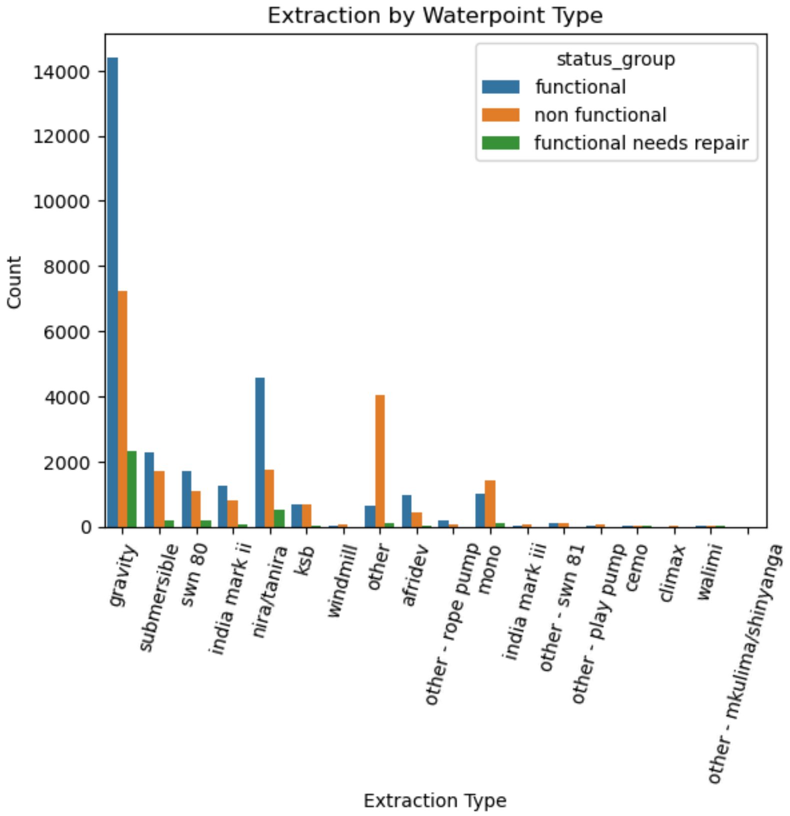
```
Pearson correlation: 0.08710911836363372
```



The Pearson Correlation of 0.087109 indicates a very weak positive correlation between gps_height and amount_tsh. This implies that elevation alone might not be a significant factor in determining the water available from a water source.

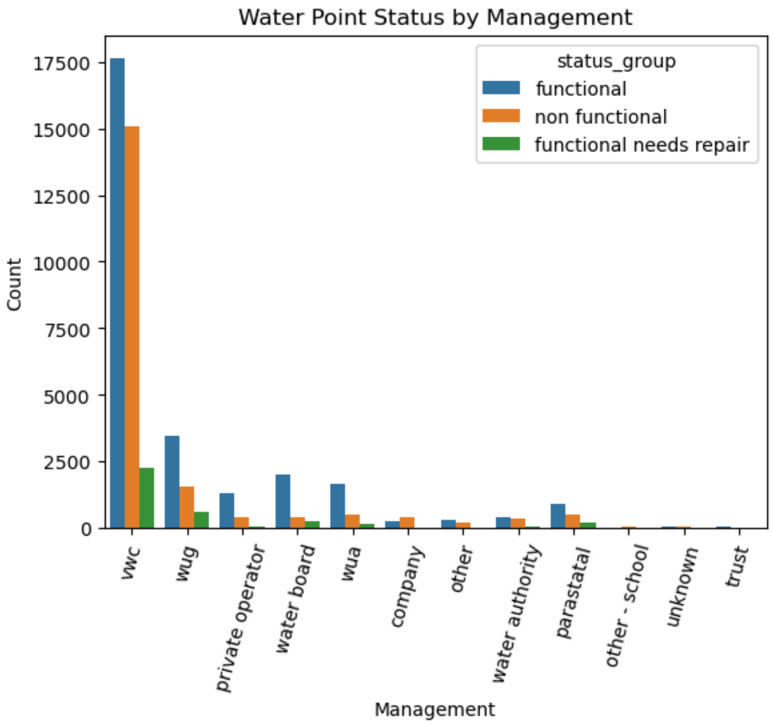
Extraction type vs. Status_group

```
sns.countplot(data=df, x='extraction_type', hue='status_group')
plt.title('Extraction by Waterpoint Type')
plt.xlabel('Extraction Type')
plt.ylabel('Count')
plt.xticks(rotation=75)
plt.show()
```



Management vs Status Group

```
sns.countplot(data=df, x='management', hue='status_group')
plt.title('Water Point Status by Management')
plt.xlabel('Management')
plt.ylabel('Count')
plt.xticks(rotation=75)
plt.show()
```



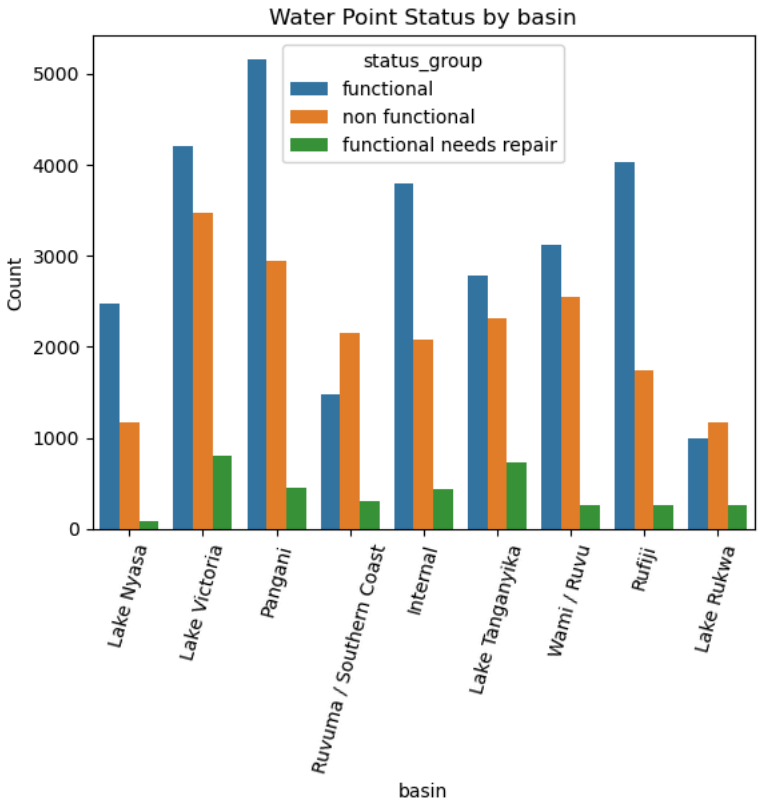
Most waterpoints are managed by vwc.

```
df.columns
```

```
Index(['id', 'amount_tsh', 'funder', 'gps_height', 'installer', 'longitude',
       'latitude', 'basin', 'region', 'lga', 'population', 'scheme_management',
       'permit', 'construction_year', 'extraction_type', 'management',
       'payment_type', 'water_quality', 'quantity', 'source',
       'waterpoint_type', 'status_group'],
      dtype='object')
```

Basin vs Status Group

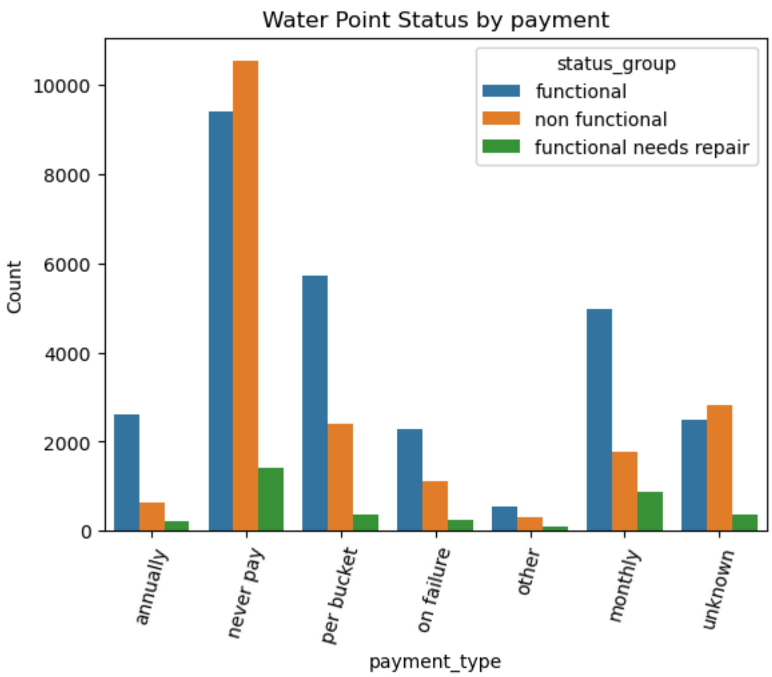
```
sns.countplot(data=df, x='basin', hue='status_group')
plt.title('Water Point Status by basin')
plt.xlabel('basin')
plt.ylabel('Count')
plt.xticks(rotation=75)
plt.show()
```



This data indicates that Pangani has the highest number of operational water points, while Lake Victoria has the highest number of non-functional water points as well as those requiring repair.

Payment Type Vs Status Group

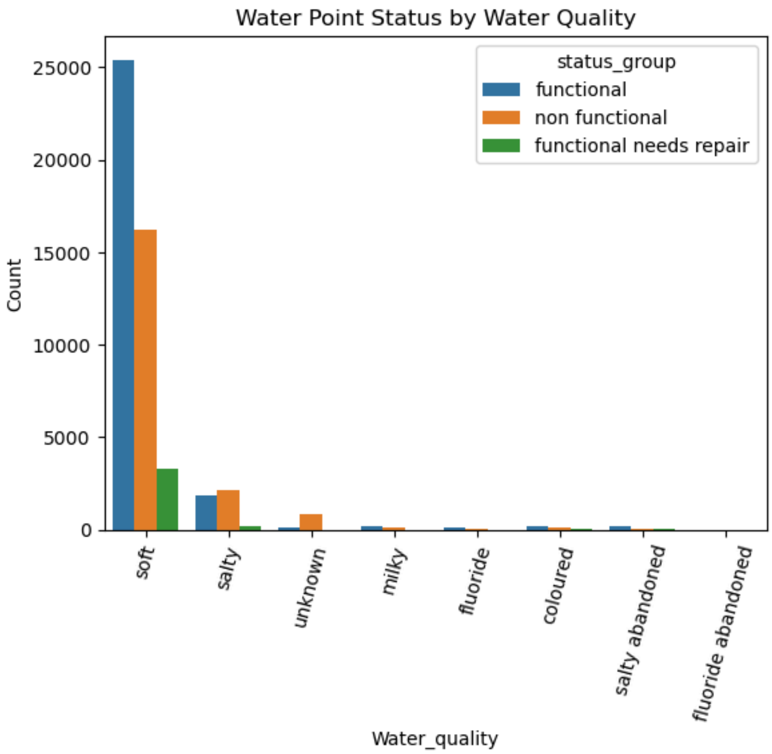
```
sns.countplot(data=df, x='payment_type', hue='status_group')
plt.title('Water Point Status by payment')
plt.xlabel('payment_type')
plt.ylabel('Count')
plt.xticks(rotation=75)
plt.show()
```



The water points lacking payment records exhibit the highest proportion of non-functional status.

Water Quality vs Status Group

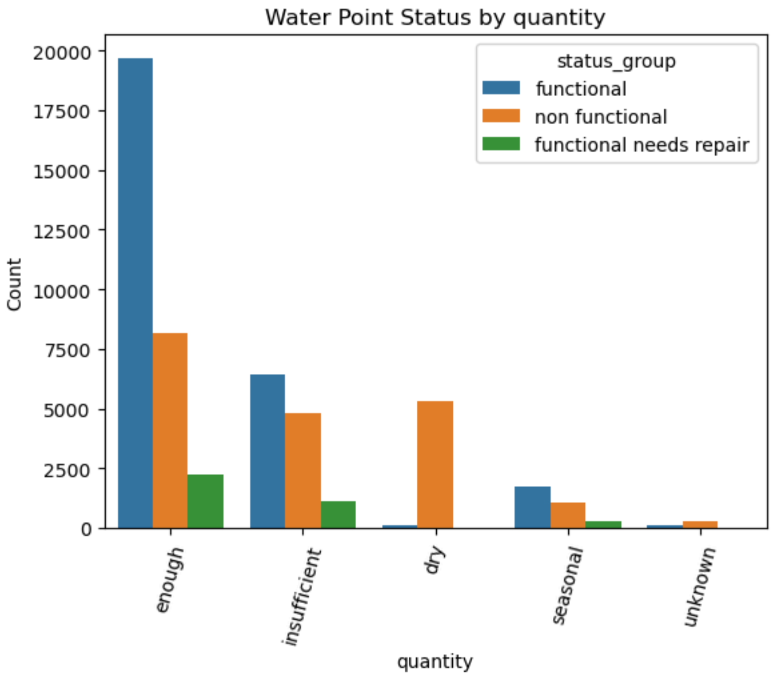
```
sns.countplot(data=df, x='water_quality', hue='status_group')
plt.title('Water Point Status by Water Quality')
plt.xlabel('Water_quality')
plt.ylabel('Count')
plt.xticks(rotation=75)
plt.show()
```



Most fucntional waterpoints have soft water.

Quantity Vs Status Group

```
#Plotting
sns.countplot(data=df, x='quantity', hue='status_group')
plt.title('Water Point Status by quantity')
plt.xlabel('quantity')
plt.ylabel('Count')
plt.xticks(rotation=75)
plt.show()
```



Functional water points generally have sufficient water, yet a considerable number of non-functional ones and those in need of repair also exhibit adequate water supply.

Waterpoint Age Vs Status Group

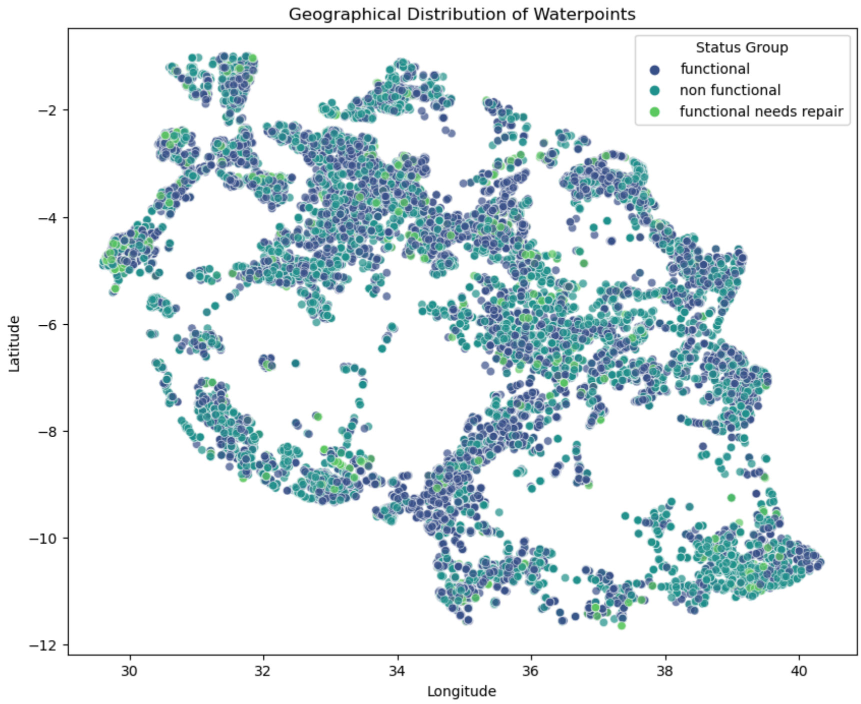
We start with feature engineering the Age column and then plot Age Vs Functionality to see whether age influences the functionality of the waterpoin.

```
# Plotting barplot of average waterpoint age for each status group
plt.figure(figsize=(10, 6))
sns.barplot(data=df, x='status_group', y='waterpoint_age', estimator=np.mean)
plt.title('Average Waterpoint Age vs Status Group')
plt.xlabel('Status Group')
plt.ylabel('Average Waterpoint Age')
plt.show()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[79], line 3
      1 # Plotting barplot of average waterpoint age for each status group
      2 plt.figure(figsize=(10, 6))
----> 3 sns.barplot(data=df, x='status_group', y='waterpoint_age',
estimator=np.mean)
      4 plt.title('Average Waterpoint Age vs Status Group')
      5 plt.xlabel('Status Group')

File ~\anaconda3\Lib\site-packages\seaborn\categorical.py:2755, in barplot(data, x,
y, hue, order, hue_order, estimator, errorbar, n_boot, units, seed, orient, color,
palette, saturation, width, errcolor, errwidth, capsize, dodge, ci, ax, **kwargs)
   2752 if estimator is len:
   2753     estimator = "size"
-> 2755 plotter = _BarPlotter(x, y, hue, data, order, hue_order,
   2756                       estimator, errorbar, n_boot, units, seed,
   2757                       orient, color, palette, saturation,
   2758                       width, errcolor, errwidth, capsize, dodge)
   2760 if ax is None:
   2761     ax = plt.gca()

File ~\anaconda3\Lib\site-packages\seaborn\categorical.py:1530, in
_BarPlotter.__init__(self, x, y, hue, data, order, hue_order, estimator, errorbar,
n_boot, units, seed, orient, color, palette, saturation, width, errcolor, errwidth,
capsize, dodge)
   1525 def __init__(self, x, y, hue, data, order, hue_order,
   1526              estimator, errorbar, n_boot, units, seed,
   1527              orient, color, palette, saturation, width,
   1528              errcolor, errwidth, capsize, dodge):
   1529     """Initialize the plotter."""
-> 1530     self.establish_variables(x, y, hue, data, orient,
   1531                              order, hue_order, units)
   1532     self.establish_colors(color, palette, saturation)
   1533     self.estimate_statistic(estimator, errorbar, n_boot, seed)

File ~\anaconda3\Lib\site-packages\seaborn\categorical.py:541, in
_CategoricalPlotter.establish_variables(self, x, y, hue, data, orient, order,
hue_order, units)
    539     if isinstance(var, str):
    540         err = f"Could not interpret input '{var}'"
--> 541         raise ValueError(err)
    543 # Figure out the plotting orientation
    544 orient = infer_orient(
    545     x, y, orient, require_numeric=self.require_numeric
```

Longtitude vs Latitude

```
# Exclude longitude values equal to zero
df_filtered = df[df['longitude'] != 0]

# Plot the scatter plot
plt.figure(figsize=(10, 8))
sns.scatterplot(data=df_filtered, x='longitude', y='latitude', hue='status_group', palette='viridis', alpha=0.7)
plt.title('Geographical Distribution of Waterpoints')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.legend(title='Status Group')
plt.show()
```



This shows the geographical distribution of the waterpoints.

```
df.columns
```

```
Index(['id', 'amount_tsh', 'funder', 'gps_height', 'installer', 'longitude',
       'latitude', 'basin', 'region', 'lga', 'population', 'scheme_management',
       'permit', 'construction_year', 'extraction_type', 'management',
       'payment_type', 'water_quality', 'quantity', 'source',
       'waterpoint_type', 'status_group'],
      dtype='object')
```

Multivariate Analysis

```
selected_numerical_columns = ['amount_tsh', 'gps_height', 'longitude', 'latitude', 'population', 'construction_year']
sns.pairplot(df, vars=selected_numerical_columns, hue='status_group')
plt.suptitle('Pair Plots of Selected Numerical Columns by Water Well Status', y=1.02)
plt.show()
```

```
C:\Users\HP 430\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\HP 430\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\HP 430\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\HP 430\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\HP 430\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\HP 430\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be
  with pd.option_context('mode.use_inf_as_na', True):
```

Multivariate Regression

```
import statsmodels.api as sm
# Selecting features and target variable
features = df[['amount_tsh', 'gps_height', 'longitude', 'latitude', 'population', 'construction_year']]
target = df['status_group'].apply(lambda x: 1 if x == 'functional' else 0)  # Assuming binary classification for simplicity

# Adding a constant for the intercept
features = sm.add_constant(features)

# Fitting the model
model = sm.Logit(target, features).fit()

# Printing the summary
print(model.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.675395
         Iterations 7
                           Logit Regression Results
==============================================================================
Dep. Variable:           status_group   No. Observations:                51280
Model:                          Logit   Df Residuals:                    51273
Method:                           MLE   Df Model:                            6
Date:                Wed, 22 May 2024   Pseudo R-squ.:                 0.01937
Time:                        20:03:56   Log-Likelihood:                -34634.
converged:                       True   LL-Null:                       -35318.
Covariance Type:            nonrobust   LLR p-value:                1.636e-292
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                -0.2199      0.047     -4.710      0.000      -0.311      -0.128
amount_tsh            0.0002   1.23e-05     16.371      0.000       0.000       0.000
gps_height            0.0004   1.77e-05     22.680      0.000       0.000       0.000
longitude             0.0099      0.002      6.363      0.000       0.007       0.013
latitude              0.0247      0.004      7.019      0.000       0.018       0.032
population         3.484e-06   1.99e-05      0.175      0.861   -3.55e-05    4.25e-05
construction_year -8.548e-05   1.43e-05     -5.973      0.000      -0.000   -5.74e-05
=====================================================================================
```

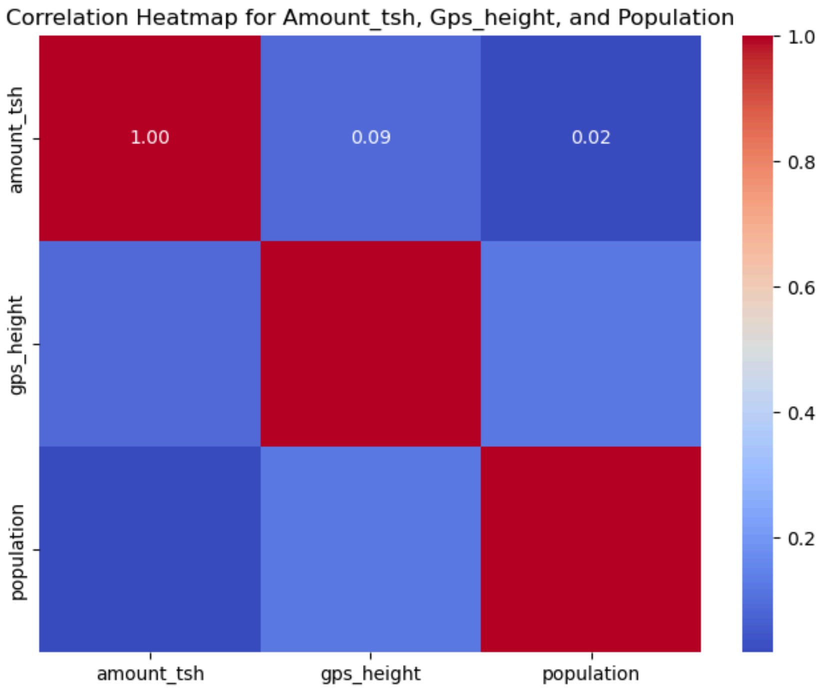
Correlation Matrix

```
# Assuming your DataFrame is named 'df'
correlation_matrix = df[['amount_tsh', 'gps_height', 'longitude', 'latitude', 'population', 'construction_year']].corr()
print(correlation_matrix)
```

```
                   amount_tsh  gps_height  longitude  latitude  population  \
amount_tsh           1.000000    0.087109   0.024593 -0.068407    0.016469
gps_height           0.087109    1.000000   0.152819 -0.115550    0.122368
longitude            0.024593    0.152819   1.000000 -0.431184    0.079686
latitude            -0.068407   -0.115550  -0.431184  1.000000   -0.041953
population           0.016469    0.122368   0.079686 -0.041953    1.000000
construction_year    0.077846    0.649768   0.404834 -0.311839    0.250472

                   construction_year
amount_tsh                  0.077846
gps_height                  0.649768
longitude                   0.404834
latitude                   -0.311839
population                  0.250472
construction_year           1.000000
```

Heatmap

```
# Computing the correlation matrix for numerical variables 'amount_tsh', 'gps_height', and 'population'
numerical_columns = ['amount_tsh', 'gps_height', 'population']
correlation_matrix = df[numerical_columns].corr()

# Plot heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap for Amount_tsh, Gps_height, and Population')
plt.show()
```



Data Preprocessing

Feature Importance

```
#Function to preprocess data
def preprocess_data(df):
    # Define numerical and categorical columns
    numerical_cols = ['amount_tsh', 'gps_height', 'population']
    categorical_cols = ['funder', 'installer', 'region', 'scheme_management', 'extraction_type', 'management', 'payment_type', 'water_qu

    # Preprocessing pipelines for numerical and categorical data
    numerical_transformer = Pipeline(steps=[
        ('imputer', SimpleImputer(strategy='median')),
        ('scaler', StandardScaler())
    ])

    categorical_transformer = Pipeline(steps=[
        ('imputer', SimpleImputer(strategy='most_frequent')),
        ('onehot', OneHotEncoder(handle_unknown='ignore'))
    ])

    # Combine numerical and categorical transformers into a ColumnTransformer
    preprocessor = ColumnTransformer(
        transformers=[
            ('num', numerical_transformer, numerical_cols),
            ('cat', categorical_transformer, categorical_cols)
        ]
    )

    # Separate target variable and features
    X = df.drop('status_group', axis=1)
    y = df['status_group']

    # Preprocess the data
    X_processed = preprocessor.fit_transform(X)

    return X_processed, y
```

```
df.columns
```

```
Index(['id', 'amount_tsh', 'funder', 'gps_height', 'installer', 'longitude',
       'latitude', 'basin', 'region', 'lga', 'population', 'scheme_management',
       'permit', 'construction_year', 'extraction_type', 'management',
       'payment_type', 'water_quality', 'quantity', 'source',
       'waterpoint_type', 'status_group'],
      dtype='object')
```

Modeling

Our objectives are to deliver thorough and practical insights that will inform strategic investments and enhance the performance of wells in Tanzania. We will start with data preprocessing and then apply the following algorithms:

```
Logistic
Decision Tree
Random Forest
Gradient Boosting
XGBoost
```

Logistic Regression

```
# Function to train a Logistic Regression model
def train_model(X_train, y_train):
    model = LogisticRegression(max_iter=1000)  # Increased max_iter to ensure convergence
    model.fit(X_train, y_train)
    return model

# Function to evaluate a model
def evaluate_model(model, X_test, y_test):
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted')
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')
    conf_matrix = confusion_matrix(y_test, y_pred)
    class_report = classification_report(y_test, y_pred)

    return accuracy, precision, recall, f1, conf_matrix, class_report


# Preprocess data
X_processed, y = preprocess_data(df)

# Split data
X_train, X_test, y_train, y_test = train_test_split(X_processed, y, test_size=0.2, random_state=42)

# Train the Logistic Regression model
model = train_model(X_train, y_train)

# Evaluate the model
accuracy, precision, recall, f1, conf_matrix, class_report = evaluate_model(model, X_test, y_test)
```

Model Evaluation

```
# Print the evaluation metrics
print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 Score: {f1}")
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(class_report)
```

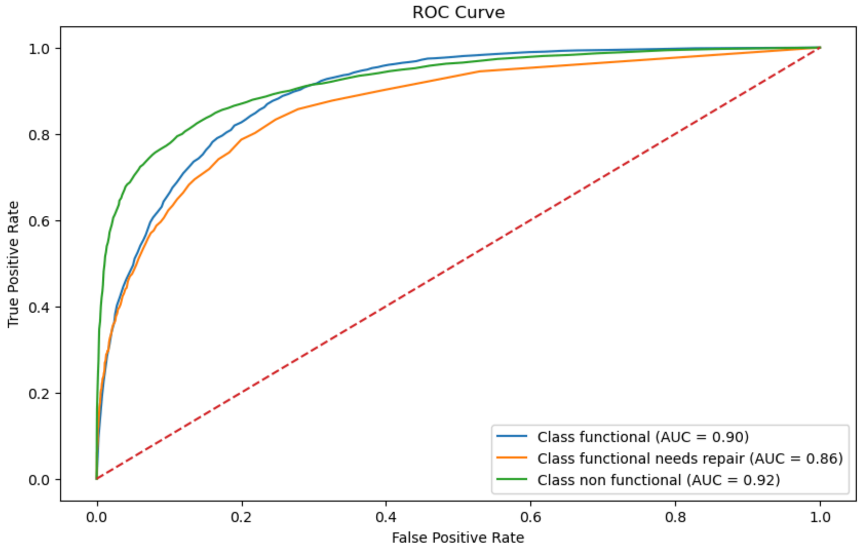
```
Accuracy: 0.7730109204368175
Precision: 0.7651272697376988
Recall: 0.7730109204368175
F1 Score: 0.7579306893391036
Confusion Matrix:
[[5007   56  538]
 [ 476  118  113]
 [1102   43 2803]]
Classification Report:
                         precision    recall  f1-score   support

             functional       0.76      0.89      0.82      5601
functional needs repair       0.54      0.17      0.26       707
         non functional       0.81      0.71      0.76      3948

               accuracy                           0.77     10256
              macro avg       0.71      0.59      0.61     10256
           weighted avg       0.77      0.77      0.76     10256
```

The model performs well overall with an accuracy of 77.30%, indicating it correctly classifies the majority of the instances. However, it struggles with the 'functional needs repair' class, as shown by the lower precision, recall, and F1-score for this class.

The Decision Tree Classifier performs reasonably well with an accuracy of around 76.8%. It is good at predicting the 'functional' and 'non functional' classes with fairly high precision and recall. The model struggles significantly with the 'functional needs repair' class, as indicated by its low precision (0.42) and recall (0.37). This suggests that the model often misclassifies waterpoints that need repair. The confusion matrix shows a substantial number of misclassifications between 'functional' and 'non functional', indicating these classes might have overlapping features that are challenging for the model to differentiate.

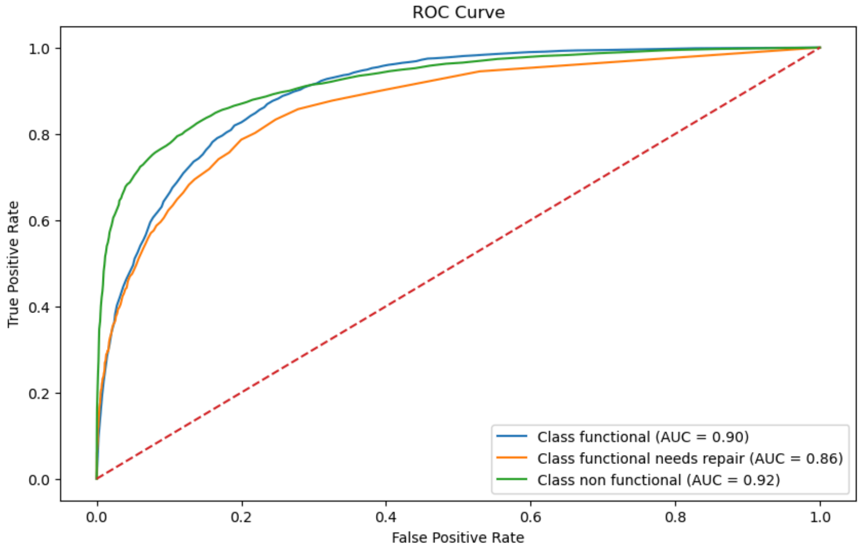
Random Forest

```
# Function to train a Random Forest model without Grid Search
def train_model(X_train, y_train):
    model = RandomForestClassifier(n_estimators=100, max_depth=None, random_state=42)
    model.fit(X_train, y_train)
    return model

# Function to evaluate a model
def evaluate_model(model, X_test, y_test):
    y_pred = model.predict(X_test)
    y_prob = model.predict_proba(X_test)

    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted')
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')
    conf_matrix = confusion_matrix(y_test, y_pred)
    class_report = classification_report(y_test, y_pred)

    # Compute ROC AUC for each class
    auc_dict = {}
    for i in range(len(model.classes_)):
        class_i_mask = (y_test == model.classes_[i])
        if np.sum(class_i_mask) > 0:
            auc_dict[f'Class {model.classes_[i]}'] = roc_auc_score(class_i_mask, y_prob[:, i])
        else:
            auc_dict[f'Class {model.classes_[i]}'] = 'Undefined (only one class present)'

    # Plot ROC curve for each class
    plt.figure(figsize=(10, 6))
    for i in range(len(model.classes_)):
        class_i_mask = (y_test == model.classes_[i])
        if np.sum(class_i_mask) > 0:
            fpr, tpr, _ = roc_curve(class_i_mask, y_prob[:, i])
            plt.plot(fpr, tpr, label=f'Class {model.classes_[i]} (AUC = {auc_dict[f"Class {model.classes_[i]}"]:.2f})')
    plt.plot([0, 1], [0, 1], linestyle='--')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend(loc='lower right')
    plt.show()

    return accuracy, precision, recall, f1, auc_dict, conf_matrix, class_report

# Preprocess data (assuming preprocess_data function is already defined)
X_processed, y = preprocess_data(df)

# Split data
X_train, X_test, y_train, y_test = train_test_split(X_processed, y, test_size=0.2, random_state=42)

# Train the Random Forest model
model = train_model(X_train, y_train)

# Evaluate the model
accuracy, precision, recall, f1, auc_dict, conf_matrix, class_report = evaluate_model(model, X_test, y_test)
```



Model Evaluation

```
# Evaluate the model
accuracy, precision, recall, f1, auc, conf_matrix, class_report = evaluate_model(model, X_test, y_test)

# Print evaluation results
print(f"Random Forest Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 Score: {f1}")
print(f"AUC: {auc}")
print(f"Confusion Matrix:\n{conf_matrix}")
print(f"Classification Report:\n{class_report}")
```

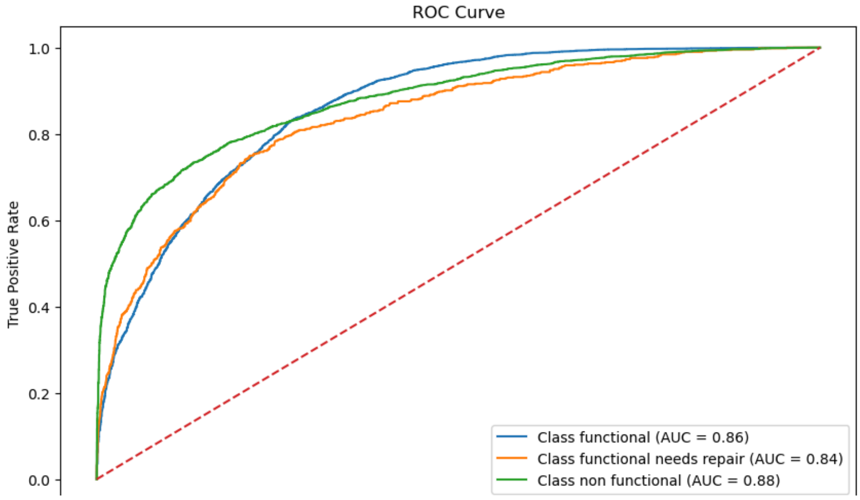



```
Random Forest Accuracy: 0.8038221528861155
Precision: 0.7977331410514492
Recall: 0.8038221528861155
F1 Score: 0.7987102844620978
AUC: {'Class functional': 0.8978929648706662, 'Class functional needs repair': 0.864S
Confusion Matrix:
[[4906  167  528]
 [ 342  250  115]
 [ 800   60 3088]]
Classification Report:
                         precision    recall  f1-score   support

             functional       0.81      0.88      0.84      5601
functional needs repair       0.52      0.35      0.42       707
         non functional       0.83      0.78      0.80      3948

               accuracy                           0.80     10256
              macro avg       0.72      0.67      0.69     10256
           weighted avg       0.80      0.80      0.80     10256
```

The model performs well overall, with high accuracy, precision, recall, and F1 scores, especially for "functional" and "non functional" classes. The AUC scores show that the model is good at distinguishing between the different classes. There is some difficulty in correctly identifying "functional needs repair" samples, which might indicate a need for further tuning or more data for that class.

Gradient Boosting Classifier

```
# Function to train a Gradient Boosting model
def train_model_gb(X_train, y_train):
    model = GradientBoostingClassifier(random_state=42)
    model.fit(X_train, y_train)
    return model


# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_processed, y, test_size=0.2, random_state=42)

# Train the Gradient Boosting model
model_gb = train_model_gb(X_train, y_train)

# Evaluate the Gradient Boosting model
accuracy_gb, precision_gb, recall_gb, f1_gb, auc_gb, conf_matrix_gb, class_report_gb = evaluate_model(model_gb, X_test, y_test)
```


ROC Curve
True Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
Class functional (AUC = 0.86)
Class functional needs repair (AUC = 0.84)
Class non functional (AUC = 0.88)