Predicting Water Pump Functionality in Tanzanian Water Wells.

1. Business Understanding

This business problem addresses a critical issue in Tanzania: the provision of clean, functional water points to its citizens. Many of the existing water pumps are either in a state of disrepair or have completely failed, creating a significant challenge for public health and development.

The core objective of this project is to build a machine learning classification model to predict the functional status of these water pumps. This predictive model will categorize each well into one of three distinct classes:

- **Functional:** The well is in working order.
- **Non-functional:** The well is completely broken and requires significant intervention.
- **Functional but needs repair:** The well is currently working but shows signs of impending failure and requires immediate maintenance to prevent it from becoming non-functional.

By accurately identifying the status of each water pump, this project aims to provide a tool that can help guide resources, streamline maintenance efforts, and ultimately improve access to clean water.

Stakeholders

This project has several key stakeholders who would benefit from the successful implementation of this model:

- **Tanzanian Ministry of Water:** As the primary government body responsible for water infrastructure, they would use the model's predictions to plan and prioritize maintenance and repair missions, ensuring resources are allocated efficiently to the areas most in need.

- **Non-Governmental Organizations (NGOs):** Organizations dedicated to development and clean water initiatives can use this model to make data-driven decisions on where to focus their efforts and funding for water well projects.
- **Local Communities and Citizens:** The direct beneficiaries of this project, who rely on the water pumps for daily life. An accurate predictive model leads to more reliable access to clean water.
- **Field Technicians and Engineers:** The on-the-ground teams responsible for repairing the water pumps. The model's output would help them with logistical planning by identifying wells that require a specific type of intervention (repair vs. full replacement).

Data: The data for this project originates from a currently active competition on the Data Driven website. The dataset comprises over 59,000 records of water wells in Tanzania. Each record contains information on the well location, technical specifications of the well, and details about the water. A list of the features and their descriptions, as provided on the website, is included for reference. The data can be obtained from the following link: https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/ (https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/)

2. Data Understanding

Column Descriptions:

- 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

In [177]:

```
#Basic Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
%matplotlib inline
import seaborn as sns
sns.set(style="whitegrid")
import warnings
warnings.filterwarnings('ignore')

from scipy.stats import loguniform

#Sklearn Modeling
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import RFE, RFECV
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE,SMOTEN
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from scipy.stats import randint
from sklearn.metrics import classification_report, accuracy_score,confusion_matrix, ro
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler, MinMaxS
from sklearn.preprocessing import label_binarize
```

In [2]:

```python
# Load the datasets

train_df = pd.read_csv('data/train.csv')
train_status = pd.read_csv('data/status.csv')
test_features = pd.read_csv('data/test.csv')

# Merge the training data
#train_df = pd.merge(train_features, train_status, on='id')

# Display initial information
print("\nInitial DataFrame Info:")
train_df.info()
print("\nInitial DataFrame Head:")
train_df.head()
```

```
Initial DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 40 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                 55765 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               59400 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      55523 non-null  object 
 21  scheme_name            31234 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 
dtypes: float64(3), int64(7), object(30)
memory usage: 18.1+ MB

Initial DataFrame Head:
```

Out[2]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_pr
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	none	
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zahanati	
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Kwa Mahundi	
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	Zahanati Ya Nanyumbu	
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	Shuleni	

5 rows × 40 columns

In [3]:
```
1 train_status.status_group.value_counts()
```

Out[3]:
```
functional                 32259
non functional             22824
functional needs repair     4317
Name: status_group, dtype: int64
```

In [4]:
```
1 print("\nInitial DataFrame Tail:")
2 train_df.tail()
```

```
Initial DataFrame Tail:
```

Out[4]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num
59395	60739	10.0	2013-05-03	Germany Republi	1210	CES	37.169807	-3.253847	Area Three Namba 27	
59396	27263	4700.0	2011-05-07	Cefa-njombe	1212	Cefa	35.249991	-9.070629	Kwa Yahona Kuvala	
59397	37057	0.0	2011-04-11	NaN	0	NaN	34.017087	-8.750434	Mashine	
59398	31282	0.0	2011-03-08	Malec	0	Musa	35.861315	-6.378573	Mshoro	
59399	26348	0.0	2011-03-23	World Bank	191	World	38.104048	-6.747464	Kwa Mzee Lugawa	

5 rows × 40 columns

In [5]:
```
1 train_df.info(verbose=False)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Columns: 40 entries, id to waterpoint_type_group
dtypes: float64(3), int64(7), object(30)
memory usage: 18.1+ MB
```

The dataset contains 59400 rows and 41 columns. 3 of the columns are floats, 7 are integers and 30 are objects.

In [6]:
```
#concise summary statistics

train_df.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	75%	
id	59400.0	37115.131768	21453.128371	0.00000	18519.750000	37061.500000	55656.500000	7.
amount_tsh	59400.0	317.650385	2997.574558	0.00000	0.000000	0.000000	20.000000	3.
gps_height	59400.0	668.297239	693.116350	-90.00000	0.000000	369.000000	1319.250000	2.
longitude	59400.0	34.077427	6.567432	0.00000	33.090347	34.908743	37.178387	4.
latitude	59400.0	-5.706033	2.946019	-11.64944	-8.540621	-5.021597	-3.326156	
num_private	59400.0	0.474141	12.236230	0.00000	0.000000	0.000000	0.000000	1.
region_code	59400.0	15.297003	17.587406	1.00000	5.000000	12.000000	17.000000	9.
district_code	59400.0	5.629747	9.633649	0.00000	2.000000	3.000000	5.000000	8.
population	59400.0	179.909983	471.482176	0.00000	0.000000	25.000000	215.000000	3.
construction_year	59400.0	1300.652475	951.620547	0.00000	0.000000	1986.000000	2004.000000	2.

In [7]:
```
#Check the dataset shape
train_df.shape
print(f" The dataset has {train_df.shape[0]} records and {train_df.shape[1]} columns")
```

```
The dataset has 59400 records and 40 columns
```

In [8]:
```
#Describe categorical features
train_df.describe(include="O").T
```

Out[8]:

	count	unique	top	freq
date_recorded	59400	356	2011-03-15	572
funder	55765	1897	Government Of Tanzania	9084
installer	55745	2145	DWE	17402
wpt_name	59400	37400	none	3563
basin	59400	9	Lake Victoria	10248
subvillage	59029	19287	Madukani	508
region	59400	21	Iringa	5294
lga	59400	125	Njombe	2503
ward	59400	2092	Igosi	307
public_meeting	56066	2	True	51011
recorded_by	59400	1	GeoData Consultants Ltd	59400
scheme_management	55523	12	VWC	36793
scheme_name	31234	2696	K	682
permit	56344	2	True	38852
extraction_type	59400	18	gravity	26780
extraction_type_group	59400	13	gravity	26780
extraction_type_class	59400	7	gravity	26780
management	59400	12	vwc	40507
management_group	59400	5	user-group	52490
payment	59400	7	never pay	25348
payment_type	59400	7	never pay	25348
water_quality	59400	8	soft	50818
quality_group	59400	6	good	50818
quantity	59400	5	enough	33186
quantity_group	59400	5	enough	33186
source	59400	10	spring	17021
source_type	59400	7	spring	17021
source_class	59400	3	groundwater	45794
waterpoint_type	59400	7	communal standpipe	28522
waterpoint_type_group	59400	6	communal standpipe	34625

In [9]:
```
#Create a dataframe copy to be used in data cleaning using copy() method
train_df1 = train_df.copy(deep=True)
train_df1[:3]
```

Out[9]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_priv
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	none	
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zahanati	
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Kwa Mahundi	

3 rows × 40 columns

In [10]:
```
test_df1 = test_features.copy(deep = True)
test_df1[:3]
```

Out[10]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_p
0	50785	0.0	2013-02-04	Dmdd	1996	DMDD	35.290799	-4.059696	Dinamu Secondary School	
1	51630	0.0	2013-02-04	Government Of Tanzania	1569	DWE	36.656709	-3.309214	Kimnyak	
2	17168	0.0	2013-02-01	NaN	1567	NaN	34.767863	-5.004344	Puma Secondary	

3 rows × 40 columns

In [11]:
```
# check for unique values in each column
for coln in train_df1:
    coln_val = train_df1[coln].unique()
    print(f" {coln},'\n', {coln_val}", "\n")
```

```
 id,'
', [69572  8776 34310 ... 37057 31282 26348]

 amount_tsh,'
', [6.00e+03 0.00e+00 2.50e+01 2.00e+01 2.00e+02 5.00e+02 5.00e+01 4.00e+03
 1.50e+03 6.00e+00 2.50e+02 1.00e+01 1.00e+03 1.00e+02 3.00e+01 2.00e+03
 4.00e+02 1.20e+03 4.00e+01 3.00e+02 2.50e+04 7.50e+02 5.00e+03 6.00e+02
 7.20e+03 2.40e+03 5.00e+00 3.60e+03 4.50e+02 4.00e+04 1.20e+04 3.00e+03
 7.00e+00 2.00e+04 2.80e+03 2.20e+03 7.00e+01 5.50e+03 1.00e+04 2.50e+03
 6.50e+03 5.50e+02 3.30e+01 8.00e+03 4.70e+03 7.00e+03 1.40e+04 1.30e+03
 1.00e+05 7.00e+02 1.00e+00 6.00e+01 3.50e+02 2.00e-01 3.50e+01 3.06e+02
 8.50e+03 1.17e+05 3.50e+03 5.20e+02 1.50e+01 6.30e+03 9.00e+03 1.50e+02
 1.20e+05 1.38e+05 3.50e+05 4.50e+03 1.30e+04 4.50e+04 2.00e+00 1.50e+04
 1.10e+04 5.00e+04 7.50e+03 1.63e+04 8.00e+02 1.60e+04 3.00e+04 5.30e+01
 5.40e+03 7.00e+04 2.50e+05 2.00e+05 2.60e+04 1.80e+04 2.60e+01 5.90e+02
 9.00e+02 9.00e+00 1.40e+03 1.70e+05 2.20e+02 3.80e+04 2.50e-01 1.20e+01
 6.00e+04 5.90e+01]

 date_recorded,'
```

In [12]:
```
for coln in test_df1:
    coln_val = test_df1[coln].unique()
    print(f" {coln},'\n', {coln_val}", "\n")
```

```
 id,'
', [50785 51630 17168 ... 28749 33492 68707]

 amount_tsh,'
', [0.00e+00 5.00e+02 3.00e+01 5.00e+00 1.00e+03 1.20e+03 2.00e+02 2.00e+01
 5.00e+01 1.50e+03 2.40e+03 7.00e+00 7.50e+03 2.00e+03 3.00e+02 1.00e+02
 1.00e+01 2.50e+02 4.00e+03 3.00e+03 2.50e+03 2.50e+01 6.00e+00 4.00e+01
 7.50e+02 4.00e+02 6.00e+02 5.00e+03 1.50e+02 6.00e+03 3.30e+01 1.80e+04
 2.20e+03 1.20e+04 3.60e+03 8.00e+03 7.00e+02 4.70e+03 4.50e+02 6.00e+01
 1.00e+04 1.50e+01 2.00e+04 6.50e+03 7.00e+01 3.00e+04 2.50e+04 3.50e+04
 1.50e+04 2.00e+05 1.00e+05 7.00e+04 2.00e-01 1.40e+04 7.20e+03 3.50e+03
 2.00e+00 4.00e+04 3.50e+02 3.50e+01 7.00e+03 3.00e+00 2.55e+03 5.00e+04
 6.00e+04 5.00e-01 5.50e+02 2.80e+03]

 date_recorded,'
', ['2013-02-04' '2013-02-01' '2013-01-22' '2013-03-27' '2013-03-04'
 '2011-03-02' '2013-01-25' '2013-01-23' '2013-03-18' '2013-10-03'
 '2013-02-27' '2012-10-11' '2011-07-29' '2013-06-03' '2011-02-24'
 '2011-03-11' '2012-10-06' '2013-02-02' '2013-03-12' '2011-03-07'
```

3. Data Cleaning

The factors that affect pump functionality can be grouped into the categories below:

1. Pump and Well Infrastructure
2. Socio-Economic and Management Factors
3. Geographical and Environmental Factors

In [13]:
```
train_df1.columns
```

Out[13]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'wpt_name', 'num_private',
       'basin', 'subvillage', 'region', 'region_code', 'district_code', 'lga',
       'ward', 'population', 'public_meeting', 'recorded_by',
       'scheme_management', 'scheme_name', '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'],
      dtype='object')
```

In [14]:
```
1 test_df1.columns
```

Out[14]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'wpt_name', 'num_private',
       'basin', 'subvillage', 'region', 'region_code', 'district_code', 'lga',
       'ward', 'population', 'public_meeting', 'recorded_by',
       'scheme_management', 'scheme_name', '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'],
      dtype='object')
```

In [15]:
```
1 train_df1.date_recorded.value_counts()
```

Out[15]:
```
2011-03-15    572
2011-03-17    558
2013-02-03    546
2011-03-14    520
2011-03-16    513
              ...
2013-01-01      1
2011-09-16      1
2011-09-09      1
2011-09-20      1
2013-12-01      1
Name: date_recorded, Length: 356, dtype: int64
```

In [16]:
```
1 test_df1.date_recorded.value_counts()
```

Out[16]:
```
2013-02-03    138
2011-03-16    137
2011-03-17    137
2011-03-18    130
2011-03-14    129
              ...
2011-09-24      1
2004-02-01      1
2011-09-02      1
2013-01-06      1
2004-01-09      1
Name: date_recorded, Length: 331, dtype: int64
```

In [17]:
```
1 train_df1.amount_tsh.value_counts()
```

Out[17]:
```
0.0         41639
500.0        3102
50.0         2472
1000.0       1488
20.0         1463
             ...
8500.0          1
6300.0          1
220.0           1
138000.0        1
12.0            1
Name: amount_tsh, Length: 98, dtype: int64
```

Null Values

In [18]:
```
1 train_df1.isnull().sum()
```

Out[18]:
```
id                         0
amount_tsh                 0
date_recorded              0
funder                  3635
gps_height                 0
installer               3655
longitude                  0
latitude                   0
wpt_name                   0
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       3877
scheme_name            28166
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
dtype: int64
```

In [19]:
```
1 test_df1.isnull().sum()
```

Out[19]:
```
id                         0
amount_tsh                 0
date_recorded              0
funder                   869
gps_height                 0
installer                877
longitude                  0
latitude                   0
wpt_name                   0
num_private                0
basin                      0
subvillage                99
region                     0
region_code                0
district_code              0
lga                        0
ward                       0
population                 0
public_meeting           821
recorded_by                0
scheme_management        969
scheme_name             7092
permit                   737
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
dtype: int64
```

Duplicates

In [20]:
```
# train
train_duplicates = train_df1.duplicated()
print( f'There are {train_duplicates.sum()} duplicates in the Train data')

#test
test_duplicates = test_df1.duplicated()
test_duplicates.sum()
print( f'There are {test_duplicates.sum()} duplicates in the Test data')

#train_status
train_status_duplicates = train_status.duplicated()
train_status_duplicates.sum()
print( f'There are {train_status_duplicates.sum()} duplicates in the Train_status data
```

```
There are 0 duplicates in the Train data
There are 0 duplicates in the Test data
There are 0 duplicates in the Train_status data
```

There are no duplicates on all the datasets.

Date time Format

In [21]:
```
#train
train_df1['date_recorded'] = pd.to_datetime(train_df1['date_recorded'], errors = 'coer
train_df1['date_recorded'] = train_df1['date_recorded'].dt.year
train_df1.date_recorded.value_counts()

```

Out[21]:
```
2011    28674
2013    24271
2012     6424
2004       30
2002        1
Name: date_recorded, dtype: int64
```

In [22]:
```
#test
test_df1['date_recorded'] = pd.to_datetime(test_df1['date_recorded'], errors = 'coerce
test_df1['date_recorded'] = test_df1['date_recorded'].dt.year
test_features.date_recorded.value_counts()
```

Out[22]:
```
2013-02-03    138
2011-03-16    137
2011-03-17    137
2011-03-18    130
2011-03-14    129
              ...
2011-09-24      1
2004-02-01      1
2011-09-02      1
2013-01-06      1
2004-01-09      1
Name: date_recorded, Length: 331, dtype: int64
```

Filling Null Values

In [23]:
```
train_df1.funder.value_counts(dropna=False, normalize = True)

```

Out[23]:
```
Government Of Tanzania    0.152929
NaN                       0.061195
Danida                    0.052424
Hesawa                    0.037071
Rwssp                     0.023131
                              ...
Kidika                    0.000017
Vn                        0.000017
Meru Concrete             0.000017
Vgovernment               0.000017
Brad                      0.000017
Name: funder, Length: 1898, dtype: float64
```

In [24]:
```
test_df1.funder.value_counts(dropna=False, normalize=True)

```

Out[24]:
```
Government Of Tanzania    0.149158
NaN                       0.058519
Danida                    0.053401
Hesawa                    0.039057
World Bank                0.023704
                              ...
Water /sema               0.000067
Nicodemu Mkumbw           0.000067
Kijiji                    0.000067
Bened                     0.000067
Mapinga Prima             0.000067
Name: funder, Length: 981, dtype: float64
```

In [25]:
```
train_df1.funder.fillna('Unknown', inplace=True)
```

In [26]:
```
test_df1.funder.fillna('Unknown', inplace=True)
```

In [27]:
```
train_df1.funder.value_counts(dropna=False, normalize=True)
```

Out[27]:
```
Government Of Tanzania    0.152929
Unknown                   0.061263
Danida                    0.052424
Hesawa                    0.037071
Rwssp                     0.023131
                              ...
Hilfe Fur Brunder         0.000017
Gurdians                  0.000017
Yaole                     0.000017
Kwa Mzee Waziri           0.000017
Esawa                     0.000017
Name: funder, Length: 1897, dtype: float64
```

In [28]:
```
1 test_df1.funder.value_counts(dropna=False, normalize=True)
```

Out[28]:
```
Government Of Tanzania    0.149158
Unknown                   0.058586
Danida                    0.053401
Hesawa                    0.039057
World Bank                0.023704
                              ...
Krf                       0.000067
Village Govt              0.000067
Dak                       0.000067
Tambalizeni               0.000067
Mapinga Prima             0.000067
Name: funder, Length: 980, dtype: float64
```

In [29]:
```
1 train_df1.installer .value_counts(dropna=False, normalize = True)
```

Out[29]:
```
DWE             0.292963
NaN             0.061532
Government      0.030724
RWE             0.020303
Commu           0.017845
                   ...
Elius Chacha    0.000017
A.D.B           0.000017
Arisan          0.000017
Norani          0.000017
WOYEGE          0.000017
Name: installer, Length: 2146, dtype: float64
```

In [30]:
```
1 #Filling the Null values for installer
2
3 train_df1.installer.fillna('Unknown', inplace=True)
4 test_df1.installer.fillna('Unknown', inplace=True)
5 train_df1.installer .value_counts(dropna=False, normalize = True)
```

Out[30]:
```
DWE                       0.292963
Unknown                   0.061582
Government                0.030724
RWE                       0.020303
Commu                     0.017845
                               ...
GDP                       0.000017
DBSP                      0.000017
Word bank                 0.000017
Region Water Department   0.000017
WOYEGE                    0.000017
Name: installer, Length: 2145, dtype: float64
```

In [31]:
```
test_df1.installer .value_counts(dropna=False, normalize = True)
```

Out[31]:
```
DWE                     0.292862
Unknown                 0.059125
Government              0.030774
RWE                     0.019663
Commu                   0.019327
                            ...
Mwika Lekura Water User 0.000067
DESK                    0.000067
FARM                    0.000067
DALDO                   0.000067
TWESA/ Community        0.000067
Name: installer, Length: 1091, dtype: float64
```

In [32]:
```
#Filling Null values for Scheme Management
train_df1.scheme_management.fillna('Unknown', inplace=True)
test_df1.scheme_management.fillna('Unknown', inplace=True)
```

In [33]:
```
#Filling Null values for Public Meeting
train_df1.public_meeting.fillna('Unknown', inplace=True)
test_df1.public_meeting.fillna('Unknown', inplace=True)
```

In [34]:
```
#Filling Null values for SubVillage
train_df1.subvillage.fillna('Unknown', inplace=True)
test_df1.subvillage.fillna('Unknown', inplace=True)
```

In [35]:
```
#Filling Null values for permit
train_df1.permit.fillna('Unknown', inplace=True)
test_df1.permit.fillna('Unknown', inplace=True)
```

In [36]:
```
1 train_df1.isna().sum()
```

Out[36]:
```
id                         0
amount_tsh                 0
date_recorded              0
funder                     0
gps_height                 0
installer                  0
longitude                  0
latitude                   0
wpt_name                   0
num_private                0
basin                      0
subvillage                 0
region                     0
region_code                0
district_code              0
lga                        0
ward                       0
population                 0
public_meeting             0
recorded_by                0
scheme_management          0
scheme_name            28166
permit                     0
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
dtype: int64
```

The Scheme name has 28,166 null values and it would not be adviasble to fill these with 'uknown' therefore the Scheme name column will be dropped.

In [37]:
```
1 #dropping scheme_name
2 train_df1.drop('scheme_name', axis = 1, inplace = True)
3 test_df1.drop('scheme_name', axis = 1, inplace = True)
```

In [38]:
```
1 train_df1.columns
```

Out[38]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'wpt_name', 'num_private',
       'basin', 'subvillage', 'region', 'region_code', 'district_code', 'lga',
       'ward', 'population', 'public_meeting', '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'],
      dtype='object')
```

In [39]:
```
1 test_df1.columns
```

Out[39]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'wpt_name', 'num_private',
       'basin', 'subvillage', 'region', 'region_code', 'district_code', 'lga',
       'ward', 'population', 'public_meeting', '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'],
      dtype='object')
```

In [40]:
```
1 train_df1.population.value_counts(dropna=False, normalize=True)
```

Out[40]:
```
0       0.359949
1       0.118266
200     0.032660
150     0.031852
250     0.028300
          ...
3241    0.000017
1960    0.000017
1685    0.000017
2248    0.000017
1439    0.000017
Name: population, Length: 1049, dtype: float64
```

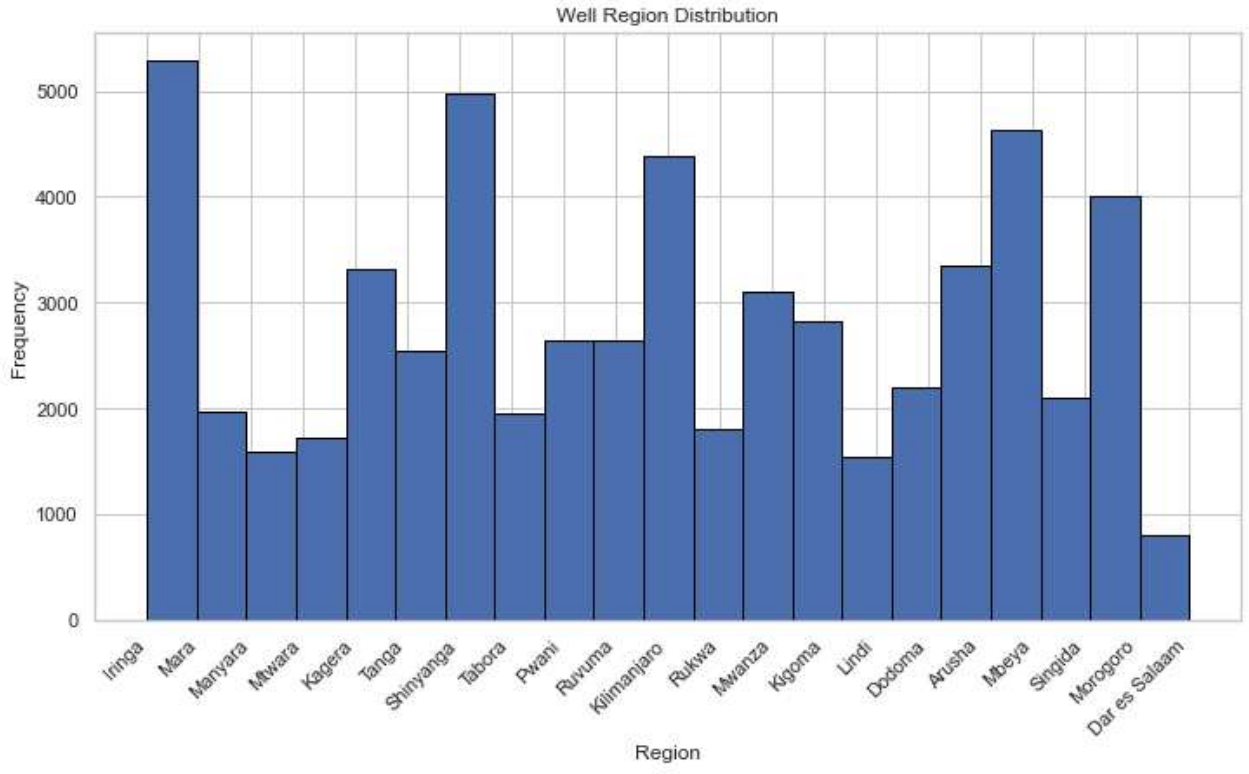
It is possible to have an area around a well with no people, therefore the poulation zero values will be left.

Geographic Location and Environmental Columns

In [41]:
```
#The columns are region, region_code, district_code, lga,subvillage,longitude,latitude,
train_df1['region'].value_counts()
```

Out[41]:
```
Iringa           5294
Shinyanga        4982
Mbeya            4639
Kilimanjaro      4379
Morogoro         4006
Arusha           3350
Kagera           3316
Mwanza           3102
Kigoma           2816
Ruvuma           2640
Pwani            2635
Tanga            2547
Dodoma           2201
Singida          2093
Mara             1969
Tabora           1959
Rukwa            1808
Mtwara           1730
Manyara          1583
Lindi            1546
Dar es Salaam     805
Name: region, dtype: int64
```

In [42]:
```
#Create a histogram of the 'Region' column
plt.figure(figsize=(10, 6))
plt.hist(train_df1['region'], bins= 21, edgecolor='black')
plt.xticks(rotation= 45, ha='right')
plt.tight_layout()
plt.title('Well Region Distribution')
plt.xlabel('Region')
plt.ylabel('Frequency')
plt.show()
```



In [43]:
```
max_reg = train_df1['region'].value_counts().idxmax()
print(f'The region with the highest number of wells present is {max_reg}')
```

```
The region with the highest number of wells present is Iringa
```

In [44]:
```
train_df1['region_code'].value_counts()
```

Out[44]:
```
11    5300
17    5011
12    4639
3     4379
5     4040
18    3324
19    3047
2     3024
16    2816
10    2640
4     2513
1     2201
13    2093
14    1979
20    1969
15    1808
6     1609
21    1583
80    1238
60    1025
90     917
7      805
99     423
9      390
24     326
8      300
40       1
Name: region_code, dtype: int64
```

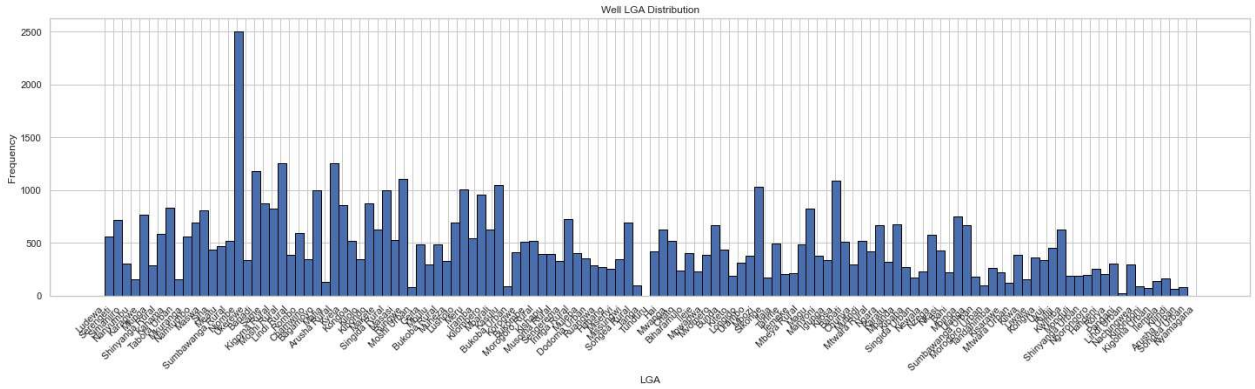
In [45]:
```
train_df1['district_code'].value_counts()
#district_code, lga,subvillage,longitude,latitude,basin, gps_height and ward
```

Out[45]:
```
1     12203
2     11173
3      9998
4      8999
5      4356
6      4074
7      3343
8      1043
30      995
33      874
53      745
43      505
13      391
23      293
63      195
62      109
60       63
0        23
80       12
67        6
Name: district_code, dtype: int64
```

In [46]:
```
1 train_df1['lga'].value_counts()
```

Out[46]:
```
Njombe          2503
Arusha Rural    1252
Moshi Rural     1251
Bariadi         1177
Rungwe          1106
                ...
Moshi Urban       79
Kigoma Urban      71
Arusha Urban      63
Lindi Urban       21
Nyamagana          1
Name: lga, Length: 125, dtype: int64
```

In [47]:
```
1 plt.figure(figsize=(20, 6))
2 plt.hist(train_df1['lga'], bins= 126, edgecolor='black')
3 plt.xticks(rotation= 45, ha='right')
4 plt.tight_layout()
5 plt.title('Well LGA Distribution')
6 plt.xlabel('LGA')
7 plt.ylabel('Frequency')
8 plt.show()
```



In [48]:
```
1 max_lag = train_df1['lga'].value_counts().idxmax()
2 print(f'The lga with the highest number of wells present is {max_lag}')
```

```
The lga with the highest number of wells present is Njombe
```

In [49]:
```
1 train_df1['subvillage'].value_counts()
```

Out[49]:
```
Madukani          508
Shuleni           506
Majengo           502
Kati              373
Unknown           371
                 ...
Bubala              1
Maswina             1
Mfunte              1
Mwamakwale          1
Juhudi Bwawani      1
Name: subvillage, Length: 19288, dtype: int64
```

In [50]:
```
1 train_df1['longitude'].value_counts()
```

Out[50]:
```
0.000000     1812
37.540901       2
33.010510       2
39.093484       2
32.972719       2
               ...
37.579803       1
33.196490       1
34.017119       1
33.788326       1
30.163579       1
Name: longitude, Length: 57516, dtype: int64
```

In [51]:
```
1 train_df1['latitude'].value_counts()
```

Out[51]:
```
-2.000000e-08    1812
-6.985842e+00       2
-3.797579e+00       2
-6.981884e+00       2
-7.104625e+00       2
                  ...
-5.726001e+00       1
-9.646831e+00       1
-8.124530e+00       1
-2.535985e+00       1
-2.598965e+00       1
Name: latitude, Length: 57517, dtype: int64
```

In [52]:
```
1 train_df1['ward'].value_counts()
```

Out[52]:
```
Igosi            307
Imalinyi         252
Siha Kati        232
Mdandu           231
Nduruma          217
                ...
Igogo              1
Kihangimahuka      1
Kirongo            1
Linda              1
Rasbura            1
Name: ward, Length: 2092, dtype: int64
```

In [53]:
```
1 train_df1['basin'].value_counts()
```

Out[53]:
```
Lake Victoria              10248
Pangani                     8940
Rufiji                      7976
Internal                    7785
Lake Tanganyika             6432
Wami / Ruvu                 5987
Lake Nyasa                  5085
Ruvuma / Southern Coast     4493
Lake Rukwa                  2454
Name: basin, dtype: int64
```

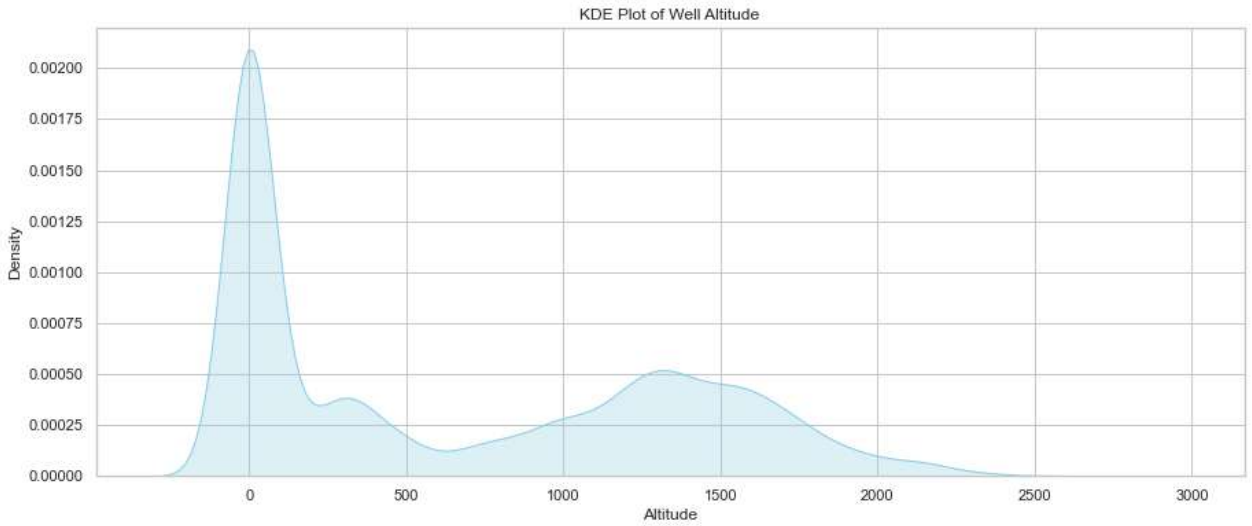
In [54]:
```
max_bas = train_df1['basin'].value_counts().idxmax()
print(f'The Water basin with the highest number of wells present is {max_bas}')
```

```
The Water basin with the highest number of wells present is Lake Victoria
```

In [55]:
```
train_df1['gps_height'].value_counts()
```

Out[55]:
```
 0       20438
-15         60
-16         55
-13         55
-20         52
           ...
 2285        1
 2424        1
 2552        1
 2413        1
 2385        1
Name: gps_height, Length: 2428, dtype: int64
```

In [56]:
```
plt.figure(figsize=(15, 6))
sns.kdeplot(data=train_df1, x='gps_height', fill=True, color='skyblue')
plt.title('KDE Plot of Well Altitude')
plt.xlabel('Altitude')
plt.ylabel('Density')
plt.show()
```



In [57]:
```
max_alt = train_df1['gps_height'].value_counts().idxmax()
print(f'The Altitude at which most wells are found is {max_alt} meters above sea level
```

```
The Altitude at which most wells are found is 0 meters above sea level
```

In [58]:
```
1 train_df1['wpt_name'].value_counts()
```

Out[58]:
```
none                    3563
Shuleni                 1748
Zahanati                 830
Msikitini                535
Kanisani                 323
                        ...
Kwa Bibi Shamba            1
Mgodi                      1
Kwa Chiyanga               1
Kasulo Primary School      1
N/Secondary                1
Name: wpt_name, Length: 37400, dtype: int64
```

In [59]:
```
1 train_df1['num_private'].value_counts()
```

Out[59]:
```
0      58643
6         81
1         73
5         46
8         46
       ...
180        1
213        1
23         1
55         1
94         1
Name: num_private, Length: 65, dtype: int64
```

In [60]:
```
1 train_df1.columns
```

Out[60]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'wpt_name', 'num_private',
       'basin', 'subvillage', 'region', 'region_code', 'district_code', 'lga',
       'ward', 'population', 'public_meeting', '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'],
      dtype='object')
```

Pump and Well Infrastructure Columns

In [61]:
```
1 # Waterpoint
2 train_df1['waterpoint_type_group'].value_counts()
```

Out[61]:
```
communal standpipe    34625
hand pump             17488
other                  6380
improved spring         784
cattle trough           116
dam                       7
Name: waterpoint_type_group, dtype: int64
```

In [62]:
```
1 train_df1['waterpoint_type'].value_counts()
```

Out[62]:
```
communal standpipe             28522
hand pump                      17488
other                           6380
communal standpipe multiple     6103
improved spring                  784
cattle trough                    116
dam                                7
Name: waterpoint_type, dtype: int64
```

Waterpoint type group and Waterpoint type group seem to have similar value counts with the only difference being that waterpoint_type has 2 groups of communal standpipe ie. single and multiple communal standpipes.

In [63]:
```
1 #Extraction
2 train_df1['extraction_type_group'].value_counts()
```

Out[63]:
```
gravity            26780
nira/tanira         8154
other               6430
submersible         6179
swn 80              3670
mono                2865
india mark ii       2400
afridev             1770
rope pump            451
other handpump       364
other motorpump      122
wind-powered         117
india mark iii        98
Name: extraction_type_group, dtype: int64
```

In [64]:
```
1 train_df1['extraction_type_class'].value_counts()
```

Out[64]:
```
gravity         26780
handpump        16456
other            6430
submersible      6179
motorpump        2987
rope pump         451
wind-powered      117
Name: extraction_type_class, dtype: int64
```

In [65]:
```
1 train_df1['extraction_type'].value_counts()
```

Out[65]:
```
gravity                      26780
nira/tanira                   8154
other                         6430
submersible                   4764
swn 80                        3670
mono                          2865
india mark ii                 2400
afridev                       1770
ksb                           1415
other - rope pump              451
other - swn 81                 229
windmill                       117
india mark iii                  98
cemo                            90
other - play pump               85
walimi                          48
climax                          32
other - mkulima/shinyanga        2
Name: extraction_type, dtype: int64
```

The extraction columns contain similar values. For ease of identification of the 'best' extraction method, the column to me kept is extraction_type_class.

In [66]:
```
1 #The columns are Construction year, Total Static Head(amount_tsh), , 'water_quality',
2 #'quality_group', 'quantity', 'quantity_group', 'source', 'source_type',
3 #'source_class', 'waterpoint_type', 'waterpoint_type_group'
4
```

In [67]:
```
1 # water quality
2 train_df1['water_quality'].value_counts()
```

Out[67]:
```
soft                 50818
salty                 4856
unknown               1876
milky                  804
coloured               490
salty abandoned        339
fluoride               200
fluoride abandoned      17
Name: water_quality, dtype: int64
```

In [68]:
```
1 train_df1['quality_group'].value_counts()
```

Out[68]:
```
good        50818
salty        5195
unknown      1876
milky         804
colored       490
fluoride      217
Name: quality_group, dtype: int64
```

In [69]:
```
# water quantity
train_df1['quantity'].value_counts()
```

Out[69]:
```
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: quantity, dtype: int64
```

In [70]:
```
train_df1['quantity_group'].value_counts()
```

Out[70]:
```
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: quantity_group, dtype: int64
```

In [71]:
```
#water source
train_df1['source'].value_counts()
```

Out[71]:
```
spring                  17021
shallow well            16824
machine dbh             11075
river                    9612
rainwater harvesting     2295
hand dtw                  874
lake                      765
dam                       656
other                     212
unknown                    66
Name: source, dtype: int64
```

In [72]:
```
train_df1['source_type'].value_counts()
```

Out[72]:
```
spring                  17021
shallow well            16824
borehole                11949
river/lake              10377
rainwater harvesting     2295
dam                       656
other                     278
Name: source_type, dtype: int64
```

In [73]:
```
train_df1['source_class'].value_counts()
```

Out[73]:
```
groundwater    45794
surface        13328
unknown          278
Name: source_class, dtype: int64
```

In [74]:
```
#Total static head
train_df1['amount_tsh'].value_counts()
```

Out[74]:
```
0.0         41639
500.0        3102
50.0         2472
1000.0       1488
20.0         1463
            ...
8500.0          1
6300.0          1
220.0           1
138000.0        1
12.0            1
Name: amount_tsh, Length: 98, dtype: int64
```

In [75]:
```
#construction year
train_df1['construction_year'].value_counts()
```

Out[75]:
```
0       20709
2010     2645
2008     2613
2009     2533
2000     2091
2007     1587
2006     1471
2003     1286
2011     1256
2004     1123
2012     1084
2002     1075
1978     1037
1995     1014
2005     1011
1999      979
1998      966
1990      954
1985      945
1980      811
1996      811
1984      779
1982      744
1994      738
1972      708
1974      676
1997      644
1992      640
1993      608
2001      540
1988      521
1983      488
1975      437
1986      434
1976      414
1970      411
1991      324
1989      316
1987      302
1981      238
1977      202
1979      192
1973      184
2013      176
1971      145
1960      102
1967       88
1963       85
1968       77
1969       59
1964       40
1962       30
1961       21
1965       19
1966       17
Name: construction_year, dtype: int64
```

Social , Economic and Management Factors

In [76]:
```
#The columns are 'payment', 'payment_type', management','management_group'scheme_manag
#'funder','population', 'public_meeting' and Installer.

```

In [77]:
```
train_df1['payment'].value_counts()
```

Out[77]:
```
never pay                25348
pay per bucket            8985
pay monthly               8300
unknown                   8157
pay when scheme fails     3914
pay annually              3642
other                     1054
Name: payment, dtype: int64
```

In [78]:
```
train_df1['payment_type'].value_counts()
```

Out[78]:
```
never pay     25348
per bucket     8985
monthly        8300
unknown        8157
on failure     3914
annually       3642
other          1054
Name: payment_type, dtype: int64
```

In [79]:
```
train_df1['management'].value_counts()
```

Out[79]:
```
vwc                 40507
wug                  6515
water board          2933
wua                  2535
private operator     1971
parastatal           1768
water authority       904
other                 844
company               685
unknown               561
other - school         99
trust                  78
Name: management, dtype: int64
```

In [80]:
```
train_df1['management_group'].value_counts()
```

Out[80]:
```
user-group    52490
commercial     3638
parastatal     1768
other           943
unknown         561
Name: management_group, dtype: int64
```

In [81]:
```
1 train_df1['scheme_management'].value_counts()
```

Out[81]:
```
VWC                 36793
WUG                  5206
Unknown              3877
Water authority      3153
WUA                  2883
Water Board          2748
Parastatal           1680
Private operator     1063
Company              1061
Other                 766
SWC                    97
Trust                  72
None                    1
Name: scheme_management, dtype: int64
```

In [82]:
```
1 train_df1['funder'].value_counts()
```

Out[82]:
```
Government Of Tanzania    9084
Unknown                   3639
Danida                    3114
Hesawa                    2202
Rwssp                     1374
                          ...
Hilfe Fur Brunder            1
Gurdians                     1
Yaole                        1
Kwa Mzee Waziri              1
Esawa                        1
Name: funder, Length: 1897, dtype: int64
```

In [83]:
```
1 train_df1['population'].value_counts()
```

Out[83]:
```
0       21381
1        7025
200      1940
150      1892
250      1681
        ...
3241        1
1960        1
1685        1
2248        1
1439        1
Name: population, Length: 1049, dtype: int64
```

In [84]:
```
1 train_df1['public_meeting'].value_counts()
```

Out[84]:
```
True       51011
False       5055
Unknown     3334
Name: public_meeting, dtype: int64
```

In [85]:
```
1 train_df1['installer'].value_counts()
```

Out[85]:
```
DWE                          17402
Unknown                       3658
Government                    1825
RWE                           1206
Commu                         1060
                             ...
GDP                              1
DBSP                             1
Word bank                        1
Region Water Department          1
WOYEGE                           1
Name: installer, Length: 2145, dtype: int64
```

In [ ]:
```
1
```

In [86]:
```
1 train_df1.recorded_by.value_counts()
```

Out[86]:
```
GeoData Consultants Ltd    59400
Name: recorded_by, dtype: int64
```

Dropping irrelevant and duplicated columns

In [87]:
```
1 train_df1
```

Out[87]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	nu
0	69572	6000.0	2011	Roman	1390	Roman	34.938093	-9.856322	none	
1	8776	0.0	2013	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zahanati	
2	34310	25.0	2013	Lottery Club	686	World vision	37.460664	-3.821329	Kwa Mahundi	
3	67743	0.0	2013	Unicef	263	UNICEF	38.486161	-11.155298	Zahanati Ya Nanyumbu	
4	19728	0.0	2011	Action In A	0	Artisan	31.130847	-1.825359	Shuleni	
...	...	...	...	...	...	...	...	...	...	
59395	60739	10.0	2013	Germany Republi	1210	CES	37.169807	-3.253847	Area Three Namba 27	
59396	27263	4700.0	2011	Cefa-njombe	1212	Cefa	35.249991	-9.070629	Kwa Yahona Kuvala	
59397	37057	0.0	2011	Unknown	0	Unknown	34.017087	-8.750434	Mashine	
59398	31282	0.0	2011	Malec	0	Musa	35.861315	-6.378573	Mshoro	
59399	26348	0.0	2011	World Bank	191	World	38.104048	-6.747464	Kwa Mzee Lugawa	

59400 rows × 39 columns

In [88]:
```
#Train
train_df2 = train_df1.drop(columns=['quantity_group','extraction_type_group', 'extract
                                    'quality_group','source_type','waterpoint_type_gro
                                    'recorded_by', 'wpt_name', 'num_private','waterpoi
                                    'management','ward', 'payment' ] ,axis = 1)
#Test
test_df2 = test_df1.drop(columns=['quantity_group','extraction_type_group', 'extractio
                                    'quality_group','source_type','waterpoint_type_gro
                                    'recorded_by', 'wpt_name', 'num_private','waterpoi
                                    'management','ward', 'payment' ] ,axis = 1)

```

In [89]:
```
train_df2
```

Out[89]:

	id	amount_tsh	date_recorded	gps_height	installer	longitude	latitude	basin	subvillage
0	69572	6000.0	2011	1390	Roman	34.938093	-9.856322	Lake Nyasa	Mnyusi B
1	8776	0.0	2013	1399	GRUMETI	34.698766	-2.147466	Lake Victoria	Nyamara
2	34310	25.0	2013	686	World vision	37.460664	-3.821329	Pangani	Majengo
3	67743	0.0	2013	263	UNICEF	38.486161	-11.155298	Ruvuma / Southern Coast	Mahakamani
4	19728	0.0	2011	0	Artisan	31.130847	-1.825359	Lake Victoria	Kyanyamisa
...	...	...	...	...	...	...	...	...	...
59395	60739	10.0	2013	1210	CES	37.169807	-3.253847	Pangani	Kiduruni
59396	27263	4700.0	2011	1212	Cefa	35.249991	-9.070629	Rufiji	Igumbilo
59397	37057	0.0	2011	0	Unknown	34.017087	-8.750434	Rufiji	Madungulu
59398	31282	0.0	2011	0	Musa	35.861315	-6.378573	Rufiji	Mwinyi
59399	26348	0.0	2011	191	World	38.104048	-6.747464	Wami / Ruvu	Kikatanyemba

59400 rows × 26 columns

In [90]:
```
1 test_df2
```

Out[90]:

	id	amount_tsh	date_recorded	gps_height	installer	longitude	latitude	basin	subvillage
0	50785	0.0	2013	1996	DMDD	35.290799	-4.059696	Internal	Magoma
1	51630	0.0	2013	1569	DWE	36.656709	-3.309214	Pangani	Kimnyak
2	17168	0.0	2013	1567	Unknown	34.767863	-5.004344	Internal	Msatu
3	45559	0.0	2013	267	FINN WATER	38.058046	-9.418672	Ruvuma / Southern Coast	Kipindimbi
4	49871	500.0	2013	1260	BRUDER	35.006123	-10.950412	Ruvuma / Southern Coast	Losonga
...	...	...	...	...	...	...	...	...	...
14845	39307	0.0	2011	34	Da	38.852669	-6.582841	Wami / Ruvu	Yombo
14846	18990	1000.0	2011	0	HIAP	37.451633	-5.350428	Pangani	Mkondoa
14847	28749	0.0	2013	1476	Unknown	34.739804	-4.585587	Internal	Juhudi
14848	33492	0.0	2013	998	DWE	35.432732	-10.584159	Lake Nyasa	Namakinga B
14849	68707	0.0	2013	481	Government	34.765054	-11.226012	Lake Nyasa	Kamba

14850 rows × 26 columns

In [91]:
```
1 print(train_df2.shape)
2 print(test_df2.shape)
```

```
(59400, 26)
(14850, 26)
```

So far the test set has 14850 rows and 27 columns, whereaas the train set has 59400 rows and 27 columns.

Latitude and Longitudes

In [92]:
```
1 train_df2['longitude'].value_counts()
```

Out[92]:
```
0.000000     1812
37.540901       2
33.010510       2
39.093484       2
32.972719       2
               ...
37.579803       1
33.196490       1
34.017119       1
33.788326       1
30.163579       1
Name: longitude, Length: 57516, dtype: int64
```

In [93]:
```
1 train_df2['latitude'].value_counts()
```

Out[93]:
```
-2.000000e-08    1812
-6.985842e+00       2
-3.797579e+00       2
-6.981884e+00       2
-7.104625e+00       2
                  ...
-5.726001e+00       1
-9.646831e+00       1
-8.124530e+00       1
-2.535985e+00       1
-2.598965e+00       1
Name: latitude, Length: 57517, dtype: int64
```

In [94]:
```
1 test_df2['latitude'].value_counts()
```

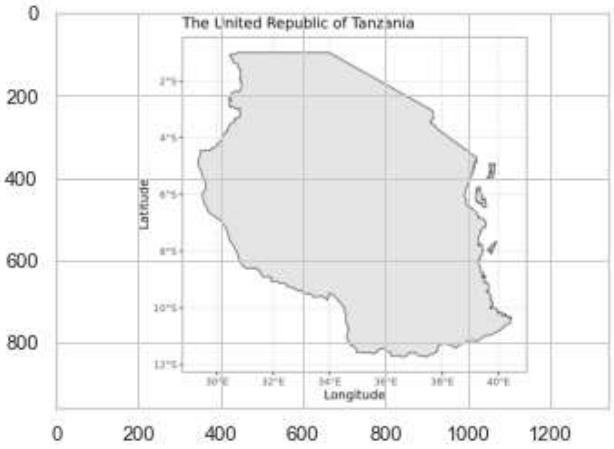
Out[94]:
```
-2.000000e-08    457
-7.105919e+00      2
-2.474560e+00      2
-7.170666e+00      2
-6.990042e+00      2
                 ...
-9.320133e+00      1
-9.114386e+00      1
-3.134371e+00      1
-3.885609e+00      1
-8.477215e+00      1
Name: latitude, Length: 14390, dtype: int64
```

In [95]:
```
1 test_df2['longitude'].value_counts()
```

Out[95]:
```
0.000000     457
37.302281      2
32.920579      2
37.260069      2
39.080573      2
              ...
30.926134      1
37.227967      1
36.032819      1
35.628949      1
35.894087      1
Name: longitude, Length: 14390, dtype: int64
```

Tanzania does not lie within the equator(latitude = 0) or the Greenwich Meridan(longitude=0) therefore rows containing zero points(0,0) will dropped.

In [96]:
```
#Import image of Tanzania
image = mpimg.imread("Images/Tanzania.png")
plt.imshow(image)
plt.show()
```



In [97]:

```
# Filter out rows where the 'Value' column is 0
train_df3 = train_df2[train_df2['longitude'] != 0]

print("\nDataFrame after dropping rows with 0:\n",train_df3)
```

DataFrame after dropping rows with 0:

	id	amount_tsh	date_recorded	gps_height	installer	longitude	\
0	69572	6000.0	2011	1390	Roman	34.938093	
1	8776	0.0	2013	1399	GRUMETI	34.698766	
2	34310	25.0	2013	686	World vision	37.460664	
3	67743	0.0	2013	263	UNICEF	38.486161	
4	19728	0.0	2011	0	Artisan	31.130847	
...	...	...	...	...	...	...	
59395	60739	10.0	2013	1210	CES	37.169807	
59396	27263	4700.0	2011	1212	Cefa	35.249991	
59397	37057	0.0	2011	0	Unknown	34.017087	
59398	31282	0.0	2011	0	Musa	35.861315	
59399	26348	0.0	2011	191	World	38.104048	

	latitude	basin	subvillage	region	...	\
0	-9.856322	Lake Nyasa	Mnyusi B	Iringa	...	
1	-2.147466	Lake Victoria	Nyamara	Mara	...	
2	-3.821329	Pangani	Majengo	Manyara	...	
3	-11.155298	Ruvuma / Southern Coast	Mahakamani	Mtwara	...	
4	-1.825359	Lake Victoria	Kyanyamisa	Kagera	...	
...	...	...	...	...	...	
59395	-3.253847	Pangani	Kiduruni	Kilimanjaro	...	
59396	-9.070629	Rufiji	Igumbilo	Iringa	...	
59397	-8.750434	Rufiji	Madungulu	Mbeya	...	
59398	-6.378573	Rufiji	Mwinyi	Dodoma	...	
59399	-6.747464	Wami / Ruvu	Kikatanyemba	Morogoro	...	

	permit	construction_year	extraction_type	management_group	\
0	False	1999	gravity	user-group	
1	True	2010	gravity	user-group	
2	True	2009	gravity	user-group	
3	True	1986	submersible	user-group	
4	True	0	gravity	other	
...	...	...	...	...	
59395	True	1999	gravity	user-group	
59396	True	1996	gravity	user-group	
59397	False	0	swn 80	user-group	
59398	True	0	nira/tanira	user-group	
59399	True	2002	nira/tanira	user-group	

	payment_type	water_quality	quantity	source	\
0	annually	soft	enough	spring	
1	never pay	soft	insufficient	rainwater harvesting	
2	per bucket	soft	enough	dam	
3	never pay	soft	dry	machine dbh	
4	never pay	soft	seasonal	rainwater harvesting	
...	...	...	...	...	
59395	per bucket	soft	enough	spring	
59396	annually	soft	enough	river	
59397	monthly	fluoride	enough	machine dbh	
59398	never pay	soft	insufficient	shallow well	
59399	on failure	salty	enough	shallow well	

	source_class	waterpoint_type
0	groundwater	communal standpipe
1	surface	communal standpipe
2	surface	communal standpipe multiple
3	groundwater	communal standpipe multiple
4	surface	communal standpipe
...	...	...
59395	groundwater	communal standpipe
59396	surface	communal standpipe

```
59397  groundwater                   hand pump
59398  groundwater                   hand pump
59399  groundwater                   hand pump

[57588 rows x 26 columns]
```

In [98]:

```
train_df3 = train_df3[train_df3['latitude'] != 0]

print("\nDataFrame after dropping rows with 0:\n",train_df3)
```

DataFrame after dropping rows with 0:

	id	amount_tsh	date_recorded	gps_height	installer	longitude	\
0	69572	6000.0	2011	1390	Roman	34.938093	
1	8776	0.0	2013	1399	GRUMETI	34.698766	
2	34310	25.0	2013	686	World vision	37.460664	
3	67743	0.0	2013	263	UNICEF	38.486161	
4	19728	0.0	2011	0	Artisan	31.130847	
...	...	...	...	...	...	...	
59395	60739	10.0	2013	1210	CES	37.169807	
59396	27263	4700.0	2011	1212	Cefa	35.249991	
59397	37057	0.0	2011	0	Unknown	34.017087	
59398	31282	0.0	2011	0	Musa	35.861315	
59399	26348	0.0	2011	191	World	38.104048	

	latitude	basin	subvillage	region	...	\
0	-9.856322	Lake Nyasa	Mnyusi B	Iringa	...	
1	-2.147466	Lake Victoria	Nyamara	Mara	...	
2	-3.821329	Pangani	Majengo	Manyara	...	
3	-11.155298	Ruvuma / Southern Coast	Mahakamani	Mtwara	...	
4	-1.825359	Lake Victoria	Kyanyamisa	Kagera	...	
...	...	...	...	...	...	...
59395	-3.253847	Pangani	Kiduruni	Kilimanjaro	...	
59396	-9.070629	Rufiji	Igumbilo	Iringa	...	
59397	-8.750434	Rufiji	Madungulu	Mbeya	...	
59398	-6.378573	Rufiji	Mwinyi	Dodoma	...	
59399	-6.747464	Wami / Ruvu	Kikatanyemba	Morogoro	...	

	permit	construction_year	extraction_type	management_group	\
0	False	1999	gravity	user-group	
1	True	2010	gravity	user-group	
2	True	2009	gravity	user-group	
3	True	1986	submersible	user-group	
4	True	0	gravity	other	
...	...	...	...	...	
59395	True	1999	gravity	user-group	
59396	True	1996	gravity	user-group	
59397	False	0	swn 80	user-group	
59398	True	0	nira/tanira	user-group	
59399	True	2002	nira/tanira	user-group	

	payment_type	water_quality	quantity	source	\
0	annually	soft	enough	spring	
1	never pay	soft	insufficient	rainwater harvesting	
2	per bucket	soft	enough	dam	
3	never pay	soft	dry	machine dbh	
4	never pay	soft	seasonal	rainwater harvesting	
...	...	...	...	...	
59395	per bucket	soft	enough	spring	
59396	annually	soft	enough	river	
59397	monthly	fluoride	enough	machine dbh	
59398	never pay	soft	insufficient	shallow well	
59399	on failure	salty	enough	shallow well	

	source_class	waterpoint_type
0	groundwater	communal standpipe
1	surface	communal standpipe
2	surface	communal standpipe multiple
3	groundwater	communal standpipe multiple
4	surface	communal standpipe
...	...	...
59395	groundwater	communal standpipe
59396	surface	communal standpipe

```
59397  groundwater                    hand pump
59398  groundwater                    hand pump
59399  groundwater                    hand pump

[57588 rows x 26 columns]
```

In [99]:
```
1 train_df3
```

Out[99]:

	id	amount_tsh	date_recorded	gps_height	installer	longitude	latitude	basin	subvillage
0	69572	6000.0	2011	1390	Roman	34.938093	-9.856322	Lake Nyasa	Mnyusi B
1	8776	0.0	2013	1399	GRUMETI	34.698766	-2.147466	Lake Victoria	Nyamara
2	34310	25.0	2013	686	World vision	37.460664	-3.821329	Pangani	Majengo
3	67743	0.0	2013	263	UNICEF	38.486161	-11.155298	Ruvuma / Southern Coast	Mahakamani
4	19728	0.0	2011	0	Artisan	31.130847	-1.825359	Lake Victoria	Kyanyamisa
...	...	...	...	...	...	...	...	...	...
59395	60739	10.0	2013	1210	CES	37.169807	-3.253847	Pangani	Kiduruni
59396	27263	4700.0	2011	1212	Cefa	35.249991	-9.070629	Rufiji	Igumbilo
59397	37057	0.0	2011	0	Unknown	34.017087	-8.750434	Rufiji	Madungulu
59398	31282	0.0	2011	0	Musa	35.861315	-6.378573	Rufiji	Mwinyi
59399	26348	0.0	2011	191	World	38.104048	-6.747464	Wami / Ruvu	Kikatanyemba

57588 rows × 26 columns

In [100]:

```
# Test
test_df3 = test_df2[test_df2['longitude'] != 0]

print("\nDataFrame after dropping rows with 0:\n",test_df3)
```

DataFrame after dropping rows with 0:

```
           id  amount_tsh  date_recorded  gps_height   installer  longitude  \
0      50785         0.0           2013        1996        DMDD  35.290799
1      51630         0.0           2013        1569         DWE  36.656709
2      17168         0.0           2013        1567     Unknown  34.767863
3      45559         0.0           2013         267  FINN WATER  38.058046
4      49871       500.0           2013        1260      BRUDER  35.006123
...      ...         ...            ...         ...         ...        ...
14845  39307         0.0           2011          34          Da  38.852669
14846  18990      1000.0           2011           0        HIAP  37.451633
14847  28749         0.0           2013        1476     Unknown  34.739804
14848  33492         0.0           2013         998         DWE  35.432732
14849  68707         0.0           2013         481  Government  34.765054

        latitude                    basin   subvillage   region  ...   permit  \
0      -4.059696                 Internal       Magoma  Manyara  ...     True
1      -3.309214                  Pangani      Kimnyak   Arusha  ...     True
2      -5.004344                 Internal        Msatu  Singida  ...  Unknown
3      -9.418672  Ruvuma / Southern Coast   Kipindimbi    Lindi  ...     True
4     -10.950412  Ruvuma / Southern Coast      Losonga   Ruvuma  ...     True
...          ...                      ...          ...      ...  ...      ...
14845  -6.582841              Wami / Ruvu        Yombo    Pwani  ...     True
14846  -5.350428                  Pangani      Mkondoa    Tanga  ...    False
14847  -4.585587                 Internal       Juhudi  Singida  ...  Unknown
14848 -10.584159              Lake Nyasa  Namakinga B   Ruvuma  ...     True
14849 -11.226012              Lake Nyasa        Kamba   Ruvuma  ...     True

       construction_year extraction_type  management_group payment_type  \
0                   2012           other        parastatal    never pay
1                   2000         gravity        user-group    never pay
2                   2010           other        user-group    never pay
3                   1987           other        user-group      unknown
4                   2000         gravity        user-group      monthly
...                  ...             ...              ...          ...
14845               1988            mono        user-group    never pay
14846               1994     nira/tanira        user-group     annually
14847               2010         gravity        user-group    never pay
14848               2009         gravity        user-group    never pay
14849               2008         gravity        user-group    never pay

      water_quality      quantity                source source_class  \
0              soft      seasonal  rainwater harvesting      surface
1              soft  insufficient                spring  groundwater
2              soft  insufficient  rainwater harvesting      surface
3              soft           dry          shallow well  groundwater
4              soft        enough                spring  groundwater
...             ...           ...                   ...          ...
14845          soft        enough                 river      surface
14846         salty  insufficient          shallow well  groundwater
14847          soft  insufficient                   dam      surface
14848          soft  insufficient                 river      surface
14849          soft           dry                spring  groundwater

         waterpoint_type
0                  other
1      communal standpipe
2                  other
3                  other
4      communal standpipe
...                   ...
14845  communal standpipe
14846           hand pump
```

```
14847  communal standpipe
14848  communal standpipe
14849  communal standpipe

[14393 rows x 26 columns]
```

In [101]:

```
test_df3 = test_df3[test_df3['latitude'] != 0]

print("\nDataFrame after dropping rows with 0:\n",test_df3)
```

DataFrame after dropping rows with 0:

```
           id  amount_tsh  date_recorded  gps_height   installer  longitude  \
0      50785         0.0           2013        1996        DMDD  35.290799
1      51630         0.0           2013        1569         DWE  36.656709
2      17168         0.0           2013        1567     Unknown  34.767863
3      45559         0.0           2013         267  FINN WATER  38.058046
4      49871       500.0           2013        1260      BRUDER  35.006123
...      ...         ...            ...         ...         ...        ...
14845  39307         0.0           2011          34          Da  38.852669
14846  18990      1000.0           2011           0        HIAP  37.451633
14847  28749         0.0           2013        1476     Unknown  34.739804
14848  33492         0.0           2013         998         DWE  35.432732
14849  68707         0.0           2013         481  Government  34.765054

        latitude                    basin   subvillage   region  ...   permit  \
0      -4.059696                 Internal       Magoma  Manyara  ...     True
1      -3.309214                  Pangani      Kimnyak   Arusha  ...     True
2      -5.004344                 Internal        Msatu  Singida  ...  Unknown
3      -9.418672  Ruvuma / Southern Coast   Kipindimbi    Lindi  ...     True
4     -10.950412  Ruvuma / Southern Coast      Losonga   Ruvuma  ...     True
...          ...                      ...          ...      ...  ...      ...
14845  -6.582841              Wami / Ruvu        Yombo    Pwani  ...     True
14846  -5.350428                  Pangani      Mkondoa    Tanga  ...    False
14847  -4.585587                 Internal       Juhudi  Singida  ...  Unknown
14848 -10.584159              Lake Nyasa  Namakinga B   Ruvuma  ...     True
14849 -11.226012              Lake Nyasa        Kamba   Ruvuma  ...     True

       construction_year extraction_type  management_group payment_type  \
0                   2012           other        parastatal    never pay
1                   2000         gravity        user-group    never pay
2                   2010           other        user-group    never pay
3                   1987           other        user-group      unknown
4                   2000         gravity        user-group      monthly
...                  ...             ...              ...          ...
14845               1988            mono        user-group    never pay
14846               1994     nira/tanira        user-group     annually
14847               2010         gravity        user-group    never pay
14848               2009         gravity        user-group    never pay
14849               2008         gravity        user-group    never pay

      water_quality      quantity                source source_class  \
0              soft      seasonal  rainwater harvesting      surface
1              soft  insufficient                spring  groundwater
2              soft  insufficient  rainwater harvesting      surface
3              soft           dry          shallow well  groundwater
4              soft        enough                spring  groundwater
...             ...           ...                   ...          ...
14845          soft        enough                 river      surface
14846         salty  insufficient          shallow well  groundwater
14847          soft  insufficient                   dam      surface
14848          soft  insufficient                 river      surface
14849          soft           dry                spring  groundwater

         waterpoint_type
0                  other
1      communal standpipe
2                  other
3                  other
4      communal standpipe
...                   ...
14845  communal standpipe
14846           hand pump
```

```
14847  communal standpipe
14848  communal standpipe
14849  communal standpipe

[14393 rows x 26 columns]
```

In [102]:

```python
# Concatenate vertically

#concat = pd.concat([train_df3, test_df3])
concat = train_df3
print("\nVertically Concatenated DataFrame (default behavior):")
print(concat)
```

```
Vertically Concatenated DataFrame (default behavior):
          id  amount_tsh  date_recorded  gps_height     installer  longitude  \
0      69572      6000.0           2011        1390         Roman  34.938093
1       8776         0.0           2013        1399       GRUMETI  34.698766
2      34310        25.0           2013         686  World vision  37.460664
3      67743         0.0           2013         263        UNICEF  38.486161
4      19728         0.0           2011           0       Artisan  31.130847
...      ...         ...            ...         ...           ...        ...
59395  60739        10.0           2013        1210           CES  37.169807
59396  27263      4700.0           2011        1212          Cefa  35.249991
59397  37057         0.0           2011           0       Unknown  34.017087
59398  31282         0.0           2011           0          Musa  35.861315
59399  26348         0.0           2011         191         World  38.104048

        latitude                    basin    subvillage       region  ...  \
0      -9.856322              Lake Nyasa      Mnyusi B       Iringa  ...
1      -2.147466           Lake Victoria       Nyamara         Mara  ...
2      -3.821329                  Pangani       Majengo      Manyara  ...
```

In [103]:
```
df= pd.concat([concat, train_status], axis = 1, join= 'inner')
df
```

Out[103]:

	id	amount_tsh	date_recorded	gps_height	installer	longitude	latitude	basin	subvillage
0	69572	6000.0	2011	1390	Roman	34.938093	-9.856322	Lake Nyasa	Mnyusi B
1	8776	0.0	2013	1399	GRUMETI	34.698766	-2.147466	Lake Victoria	Nyamara
2	34310	25.0	2013	686	World vision	37.460664	-3.821329	Pangani	Majengo
3	67743	0.0	2013	263	UNICEF	38.486161	-11.155298	Ruvuma / Southern Coast	Mahakamani
4	19728	0.0	2011	0	Artisan	31.130847	-1.825359	Lake Victoria	Kyanyamisa
...	...	...	...	...	...	...	...	...	...
59395	60739	10.0	2013	1210	CES	37.169807	-3.253847	Pangani	Kiduruni
59396	27263	4700.0	2011	1212	Cefa	35.249991	-9.070629	Rufiji	Igumbilo
59397	37057	0.0	2011	0	Unknown	34.017087	-8.750434	Rufiji	Madungulu
59398	31282	0.0	2011	0	Musa	35.861315	-6.378573	Rufiji	Mwinyi
59399	26348	0.0	2011	191	World	38.104048	-6.747464	Wami / Ruvu	Kikatanyemba

57588 rows × 28 columns

In [104]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 57588 entries, 0 to 59399
Data columns (total 28 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 57588 non-null  int64  
 1   amount_tsh         57588 non-null  float64
 2   date_recorded      57588 non-null  int64  
 3   gps_height         57588 non-null  int64  
 4   installer          57588 non-null  object 
 5   longitude          57588 non-null  float64
 6   latitude           57588 non-null  float64
 7   basin              57588 non-null  object 
 8   subvillage         57588 non-null  object 
 9   region             57588 non-null  object 
 10  region_code        57588 non-null  int64  
 11  district_code      57588 non-null  int64  
 12  lga                57588 non-null  object 
 13  population         57588 non-null  int64  
 14  public_meeting     57588 non-null  object 
 15  scheme_management  57588 non-null  object 
 16  permit             57588 non-null  object 
 17  construction_year  57588 non-null  int64  
 18  extraction_type    57588 non-null  object 
 19  management_group   57588 non-null  object 
 20  payment_type       57588 non-null  object 
 21  water_quality      57588 non-null  object 
 22  quantity           57588 non-null  object 
 23  source             57588 non-null  object 
 24  source_class       57588 non-null  object 
 25  waterpoint_type    57588 non-null  object 
 26  id                 57588 non-null  int64  
 27  status_group       57588 non-null  object 
dtypes: float64(3), int64(8), object(17)
memory usage: 12.7+ MB
```

In [105]:
```
1 df.shape
```

Out[105]:
```
(57588, 28)
```

In [106]:
```
1 df.columns
```

Out[106]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'gps_height', 'installer',
       'longitude', 'latitude', 'basin', 'subvillage', 'region', 'region_code',
       'district_code', 'lga', 'population', 'public_meeting',
       'scheme_management', 'permit', 'construction_year', 'extraction_type',
       'management_group', 'payment_type', 'water_quality', 'quantity',
       'source', 'source_class', 'waterpoint_type', 'id', 'status_group'],
      dtype='object')
```

In [107]:

```python
# Create a new DataFrame without 'col_B'
df_without_id = df.drop(columns=['id'])

print("\nDataFrame after dropping 'id':")
print(df_without_id)

# The original DataFrame is unchanged
print("\nOriginal DataFrame (unchanged):")
print(df)
```

```
DataFrame after dropping 'id':
       amount_tsh  date_recorded  gps_height     installer  longitude  \
0          6000.0           2011        1390         Roman  34.938093
1             0.0           2013        1399       GRUMETI  34.698766
2            25.0           2013         686  World vision  37.460664
3             0.0           2013         263        UNICEF  38.486161
4             0.0           2011           0       Artisan  31.130847
...           ...            ...         ...           ...        ...
59395        10.0           2013        1210           CES  37.169807
59396      4700.0           2011        1212          Cefa  35.249991
59397         0.0           2011           0       Unknown  34.017087
59398         0.0           2011           0          Musa  35.861315
59399         0.0           2011         191         World  38.104048

        latitude                   basin    subvillage       region  \
0      -9.856322               Lake Nyasa      Mnyusi B       Iringa
1      -2.147466            Lake Victoria       Nyamara         Mara
2      -3.821329                  Pangani       Majengo      Manyara
```

In [108]:
```
1 df_without_id.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 57588 entries, 0 to 59399
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   amount_tsh         57588 non-null  float64
 1   date_recorded      57588 non-null  int64  
 2   gps_height         57588 non-null  int64  
 3   installer          57588 non-null  object 
 4   longitude          57588 non-null  float64
 5   latitude           57588 non-null  float64
 6   basin              57588 non-null  object 
 7   subvillage         57588 non-null  object 
 8   region             57588 non-null  object 
 9   region_code        57588 non-null  int64  
 10  district_code      57588 non-null  int64  
 11  lga                57588 non-null  object 
 12  population         57588 non-null  int64  
 13  public_meeting     57588 non-null  object 
 14  scheme_management  57588 non-null  object 
 15  permit             57588 non-null  object 
 16  construction_year  57588 non-null  int64  
 17  extraction_type    57588 non-null  object 
 18  management_group   57588 non-null  object 
 19  payment_type       57588 non-null  object 
 20  water_quality      57588 non-null  object 
 21  quantity           57588 non-null  object 
 22  source             57588 non-null  object 
 23  source_class       57588 non-null  object 
 24  waterpoint_type    57588 non-null  object 
 25  status_group       57588 non-null  object 
dtypes: float64(3), int64(6), object(17)
memory usage: 11.9+ MB
```

In [109]:
```
1 df_without_id.isna().sum()
```

Out[109]:
```
amount_tsh           0
date_recorded        0
gps_height           0
installer            0
longitude            0
latitude             0
basin                0
subvillage           0
region               0
region_code          0
district_code        0
lga                  0
population           0
public_meeting       0
scheme_management    0
permit               0
construction_year    0
extraction_type      0
management_group     0
payment_type         0
water_quality        0
quantity             0
source               0
source_class         0
waterpoint_type      0
status_group         0
dtype: int64
```

In [110]:
```
1 df_without_id.status_group.value_counts()
```

Out[110]:
```
functional                 31389
non functional             22268
functional needs repair     3931
Name: status_group, dtype: int64
```

In [111]:

```
df_without_id = df_without_id.drop(columns=['region_code','district_code'], axis = 1)

print("\nDataFrame after dropping 'id':")
print(df_without_id)
```

DataFrame after dropping 'id':

	amount_tsh	date_recorded	gps_height	installer	longitude	\
0	6000.0	2011	1390	Roman	34.938093	
1	0.0	2013	1399	GRUMETI	34.698766	
2	25.0	2013	686	World vision	37.460664	
3	0.0	2013	263	UNICEF	38.486161	
4	0.0	2011	0	Artisan	31.130847	
...	...	...	...	...	...	
59395	10.0	2013	1210	CES	37.169807	
59396	4700.0	2011	1212	Cefa	35.249991	
59397	0.0	2011	0	Unknown	34.017087	
59398	0.0	2011	0	Musa	35.861315	
59399	0.0	2011	191	World	38.104048	

	latitude	basin	subvillage	region	\
0	-9.856322	Lake Nyasa	Mnyusi B	Iringa	
1	-2.147466	Lake Victoria	Nyamara	Mara	
2	-3.821329	Pangani	Majengo	Manyara	
3	-11.155298	Ruvuma / Southern Coast	Mahakamani	Mtwara	
4	-1.825359	Lake Victoria	Kyanyamisa	Kagera	
...	...	...	...	...	
59395	-3.253847	Pangani	Kiduruni	Kilimanjaro	
59396	-9.070629	Rufiji	Igumbilo	Iringa	
59397	-8.750434	Rufiji	Madungulu	Mbeya	
59398	-6.378573	Rufiji	Mwinyi	Dodoma	
59399	-6.747464	Wami / Ruvu	Kikatanyemba	Morogoro	

	lga	...	construction_year	extraction_type	\
0	Ludewa	...	1999	gravity	
1	Serengeti	...	2010	gravity	
2	Simanjiro	...	2009	gravity	
3	Nanyumbu	...	1986	submersible	
4	Karagwe	...	0	gravity	
...	...	...	...	...	
59395	Hai	...	1999	gravity	
59396	Njombe	...	1996	gravity	
59397	Mbarali	...	0	swn 80	
59398	Chamwino	...	0	nira/tanira	
59399	Morogoro Rural	...	2002	nira/tanira	

	management_group	payment_type	water_quality	quantity	\
0	user-group	annually	soft	enough	
1	user-group	never pay	soft	insufficient	
2	user-group	per bucket	soft	enough	
3	user-group	never pay	soft	dry	
4	other	never pay	soft	seasonal	
...	...	...	...	...	
59395	user-group	per bucket	soft	enough	
59396	user-group	annually	soft	enough	
59397	user-group	monthly	fluoride	enough	
59398	user-group	never pay	soft	insufficient	
59399	user-group	on failure	salty	enough	

	source	source_class	waterpoint_type	\
0	spring	groundwater	communal standpipe	
1	rainwater harvesting	surface	communal standpipe	
2	dam	surface	communal standpipe multiple	
3	machine dbh	groundwater	communal standpipe multiple	
4	rainwater harvesting	surface	communal standpipe	
...	...	...	...	
59395	spring	groundwater	communal standpipe	
59396	river	surface	communal standpipe	

```
59397           machine dbh  groundwater                  hand pump
59398          shallow well  groundwater                  hand pump
59399          shallow well  groundwater                  hand pump

         status_group
0          functional
1          functional
2          functional
3      non functional
4          functional
...                ...
59395      functional
59396      functional
59397      functional
59398      functional
59399      functional

[57588 rows x 24 columns]
```

In [112]:
```
df_without_id['date_recorded']= pd.to_datetime(df_without_id['date_recorded'])
df_without_id['date_recorded'].dtypes
```

Out[112]:
```
dtype('<M8[ns]')
```

In [113]:
```
df_without_id['construction_year'].dtypes
```

Out[113]:
```
dtype('int64')
```

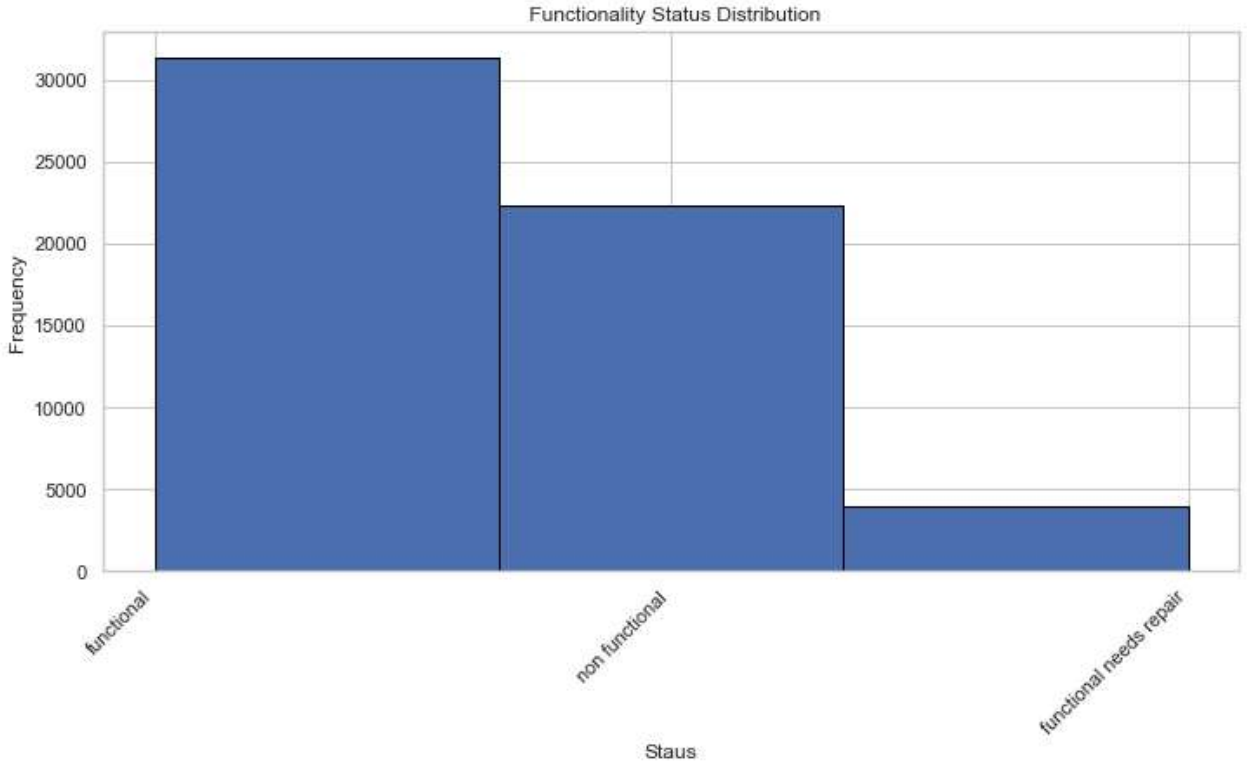
In [114]:
```
# convert permit to yes and no
mapping_dict = {
    True: 'Yes',
    False: 'No',
    'Unknown': 'No',
    np.nan: 'No' # You can also fill NaNs here if they exist
}

# Use the dictionary to replace all values at once
df_without_id['permit'] = df_without_id['permit'].replace(mapping_dict)

df_without_id.permit.value_counts()

```

Out[114]:
```
Yes    38100
No     19488
Name: permit, dtype: int64
```

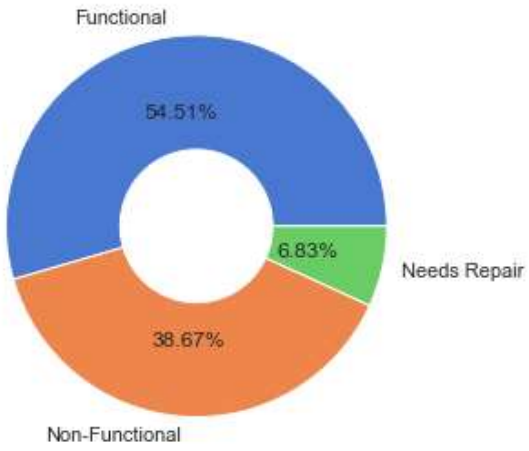
Univariate Analysis

In [115]:

```
### status_group distribution

plt.figure(figsize=(10, 6))
plt.hist(df_without_id['status_group'], bins= 3, edgecolor='black')
plt.xticks(rotation= 45, ha='right')
plt.tight_layout()
plt.title(' Functionality Status Distribution')
plt.xlabel('Staus')
plt.ylabel('Frequency')
plt.show();



class_imb = df_without_id.status_group.value_counts(ascending=False)
label = ["Functional", "Non-Functional", "Needs Repair"]

#pie chart
color = sns.color_palette("muted")
plt.pie(class_imb, labels=label, autopct="%.2f%%", wedgeprops=dict(width=.6), colors=c
plt.tight_layout()
;
```



Out[115]: ''



observation

- Most wells are fully functional, indicating a class imbalance in the 3 classes.

Categorical Features

In [116]:

```
#Get value counts for a few key categorical features
categorical_features = ['status_group', 'installer', 'basin', 'water_quality', 'extrac

for feature in categorical_features:
    print(f"\n--- Value Counts for: {feature} ---")
    print(df_without_id[feature].value_counts())

# Plot bar charts for key categorical features
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(15, 12))
fig.suptitle('Bar Plots of Categorical Features', fontsize=20)

# The target variable: status_group
sns.countplot(x='status_group', data=df_without_id, ax=axes[0, 0], palette='viridis')
axes[0, 0].set_title('Distribution of Water Well Pump Status')

# categorical feature: water_quality
sns.countplot(x='water_quality', data=df_without_id, ax=axes[0, 1], palette='plasma')
axes[0, 1].set_title('Distribution of Water Quality')
axes[0, 1].tick_params(axis='x', rotation=45)

# categorical feature: extraction_type_group
sns.countplot(x='extraction_type', data=df_without_id, ax=axes[1, 0], palette='cividis
axes[1, 0].set_title('Distribution of Extraction Type Group')
axes[1, 0].tick_params(axis='x', rotation=45)

#  categorical feature: management
sns.countplot(x='basin', data=df_without_id, ax=axes[1, 1], palette='inferno')
axes[1, 1].set_title('Distribution of basins')
axes[1, 1].tick_params(axis='x', rotation=45)

plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```

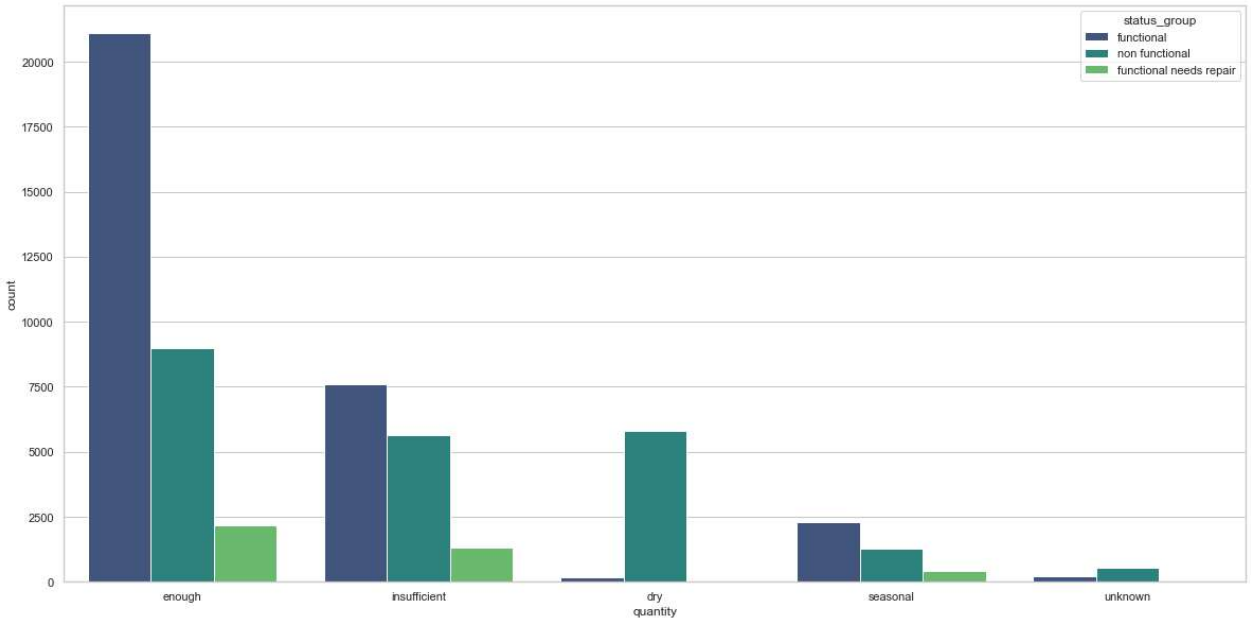
```
--- Value Counts for: status_group ---
functional                 31389
non functional             22268
functional needs repair     3931
Name: status_group, dtype: int64

--- Value Counts for: installer ---
DWE              16255
Unknown           3639
Government        1670
RWE               1181
Commu             1060
                 ...
BIORE                1
St Gasper            1
Segera Estate        1
GDP                  1
WOYEGE               1
```

Bivariate Analysis

Hydrological Features

In [117]:

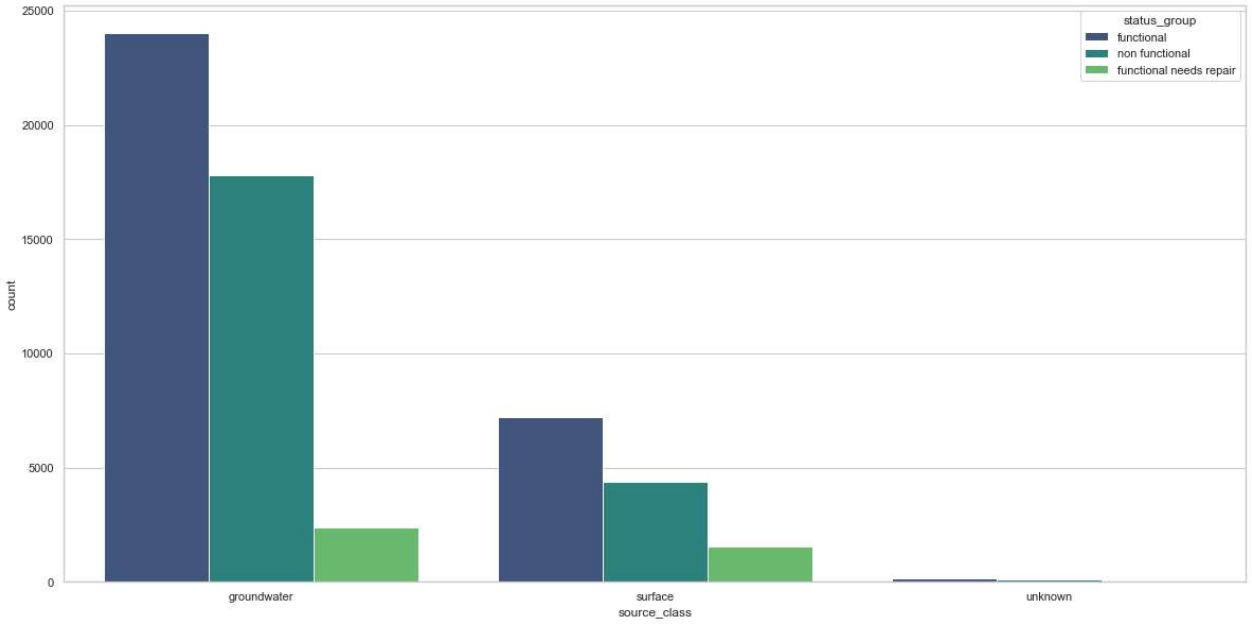
```
#Quantity
plt.figure(figsize=(20,10))
ax = sns.countplot(x='quantity', hue="status_group", data=df_without_id, palette='viri
```



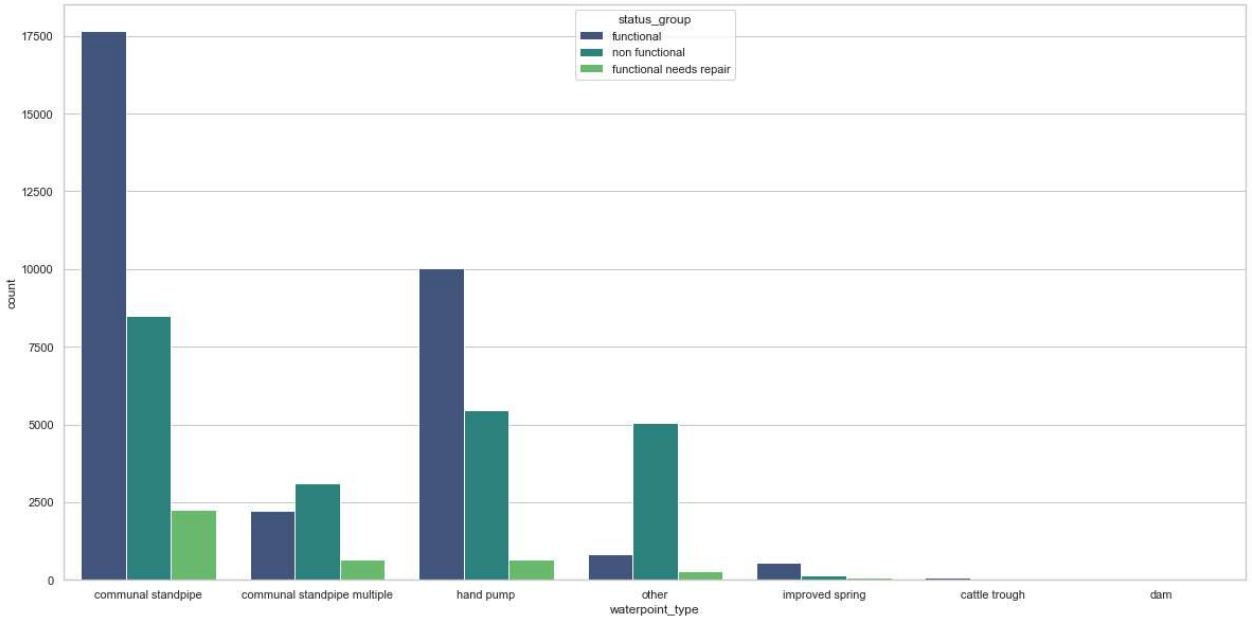
In [118]:

```
#Quality
plt.figure(figsize=(20,10))
ax = sns.countplot(x='water_quality', hue="status_group", data=df_without_id, palette=
plt.title('Pump Status by Payment Type', fontsize=16)
plt.xlabel('Payment Type')
plt.ylabel('Count')
plt.show()
```

In [119]:
```
#Water Source
plt.figure(figsize=(20,10))
ax = sns.countplot(x='source_class', hue="status_group", data=df_without_id, palette='
```

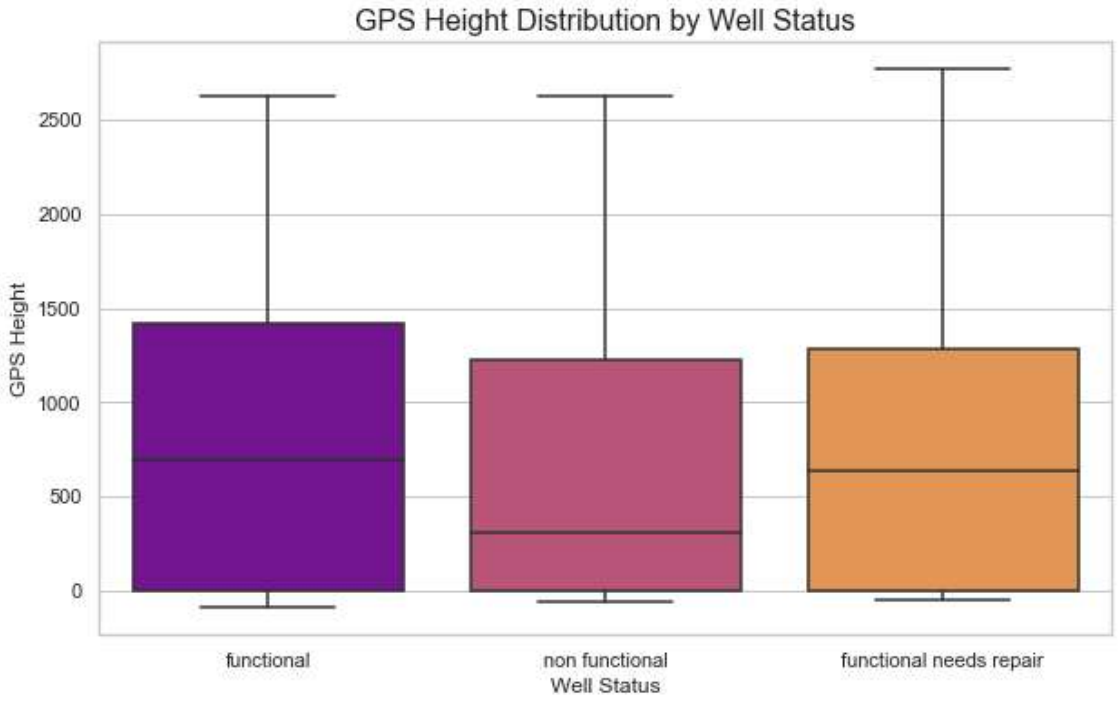


In [120]:
```
#Waterpoint type
plt.figure(figsize=(20,10))
ax = sns.countplot(x='waterpoint_type', hue="status_group", data=df_without_id, palett
```



In [121]:

```
#gps_height vs status_group
plt.figure(figsize=(10, 6))
sns.boxplot(x='status_group', y='gps_height', data=df_without_id, palette='plasma')
plt.title('GPS Height Distribution by Well Pump Status', fontsize=16)
plt.xlabel('Well Status')
plt.ylabel('GPS Height')
plt.show()
```



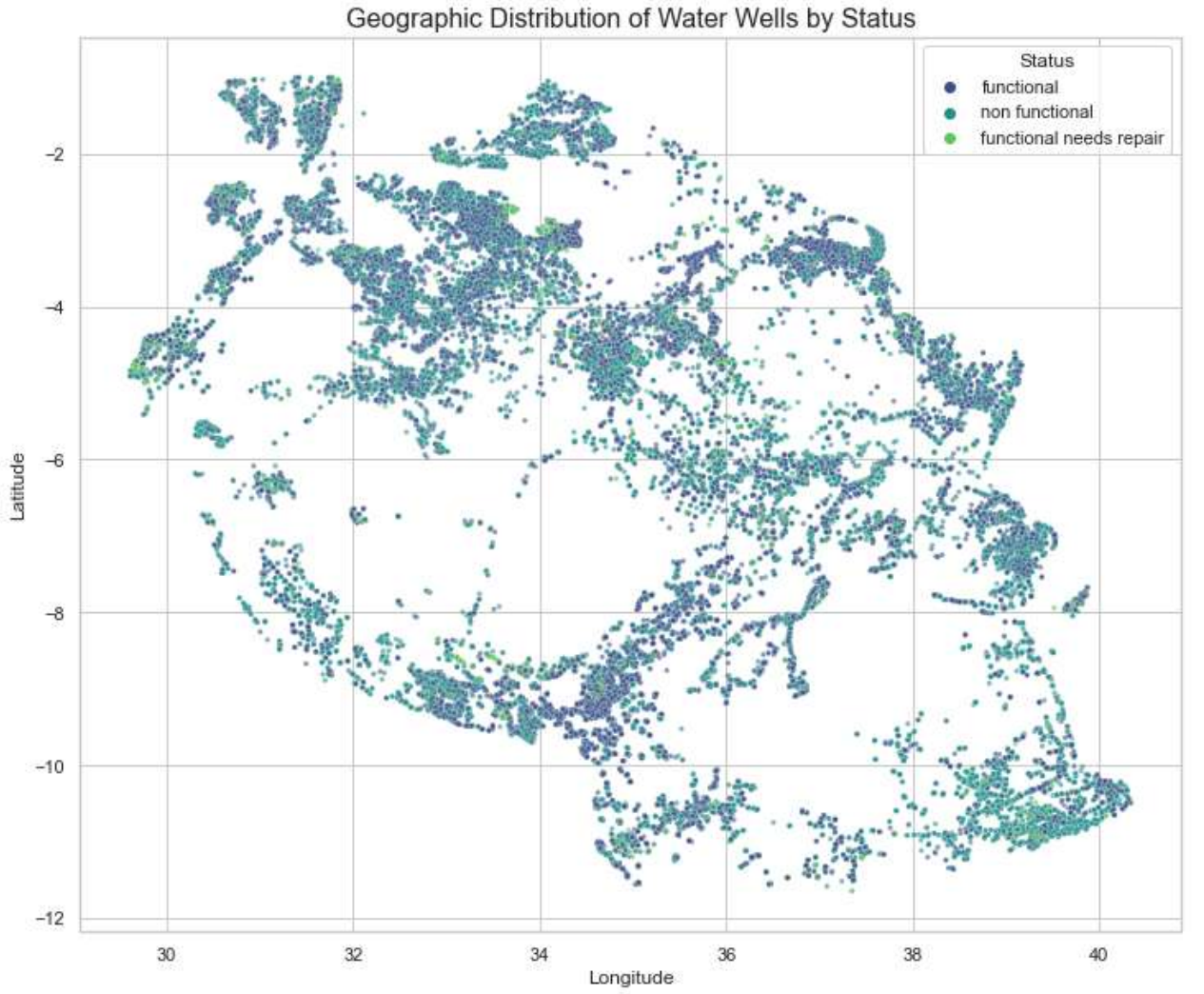
Observation

- Most functional pumps are found at a communalstandpipe water point.
- Water quality in most of the functional pumps is soft.
- Majority of the fuctional pipes have enough water quantity and are from a groundwater source.

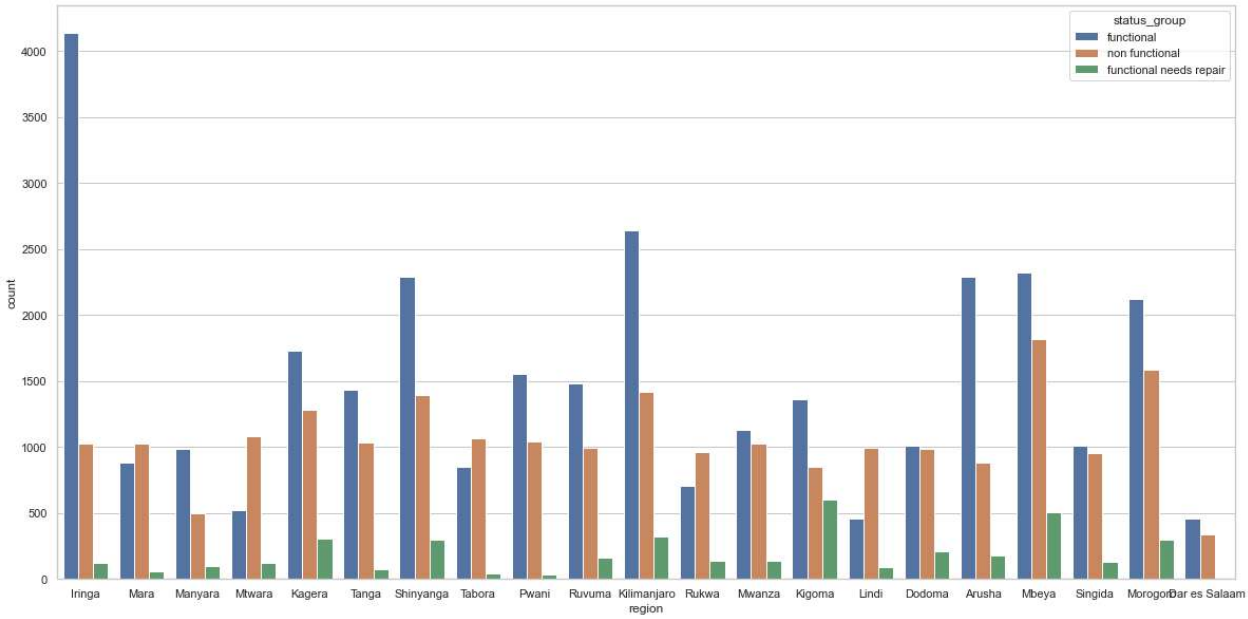
Geographical Features

In [122]:

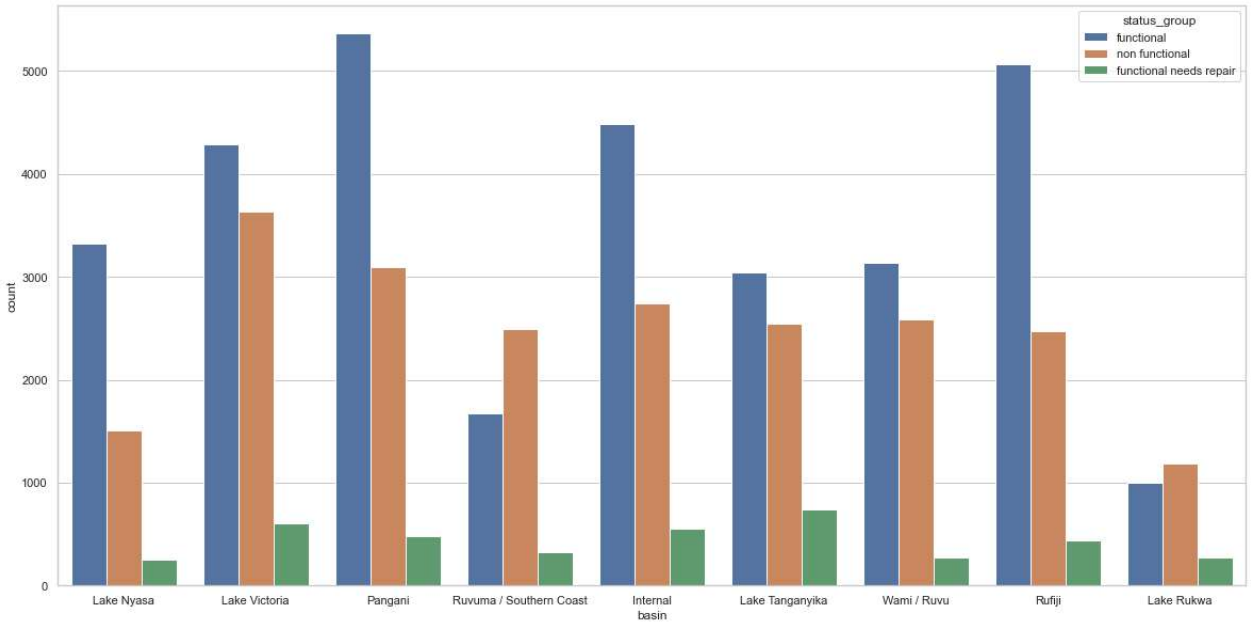
```
# scatter plot of well locations
plt.figure(figsize=(12, 10))
sns.scatterplot(
    data=df,
    x='longitude',
    y='latitude',
    hue='status_group',
    palette='viridis',
    s=10,  # size of points
    alpha=0.6 # transparency
)
plt.title('Geographic Distribution of Water Well Pumps by Status', fontsize=16)
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.legend(title='Status')
plt.grid(True)
plt.show()
```



In [123]:
```
#Region
plt.figure(figsize=(20,10))
ax = sns.countplot(x='region', hue="status_group", data=df_without_id)
```



In [124]:
```
#basin

plt.figure(figsize=(20,10))
ax = sns.countplot(x='basin', hue="status_group", data=df_without_id)
```



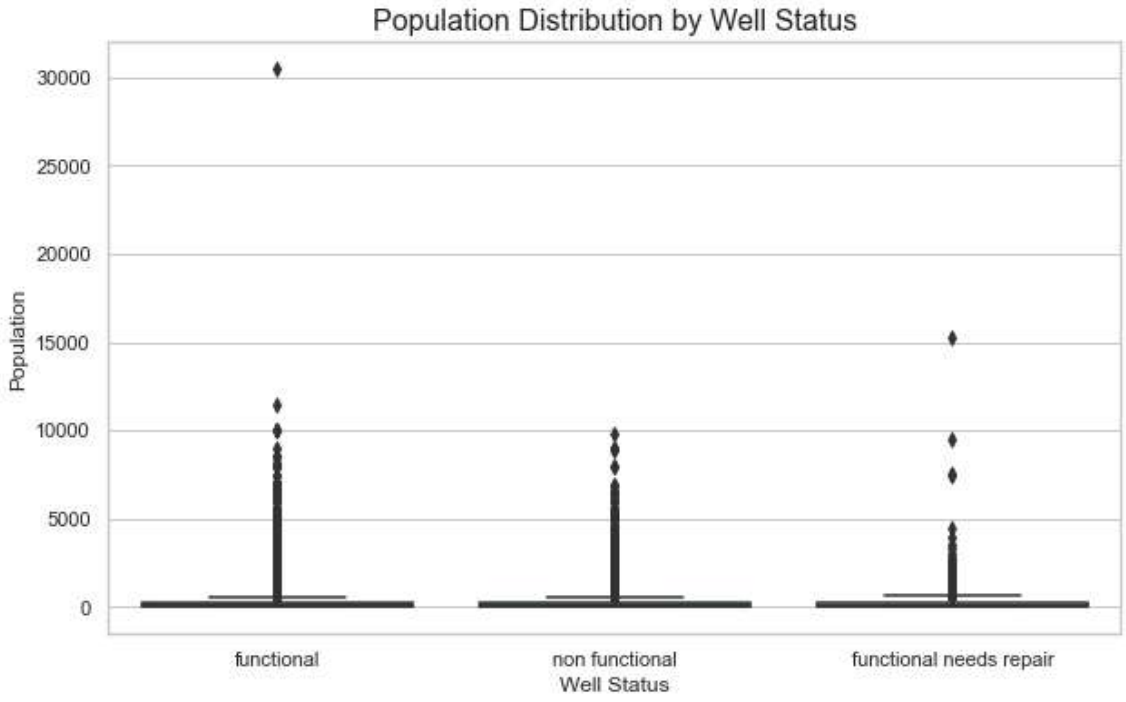
Observation

- Iringa region has the highest number of functional pumps.
- Mbeya region has the highest number of non functional pumps.
- Kigoma region has the highest number of pumps that need repair.
- Pangani basin has majority of the functional pumps
- Lake Victoria has majority of the non-functional pumps.

From the geographical plot, it appears that certain regions have a higher concentration of non-functional wells

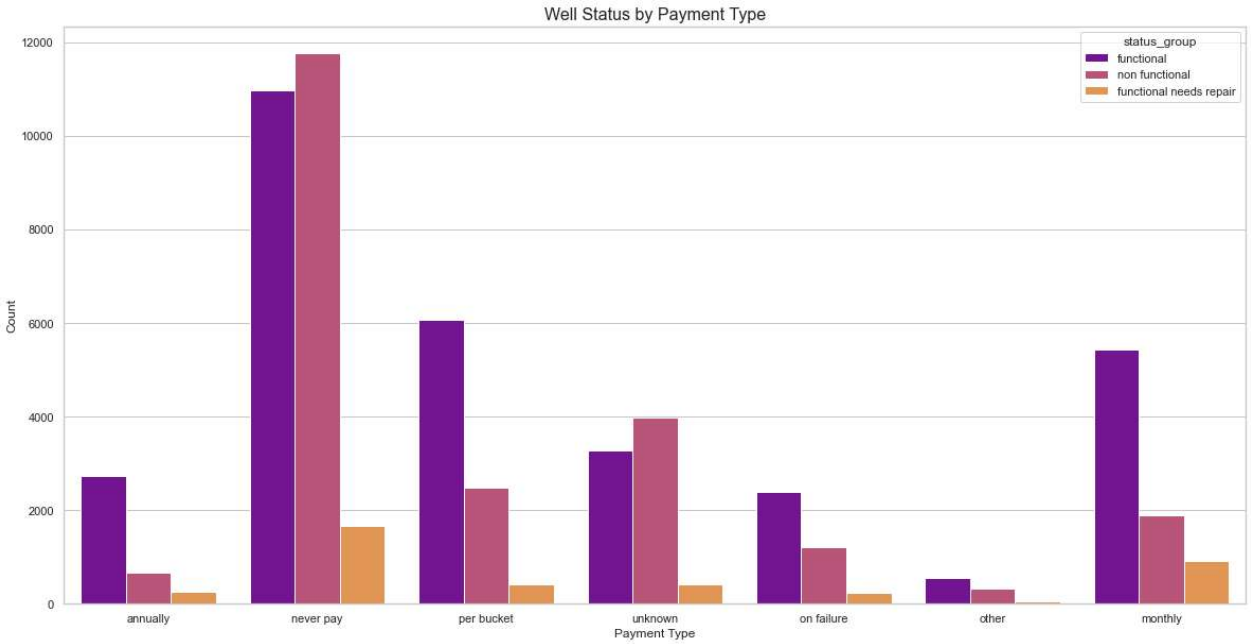
Socio-Economic Features

In [125]:
```
#population vs status_group
plt.figure(figsize=(10, 6))
sns.boxplot(x='status_group', y='population', data=df_without_id, palette='viridis')
plt.title('Population Distribution by Pump Functionality Status', fontsize=16)
plt.xlabel('Well Status')
plt.ylabel('Population')
plt.show()

```



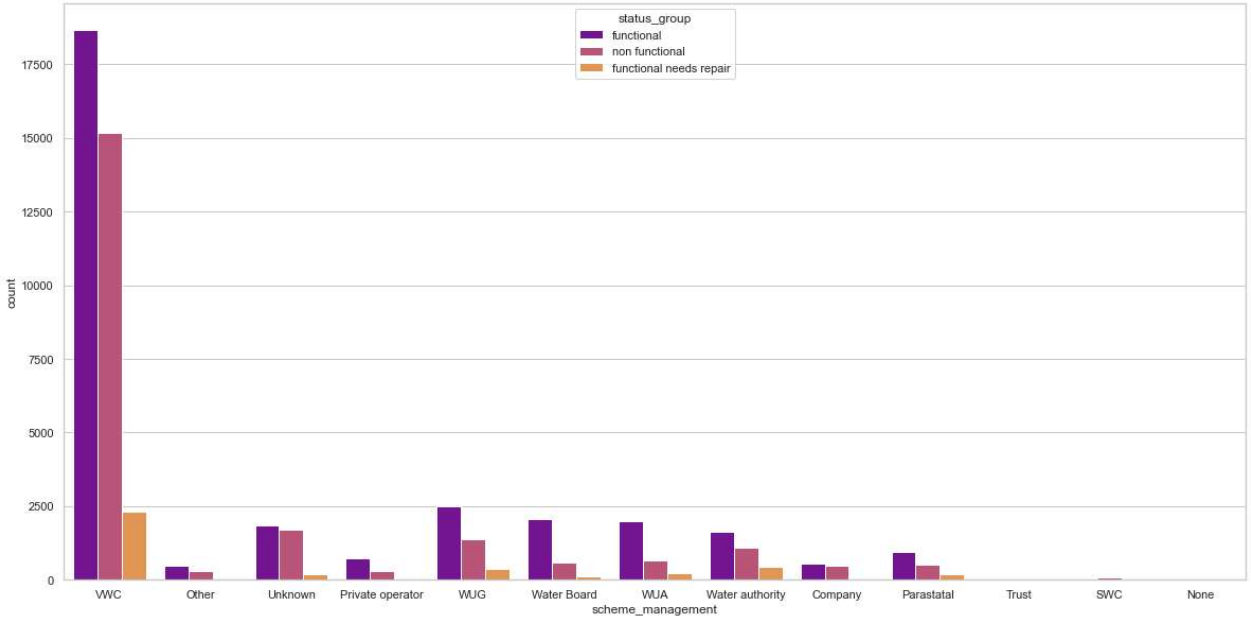
In [126]:

```
#payment type
plt.figure(figsize=(20,10))
ax = sns.countplot(x='payment_type', hue="status_group", data=df_without_id, palette='
plt.title('Well Status by Payment Type', fontsize=16)
plt.xlabel('Payment Type')
plt.ylabel('Count')
plt.show()
```

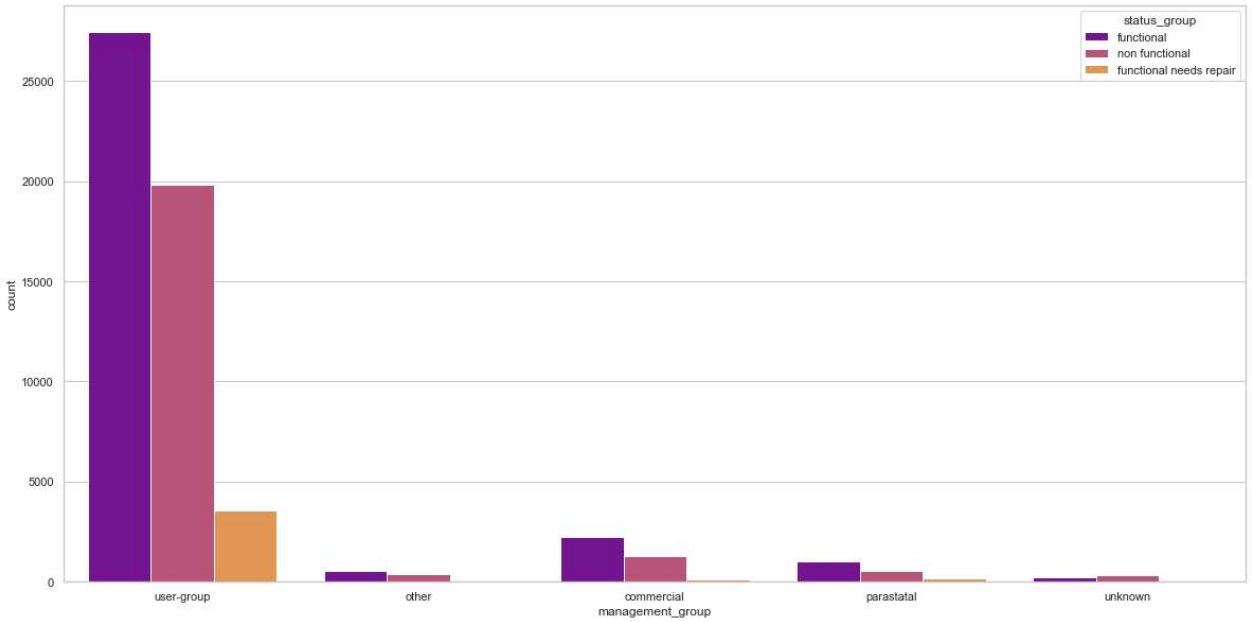


In [127]:

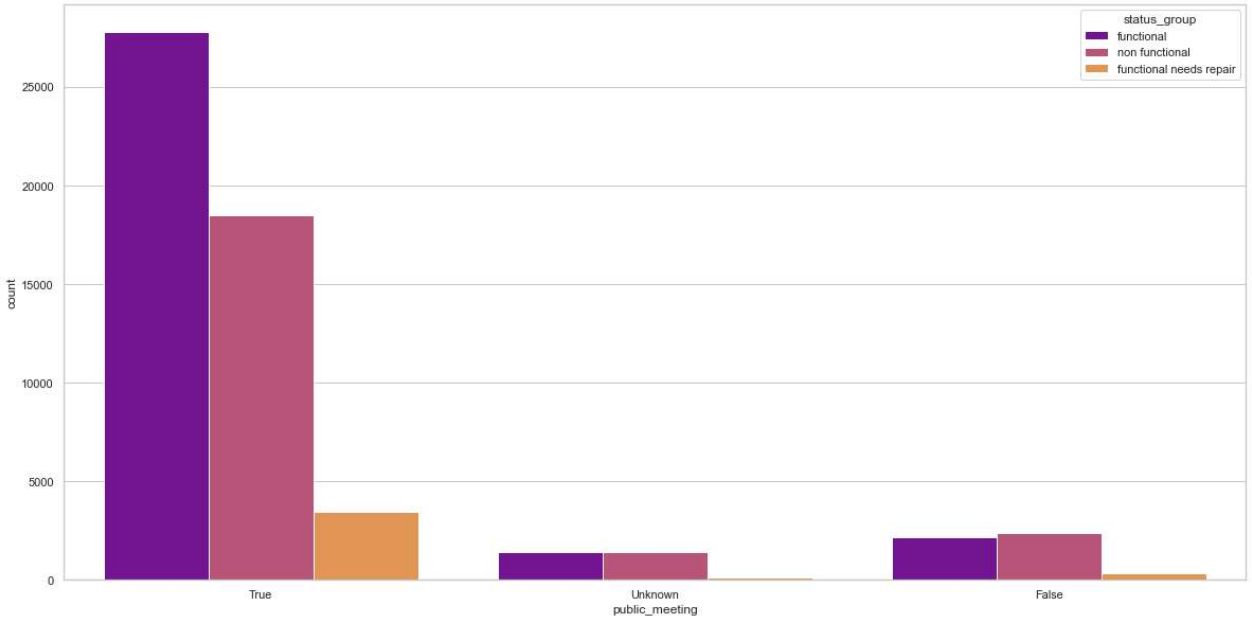
```
#Scheme Management
plt.figure(figsize=(20,10))
ax = sns.countplot(x='scheme_management', hue="status_group", data=df_without_id, pale
```



In [128]:
```
#management group
plt.figure(figsize=(20,10))
ax = sns.countplot(x='management_group', hue="status_group", data=df_without_id, palet
```

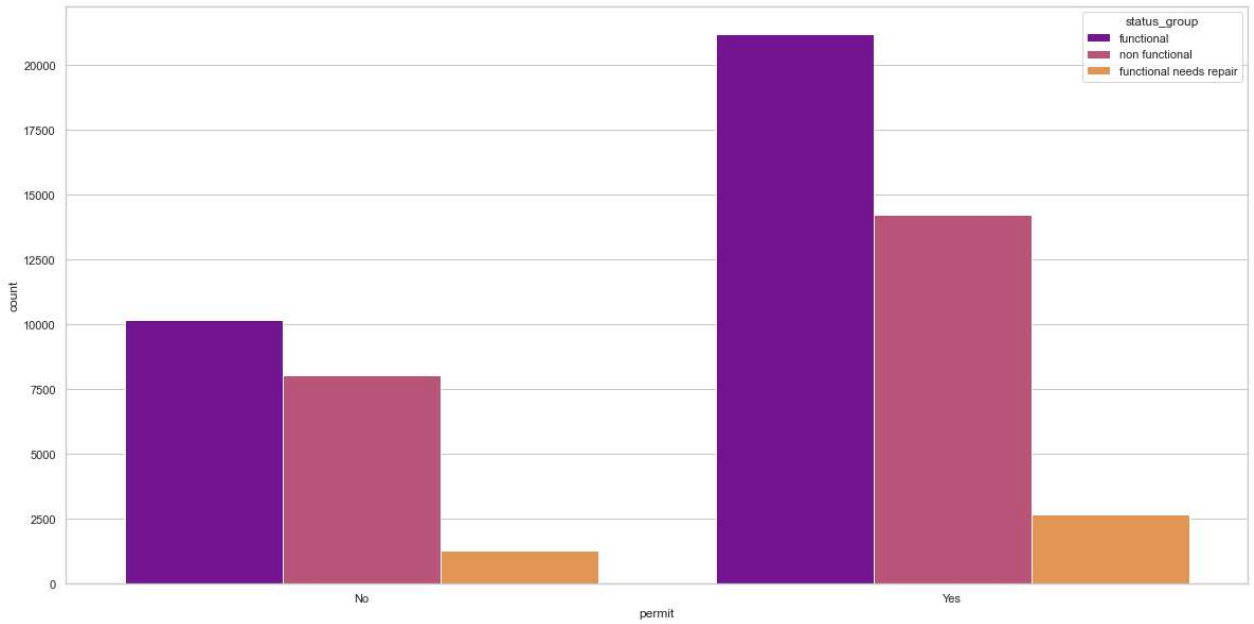


In [129]:
```
#Public meeting
plt.figure(figsize=(20,10))
ax = sns.countplot(x='public_meeting', hue="status_group", data=df_without_id, palette
```



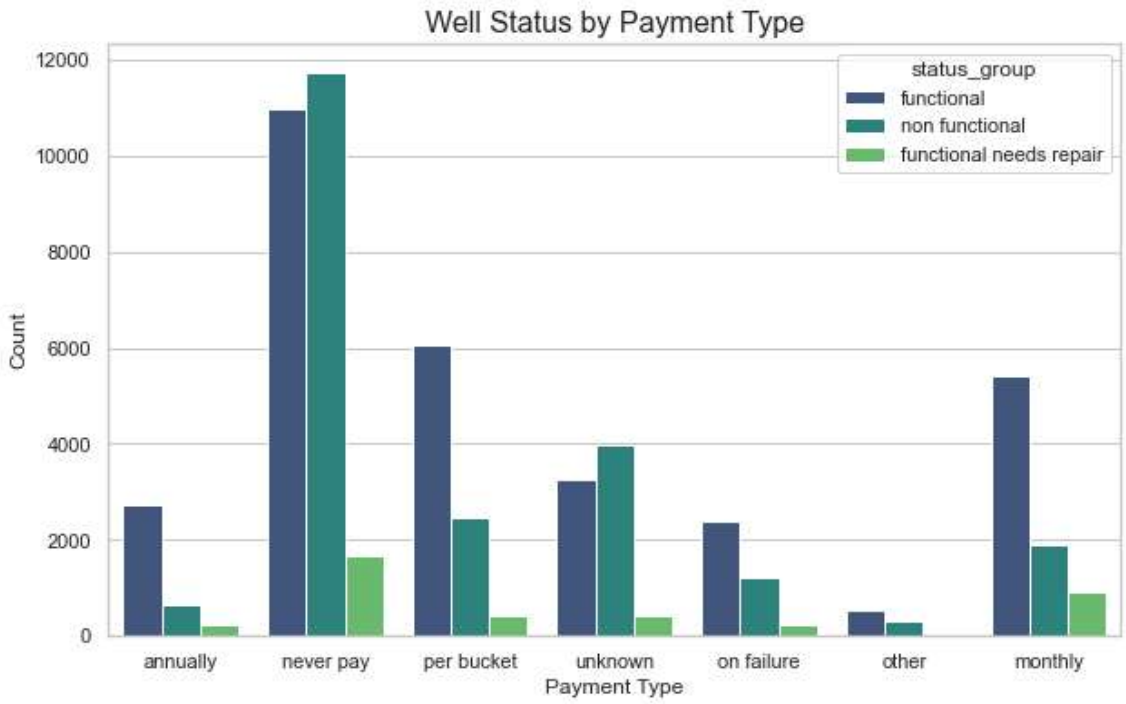
In [130]:

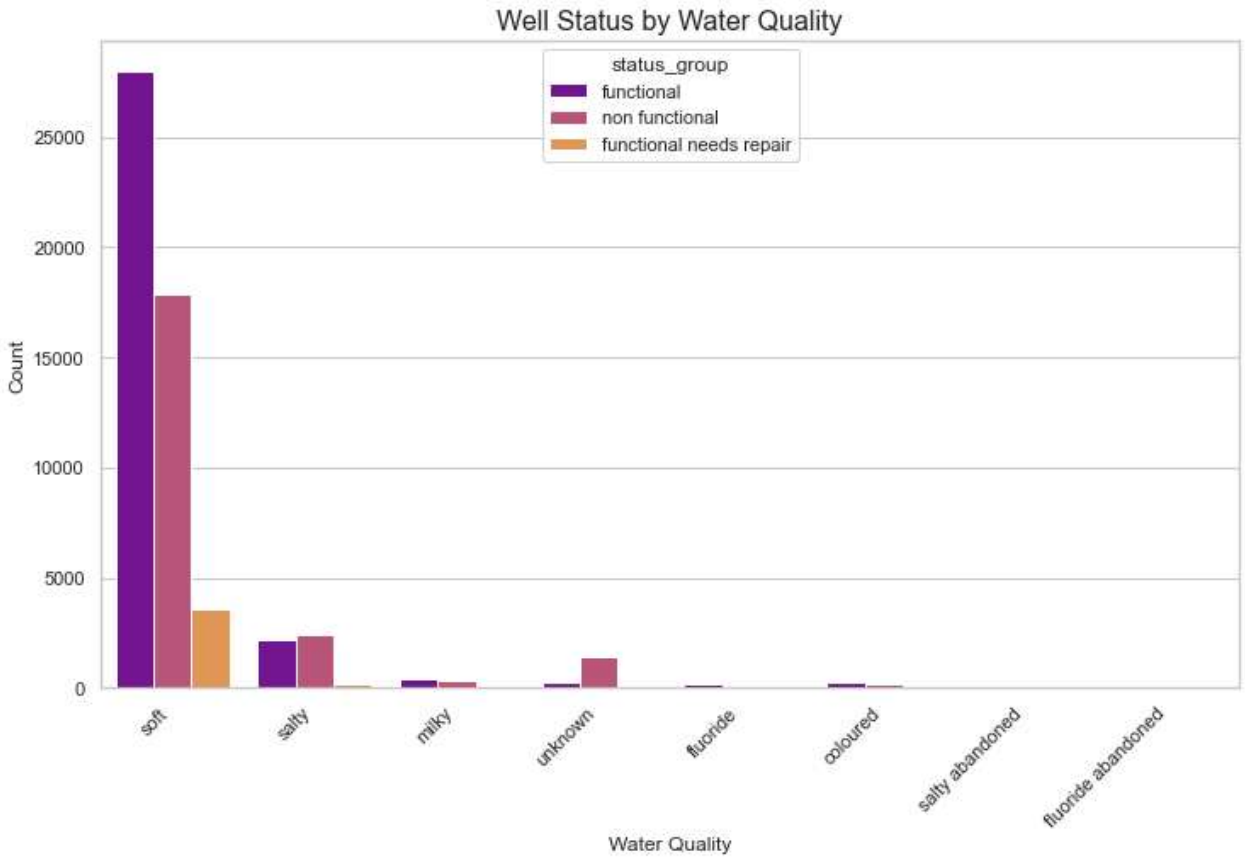
```
1 plt.figure(figsize=(20,10))
2 ax = sns.countplot(x='permit', hue="status_group", data=df_without_id, palette='plasma
```



In [131]:

```
# Relationship between `payment_type` and `status_group`
plt.figure(figsize=(10, 6))
sns.countplot(x='payment_type', hue='status_group', data=df_without_id, palette='virid
plt.title('Well Status by Payment Type', fontsize=16)
plt.xlabel('Payment Type')
plt.ylabel('Count')
plt.show()

 # Relationship between `water_quality` and `status_group`
plt.figure(figsize=(12, 7))
sns.countplot(x='water_quality', hue='status_group', data=df_without_id, palette='plas
plt.title('Well Status by Water Quality', fontsize=16)
plt.xlabel('Water Quality')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right')
plt.show()
```





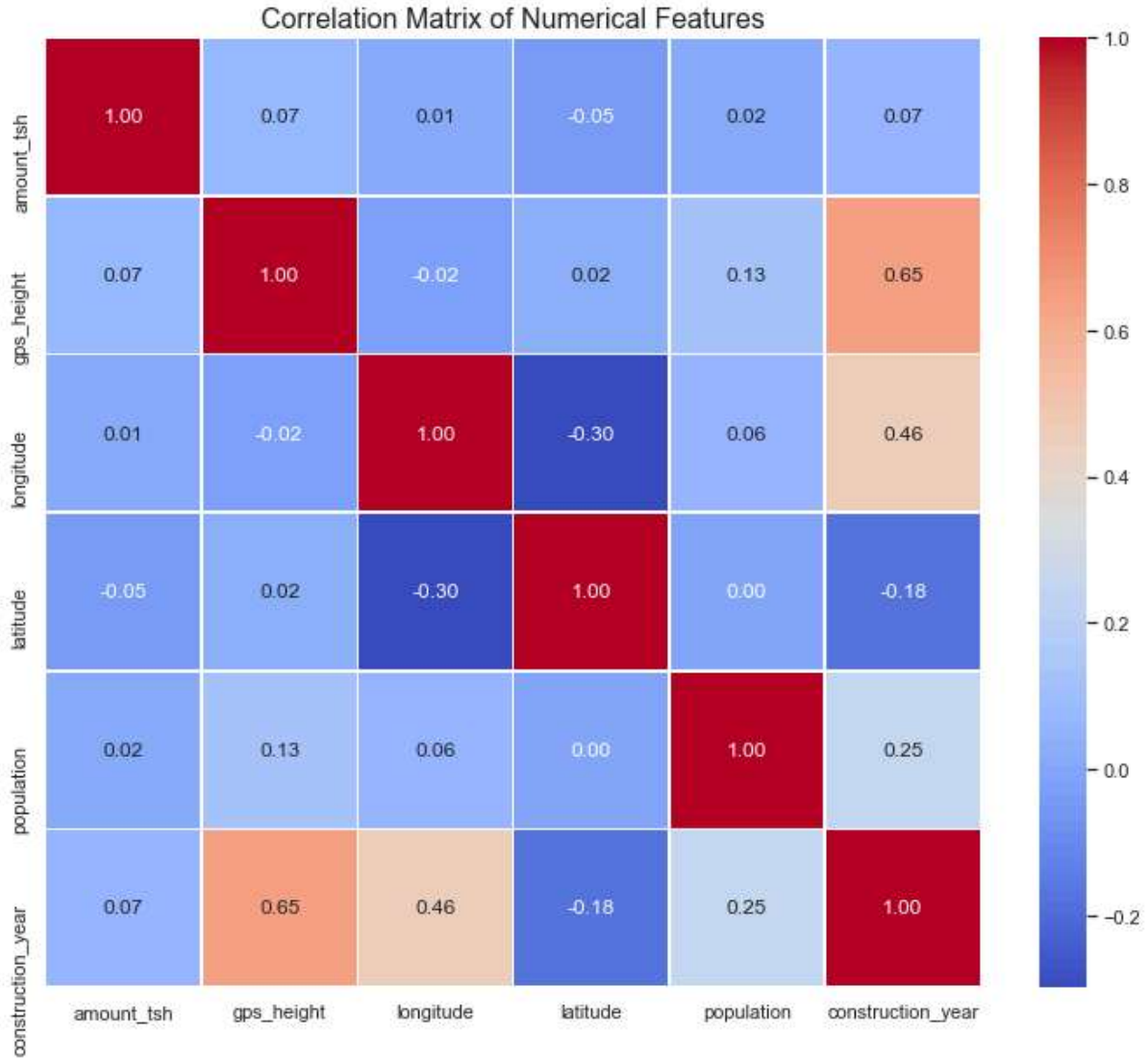
Observation

- Most non-functional pumps and pumps that need repair are found in wells that do not charge for water.
- Highest number of all pumps are found in water schemes managed by VWC
- When pumps are managed by the users, they are more likely to be functional.
- Participation in public meetings influence the pump functionality at the different wells.
- Having a permit ifluences the functionality of the pumps at different wells.

Multivariate Analysis

In [132]:

```
# Select only numerical columns for the correlation matrix
numerical_df = df_without_id.select_dtypes(include=np.number)

# Calculate the correlation matrix
corr_matrix = numerical_df.corr()

# Plot the heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True,cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title('Correlation Matrix of Numerical Features', fontsize=16)
plt.show()
```



4. Preprocessing

Null values

In [133]:
```
#create a copy for modeling

df2 = df_without_id.copy(deep=True)
df2
```

Out[133]:

	amount_tsh	date_recorded	gps_height	installer	longitude	latitude	basin	subvillage
0	6000.0	1970-01-01 00:00:00.000002011	1390	Roman	34.938093	-9.856322	Lake Nyasa	Mnyusi B
1	0.0	1970-01-01 00:00:00.000002013	1399	GRUMETI	34.698766	-2.147466	Lake Victoria	Nyamara
2	25.0	1970-01-01 00:00:00.000002013	686	World vision	37.460664	-3.821329	Pangani	Majengo
3	0.0	1970-01-01 00:00:00.000002013	263	UNICEF	38.486161	-11.155298	Ruvuma / Southern Coast	Mahakamani
4	0.0	1970-01-01 00:00:00.000002011	0	Artisan	31.130847	-1.825359	Lake Victoria	Kyanyamisa
...	...	...	...	...	...	...	...	...

In [134]:
```
df2.isnull().sum().any()
```

Out[134]:
```
False
```

In [135]:
```
rows_with_nan = df2[df2.isnull().any(axis=1)]
print(rows_with_nan)
```

```
Empty DataFrame
Columns: [amount_tsh, date_recorded, gps_height, installer, longitude, latitude, basin, s
ubvillage, region, lga, population, public_meeting, scheme_management, permit, constructi
on_year, extraction_type, management_group, payment_type, water_quality, quantity, sourc
e, source_class, waterpoint_type, status_group]
Index: []

[0 rows x 24 columns]
```

In [136]:
```
df2.duplicated().sum()
```

Out[136]:
```
23
```

In [137]:
```
# Display only the subsequent duplicate rows
subsequent_duplicates = df2[df2.duplicated()]
print(subsequent_duplicates)
```

```
50878  37.269036 -7.104923    Wami / Ruvu       Songa  Morogoro  Mvomero  ...
51319  37.252194 -7.103742    Wami / Ruvu  Doma Store  Morogoro  Mvomero  ...
51584  37.543401 -6.958716    Wami / Ruvu     Majengo  Morogoro  Mvomero  ...
51672  37.318911 -7.177155    Wami / Ruvu     Mdugile  Morogoro  Mvomero  ...
56544  37.542785 -6.965834    Wami / Ruvu    Gudugudu  Morogoro  Mvomero  ...
57423  37.540901 -6.959749    Wami / Ruvu     Majengo  Morogoro  Mvomero  ...
57824  37.375717 -7.056372    Wami / Ruvu     Mission  Morogoro  Mvomero  ...

       construction_year extraction_type management_group payment_type  \
8630                1974         gravity       user-group    never pay
8979                1974         gravity       user-group    never pay
10267               1971          swn 80       user-group    never pay
13864               1971         gravity       user-group    never pay
24995               1974         gravity       user-group    never pay
28701               1986     nira/tanira       user-group    never pay
29367               2003  other - swn 81       user-group    never pay
29872               2008     nira/tanira       user-group    never pay
30760               1980     nira/tanira       user-group    never pay
37766               1980          swn 80       user-group    never pay
38604               1985          swn 80       user-group    never pay
```

In [138]:
```
# Drop duplicates and create a new DataFrame
df3 = df2.drop_duplicates()
print(df3.duplicated().sum())
```

```
0
```

In [139]:
```
df3.status_group.unique()
```

Out[139]:
```
array(['functional', 'non functional', 'functional needs repair'],
      dtype=object)
```

In [140]:
```
df3.permit.unique()
```

Out[140]:
```
array(['No', 'Yes'], dtype=object)
```

In [141]:
```
df3.public_meeting.value_counts()
```

Out[141]:
```
True       49714
False       4875
Unknown     2976
Name: public_meeting, dtype: int64
```

In [142]:

```
mapping_dict = {
    True: 'Yes',
    False: 'No'}

# Use the dictionary to replace all values at once
df3['public_meeting'] = df3['public_meeting'].replace(mapping_dict)

print(df3)
```

```
       amount_tsh                 date_recorded  gps_height     installer  \
0          6000.0 1970-01-01 00:00:00.000002011        1390         Roman
1             0.0 1970-01-01 00:00:00.000002013        1399       GRUMETI
2            25.0 1970-01-01 00:00:00.000002013         686  World vision
3             0.0 1970-01-01 00:00:00.000002013         263        UNICEF
4             0.0 1970-01-01 00:00:00.000002011           0       Artisan
...           ...                           ...         ...           ...
59395        10.0 1970-01-01 00:00:00.000002013        1210           CES
59396      4700.0 1970-01-01 00:00:00.000002011        1212          Cefa
59397         0.0 1970-01-01 00:00:00.000002011           0       Unknown
59398         0.0 1970-01-01 00:00:00.000002011           0          Musa
59399         0.0 1970-01-01 00:00:00.000002011         191         World

       longitude   latitude                    basin    subvillage  \
0      34.938093  -9.856322              Lake Nyasa      Mnyusi B
1      34.698766  -2.147466           Lake Victoria       Nyamara
2      37.460664  -3.821329                 Pangani       Majengo
3      38.486161 -11.155298  Ruvuma / Southern Coast    Mahakamani
4      31.130847  -1.825359           Lake Victoria    Kyanyamisa
...          ...        ...                     ...           ...
59395  37.169807  -3.253847                 Pangani      Kiduruni
59396  35.249991  -9.070629                  Rufiji      Igumbilo
59397  34.017087  -8.750434                  Rufiji     Madungulu
59398  35.861315  -6.378573                  Rufiji        Mwinyi
59399  38.104048  -6.747464            Wami / Ruvu  Kikatanyemba

            region             lga  ...  construction_year extraction_type  \
0           Iringa          Ludewa  ...               1999         gravity
1             Mara       Serengeti  ...               2010         gravity
2          Manyara       Simanjiro  ...               2009         gravity
3           Mtwara        Nanyumbu  ...               1986     submersible
4           Kagera         Karagwe  ...                  0         gravity
...            ...             ...  ...                ...             ...
59395  Kilimanjaro             Hai  ...               1999         gravity
59396       Iringa          Njombe  ...               1996         gravity
59397        Mbeya         Mbarali  ...                  0          swn 80
59398       Dodoma        Chamwino  ...                  0     nira/tanira
59399     Morogoro  Morogoro Rural  ...               2002     nira/tanira

      management_group payment_type  water_quality      quantity  \
0           user-group     annually           soft        enough
1           user-group    never pay           soft  insufficient
2           user-group   per bucket           soft        enough
3           user-group    never pay           soft           dry
4                other    never pay           soft      seasonal
...                ...          ...            ...           ...
59395       user-group   per bucket           soft        enough
59396       user-group     annually           soft        enough
59397       user-group      monthly       fluoride        enough
59398       user-group    never pay           soft  insufficient
59399       user-group   on failure          salty        enough

                    source source_class             waterpoint_type  \
0                   spring  groundwater           communal standpipe
1      rainwater harvesting      surface           communal standpipe
2                      dam      surface  communal standpipe multiple
3             machine dbh  groundwater  communal standpipe multiple
4      rainwater harvesting      surface           communal standpipe
...                    ...          ...                         ...
59395               spring  groundwater           communal standpipe
59396                river      surface           communal standpipe
59397         machine dbh  groundwater                    hand pump
59398        shallow well  groundwater                    hand pump
```

```
59399          shallow well  groundwater                   hand pump

         status_group
0          functional
1          functional
2          functional
3      non functional
4          functional
...                ...
59395      functional
59396      functional
59397      functional
59398      functional
59399      functional

[57565 rows x 24 columns]
```

In [143]:

```python

#df3['status_group'] = df3['status_group'].apply(lambda x: 1 if x == 'functional' else

# Handle missing values and high cardinality for categorical features

for col in ['installer', 'subvillage', 'scheme_management', 'public_meeting', 'permit'
    # Replace unkown with mode
    if df3[col].dtype == 'object':
        mode = df3[col].mode()[0]
        df3[col].replace('Unknown', mode, inplace=True)

    # Group infrequent categories into 'other'
    counts = df3[col].value_counts(normalize=True)
    infrequent_categories = counts[counts < 0.05].index
    df3[col] = df3[col].apply(lambda x: 'other' if x in infrequent_categories else x)

 #Handle missing/zero values for numerical features
for col in ['population', 'construction_year']:

    # Replace zeros with NaNs, as they likely mean missing data
    median= df3[col].median()
    df3[col].replace(0, median, inplace=True)

# Feature Engineering: 'pump_age'
# Asumption: the recording date is from 2013, a common reference point for this datase
df3['date_recorded'] = pd.to_datetime(df3['date_recorded'])
df3['age'] = df3['date_recorded'].dt.year - df3['construction_year']

# Drop original features we no longer need after engineering
df3.drop(['date_recorded', 'construction_year'], axis=1, inplace=True)

```

In [144]:
```
1 df3
```

Out[144]:

	amount_tsh	gps_height	installer	longitude	latitude	basin	subvillage	region	lga	pop
0	6000.0	1390	other	34.938093	-9.856322	Lake Nyasa	other	Iringa	Ludewa	
1	0.0	1399	other	34.698766	-2.147466	Lake Victoria	other	Mara	Serengeti	
2	25.0	686	other	37.460664	-3.821329	Pangani	other	Manyara	Simanjiro	
3	0.0	263	other	38.486161	-11.155298	Ruvuma / Southern Coast	other	Mtwara	Nanyumbu	
4	0.0	0	other	31.130847	-1.825359	Lake Victoria	other	Kagera	Karagwe	
...	...	...	...	...	...	...	...	...	...	
59395	10.0	1210	other	37.169807	-3.253847	Pangani	other	Kilimanjaro	Hai	
59396	4700.0	1212	other	35.249991	-9.070629	Rufiji	other	Iringa	Njombe	
59397	0.0	0	DWE	34.017087	-8.750434	Rufiji	other	Mbeya	Mbarali	
59398	0.0	0	other	35.861315	-6.378573	Rufiji	other	Dodoma	Chamwino	
59399	0.0	191	other	38.104048	-6.747464	Wami / Ruvu	other	Morogoro	Morogoro Rural	

57565 rows × 23 columns

In [145]:
```
1 df3.status_group.value_counts()
```

Out[145]:
```
functional                 31380
non functional             22256
functional needs repair     3929
Name: status_group, dtype: int64
```

In [146]:

```
# Filter out rows where the 'Category' column contains 'other'
values_to_remove = ['other', 'Other', 'unknown', 'Unknown']
df4 = df3[~df3['installer'].isin(values_to_remove)]
print("Filtered by 'Category' column:")
print(df4)

```

Filtered by 'Category' column:

	amount_tsh	gps_height	installer	longitude	latitude	basin	\
5	20.0	0	DWE	39.172796	-4.765587	Pangani	
7	0.0	0	DWE	32.620617	-4.226198	Lake Tanganyika	
15	0.0	1645	DWE	31.444121	-8.274962	Lake Tanganyika	
16	500.0	1703	DWE	34.642439	-9.106185	Rufiji	
17	0.0	1656	DWE	34.569266	-9.085515	Rufiji	
...	...	...	...	...	...	...	
59386	0.0	1786	DWE	31.738789	-8.532013	Lake Rukwa	
59388	0.0	1414	DWE	30.692400	-3.593827	Lake Tanganyika	
59389	0.0	783	DWE	30.646486	-7.365418	Lake Tanganyika	
59390	0.0	1715	DWE	31.370848	-8.258160	Lake Tanganyika	
59397	0.0	0	DWE	34.017087	-8.750434	Rufiji	

	subvillage	region	lga	population	...	\
5	other	Tanga	Mkinga	1	...	
7	other	Shinyanga	Kahama	35	...	
15	other	Rukwa	Sumbawanga Rural	200	...	
16	other	Iringa	Njombe	35	...	
17	other	Iringa	Njombe	50	...	
...	...	...	...	...	...	
59386	other	Rukwa	Sumbawanga Rural	1000	...	
59388	other	Kigoma	Kibondo	500	...	
59389	other	Rukwa	Nkasi	1500	...	
59390	other	Rukwa	Sumbawanga Rural	150	...	
59397	other	Mbeya	Mbarali	35	...	

	extraction_type	management_group	payment_type	water_quality	\
5	submersible	user-group	per bucket	salty	
7	nira/tanira	user-group	unknown	milky	
15	swn 80	user-group	never pay	soft	
16	gravity	user-group	monthly	soft	
17	gravity	user-group	on failure	soft	
...	...	...	...	...	
59386	india mark ii	user-group	never pay	soft	
59388	gravity	user-group	unknown	soft	
59389	india mark ii	user-group	never pay	soft	
59390	swn 80	user-group	never pay	soft	
59397	swn 80	user-group	monthly	fluoride	

	quantity	source	source_class	waterpoint_type	\
5	enough	other	unknown	communal standpipe multiple	
7	enough	shallow well	groundwater	hand pump	
15	enough	machine dbh	groundwater	hand pump	
16	dry	river	surface	communal standpipe	
17	dry	river	surface	communal standpipe	
...	...	...	...	...	
59386	enough	machine dbh	groundwater	hand pump	
59388	insufficient	spring	groundwater	improved spring	
59389	enough	machine dbh	groundwater	hand pump	
59390	insufficient	machine dbh	groundwater	hand pump	
59397	enough	machine dbh	groundwater	hand pump	

	status_group	age
5	functional	-39
7	non functional	-18
15	functional	-21
16	non functional	-8
17	non functional	-8
...	...	..
59386	functional	-39
59388	functional	-25
59389	functional	-39

```
59390      functional -21
59397      functional -18

[19889 rows x 23 columns]
```

In [147]:

```
required = ['age','amount_tsh', 'extraction_type','source','water_quality',
            'quantity','payment_type','management_group','installer','public_meeting',
             'population','longitude', 'latitude',
       'basin','region', 'gps_height', 'permit','status_group']
df5 = df4[required]
df5
```

Out[147]:

	age	amount_tsh	extraction_type	source	water_quality	quantity	payment_type	management_group
5	-39	20.0	submersible	other	salty	enough	per bucket	user-group
7	-18	0.0	nira/tanira	shallow well	milky	enough	unknown	user-group
15	-21	0.0	swn 80	machine dbh	soft	enough	never pay	user-group
16	-8	500.0	gravity	river	soft	dry	monthly	user-group
17	-8	0.0	gravity	river	soft	dry	on failure	user-group
...	...	...	...	...	...	...	...	...
59386	-39	0.0	india mark ii	machine dbh	soft	enough	never pay	user-group
59388	-25	0.0	gravity	spring	soft	insufficient	unknown	user-group
59389	-39	0.0	india mark ii	machine dbh	soft	enough	never pay	user-group
59390	-21	0.0	swn 80	machine dbh	soft	insufficient	never pay	user-group
59397	-18	0.0	swn 80	machine dbh	fluoride	enough	monthly	user-group

19889 rows × 18 columns

In [148]:

```
df5.public_meeting.value_counts()
```

Out[148]:

```
Yes    18262
No      1627
Name: public_meeting, dtype: int64
```

In [149]:

```
df5.status_group.value_counts()
```

Out[149]:

```
functional                10898
non functional             7238
functional needs repair    1753
Name: status_group, dtype: int64
```

Splitting The Dataset

In [150]:
```
 #Define feature and target variables
X = df5.drop('status_group', axis=1)
y = df5['status_group']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
```

In [ ]:
```

```

In [151]:
```
# resulting shapes
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(15911, 17)
(3978, 17)
(15911,)
(3978,)
```

In [152]:
```
#train set class distribution
y_train.value_counts(normalize=True)
```

Out[152]:
```
functional                 0.547923
non functional             0.363899
functional needs repair    0.088178
Name: status_group, dtype: float64
```

In [153]:
```
#test set class distribution
y_test.value_counts(normalize=True)
```

Out[153]:
```
functional                 0.548014
non functional             0.364002
functional needs repair    0.087984
Name: status_group, dtype: float64
```

In [154]:
```
X.columns
```

Out[154]:
```
Index(['age', 'amount_tsh', 'extraction_type', 'source', 'water_quality',
       'quantity', 'payment_type', 'management_group', 'installer',
       'public_meeting', 'population', 'longitude', 'latitude', 'basin',
       'region', 'gps_height', 'permit'],
      dtype='object')
```

Scaling and Imputing

In [155]:
```
# Identify numerical and categorical columns after dropping the original ones
numerical_features = X.select_dtypes(include=np.number).columns.tolist()
categorical_features = X.select_dtypes(include='object').columns.tolist()

# Imputation for numerical features
num_imputer = SimpleImputer(strategy='median')
X_train[numerical_features] = num_imputer.fit_transform(X_train[numerical_features])
X_test[numerical_features] = num_imputer.transform(X_test[numerical_features])

# Imputation for categorical features
cat_imputer = SimpleImputer(strategy='most_frequent')
X_train[categorical_features] = cat_imputer.fit_transform(X_train[categorical_features
X_test[categorical_features] = cat_imputer.transform(X_test[categorical_features])

# One-Hot Encoding
encoder = OneHotEncoder(handle_unknown='ignore', sparse_output=False)

# Fit the encoder only on the training data
encoder.fit(X_train[categorical_features])

# Transform both training and test data
X_train_encoded = encoder.transform(X_train[categorical_features])
X_test_encoded = encoder.transform(X_test[categorical_features])

# Create DataFrames with the new encoded columns
X_train_encoded_df = pd.DataFrame(X_train_encoded, columns=encoder.get_feature_names_o
X_test_encoded_df = pd.DataFrame(X_test_encoded, columns=encoder.get_feature_names_out

# Combine numerical and encoded categorical data
X_train_processed = pd.concat([X_train[numerical_features], X_train_encoded_df], axis=
X_test_processed = pd.concat([X_test[numerical_features], X_test_encoded_df], axis=1)

# Scaling numerical features
scaler = StandardScaler()
X_train_processed[numerical_features] = scaler.fit_transform(X_train_processed[numeric
X_test_processed[numerical_features] = scaler.transform(X_test_processed[numerical_fea
```

In [156]:
```
X_train_processed.head()
```

Out[156]:

	age	amount_tsh	population	longitude	latitude	gps_height	extraction_type_afridev	extraction_ty
27943	0.188324	-0.098243	-0.378176	0.046232	0.203454	1.215912	0.0	
3829	-0.660201	-0.098243	0.143669	1.624994	0.187870	-0.718706	0.0	
25837	0.376885	-0.098243	-0.220939	1.649475	-0.055766	-1.009408	0.0	
21953	0.376885	-0.098243	-0.300697	-0.457378	0.862623	-0.984698	0.0	
25494	-0.094518	-0.098243	-0.045471	1.798010	-0.980121	-1.042838	0.0	

5 rows × 92 columns

In [157]:
```
1 X_test_processed.head()
```

Out[157]:

	age	amount_tsh	population	longitude	latitude	gps_height	extraction_type_afridev	extraction_ty
55740	0.376885	-0.098243	-0.300697	-0.440700	0.846989	-0.984698	0.0	
8636	0.282605	-0.098243	0.075305	1.673478	0.023337	-0.975977	0.0	
20363	-0.943043	-0.098243	0.531065	-1.542353	0.751496	1.051666	0.0	
16892	0.376885	-0.098243	-0.300697	-0.312746	-1.146366	-0.984698	0.0	
42741	0.376885	-0.098243	-0.300697	-0.877308	0.849581	-0.984698	0.0	

5 rows × 92 columns

In [158]:
```
1 y_train.value_counts()
```

Out[158]:
```
functional                 8718
non functional             5790
functional needs repair    1403
Name: status_group, dtype: int64
```

5. Modelling

Baseline Model

In [159]:
```
1 lr = LogisticRegression(random_state = 42 , multi_class = 'multinomial', max_iter= 100
2 lr.fit(X_train_processed, y_train)
```

Out[159]:
```
LogisticRegression
LogisticRegression(max_iter=1000, multi_class='multinomial', random_state=42)
```

In [160]:
```
1 print(f" the model score on training dataset is {lr.score(X_train_processed, y_train)*
```

```
the model score on training dataset is 72.51%
```

In [161]:
```
1 y_pred = lr.predict(X_test_processed)
2
3 #accuracy
4 accuracy_score(y_test, y_pred)*100
```

Out[161]:
```
72.54901960784314
```

In [162]:
```
conf = confusion_matrix(y_test, y_pred)
sns.heatmap(conf, annot=True, fmt = 'd');
```

In [163]:
```
print(classification_report(y_test, y_pred))
```

```
                        precision    recall  f1-score   support

            functional       0.70      0.91      0.79      2180
functional needs repair       0.47      0.04      0.08       350
         non functional       0.79      0.62      0.69      1448

              accuracy                           0.73      3978
             macro avg       0.65      0.52      0.52      3978
          weighted avg       0.71      0.73      0.69      3978
```

In [183]:
```
# Apply SMOTE to the preprocessed training data
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_train_processed, y_train)


# Initialize and train the logistic regression model
model = LogisticRegression(random_state = 42 , multi_class = 'multinomial', max_iter=
model.fit(X_resampled, y_resampled)

# Make predictions and evaluate the model
y_pred = model.predict(X_test_processed)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.618149824032177

Classification Report:
                        precision    recall  f1-score   support

            functional       0.77      0.62      0.69      2180
functional needs repair       0.21      0.63      0.31       350
         non functional       0.77      0.61      0.68      1448

              accuracy                           0.62      3978
             macro avg       0.58      0.62      0.56      3978
          weighted avg       0.72      0.62      0.65      3978
```

Random Forest

In [164]:

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Initialize the Random Forest Classifier
# n_estimators: The number of trees in the forest. More trees generally lead to better
# max_depth: The maximum depth of each tree. This helps prevent overfitting.
# random_state: Ensures reproducibility of the results.
rf_classifier = RandomForestClassifier(n_estimators=100, max_depth=10, random_state=42

# Train the Random Forest model on your processed training data
rf_classifier.fit(X_train_processed, y_train)

# Make predictions on the processed test data
y_pred_rf = rf_classifier.predict(X_test_processed)

# Calculate and print the accuracy
accuracy_rf = accuracy_score(y_test, y_pred_rf) * 100
print(f"Random Forest Model Accuracy: {accuracy_rf:.2f}%")

# Generate and print the classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Model Accuracy: 75.11%

Classification Report:
                         precision    recall  f1-score   support

             functional       0.71      0.95      0.81      2180
functional needs repair       0.68      0.08      0.14       350
         non functional       0.87      0.61      0.72      1448

               accuracy                           0.75      3978
              macro avg       0.76      0.55      0.56      3978
           weighted avg       0.77      0.75      0.72      3978
```

In [167]:

```python
# Train the Random Forest on Smote training data
rf_classifier.fit(X_resampled, y_resampled)

# predictions on the processed test
y_pred_rf_smote = rf_classifier.predict(X_test_processed)

# Calculate and print the accuracy
accuracy_rf = accuracy_score(y_test, y_pred_rf_smote) * 100
print(f"Random Forest Model Accuracy: {accuracy_rf:.2f}%")

# Generate and print the classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred_rf_smote))
```

```
Random Forest Model Accuracy: 68.88%

Classification Report:
                         precision    recall  f1-score   support

             functional       0.79      0.72      0.75      2180
functional needs repair       0.26      0.67      0.38       350
         non functional       0.85      0.65      0.74      1448

               accuracy                           0.69      3978
              macro avg       0.63      0.68      0.62      3978
           weighted avg       0.77      0.69      0.71      3978
```

XGBOOST

In [168]:

```
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score

# Initialize the XGBoost Classifier
xgb_classifier = XGBClassifier(objective='multi:softmax', num_class=len(np.unique(y_tr
                               n_estimators=100, learning_rate=0.1, use_label_encoder=
                               eval_metric='mlogloss', random_state=42)

# Train the XGBoost model on your processed training data
xgb_classifier.fit(X_train_processed, y_train)

# Make predictions on the processed test data
y_pred_xgb = xgb_classifier.predict(X_test_processed)

# Calculate and print the accuracy
accuracy_xgb = accuracy_score(y_test, y_pred_xgb) * 100
print(f"XGBoost Model Accuracy: {accuracy_xgb:.2f}%")
# Generate and print the classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred_xgb))
```

```
[00:10:26] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\le
arner.cc:516:
Parameters: { use_label_encoder } might not be used.

  This may not be accurate due to some parameters are only used in language bindings bu
t
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


XGBoost Model Accuracy: 77.53%

Classification Report:
                         precision    recall  f1-score   support

             functional       0.75      0.93      0.83      2180
functional needs repair       0.58      0.21      0.31       350
         non functional       0.87      0.67      0.76      1448
```

SMOTE XGBOOST model

In [169]:

```
xgb_classifier.fit(X_resampled, y_resampled)

# Make predictions on the processed test data
y_pred_xgb_smote = xgb_classifier.predict(X_test_processed)

# Calculate and print the accuracy
accuracy_xgb_smote = accuracy_score(y_test, y_pred_xgb_smote) * 100
print(f"XGBoost Model Accuracy: {accuracy_xgb:.2f}%")

print("\nClassification Report:")
print(classification_report(y_test, y_pred_xgb_smote))
```

```
[00:10:57] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\le
arner.cc:516:
Parameters: { use_label_encoder } might not be used.

  This may not be accurate due to some parameters are only used in language bindings bu
t
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


XGBoost Model Accuracy: 77.53%

Classification Report:
                         precision    recall  f1-score   support

             functional       0.80      0.74      0.77      2180
functional needs repair       0.28      0.61      0.38       350
         non functional       0.84      0.69      0.76      1448
```

Model 3 Randomized Search for Hyperparameter Tuning

In [170]:

```
# Define the model to be tuned
model = XGBClassifier(objective='multi:softmax', num_class=len(np.unique(y_train)),
                                n_estimators=100, learning_rate=0.1, use_label_encoder=
                                eval_metric='mlogloss', random_state=42)

# Define the hyperparameter distributions to sample from
# Use distributions instead of a fixed grid for continuous hyperparameters
param_distributions = {
    'C': loguniform(1e-4, 1e2),
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
    'penalty': ['l1', 'l2', 'elasticnet', 'none'],
    'class_weight': [None, 'balanced'],
    'l1_ratio': [0, 0.5, 1]
}


# Perform random search
random_search = RandomizedSearchCV(model, param_distributions, n_iter=10, cv=5, scorin

# Fit the random search to training data
# X_resampled and y_resampled are from your previous steps
random_search.fit(X_resampled, y_resampled)

# Print the best parameters and the best score
print("Best parameters: ", random_search.best_params_)
print("Best cross-validation score: {:.2f}".format(random_search.best_score_))
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[00:15:05] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\lear
ner.cc:516:
Parameters: { C, l1_ratio, penalty, solver, use_label_encoder } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


Best parameters:  {'C': 0.014495162994032825, 'class_weight': None, 'l1_ratio': 1, 'penal
ty': 'none', 'solver': 'newton-cg'}
Best cross-validation score: 0.77
```

FINAL MODEL with Best Parameters

In [172]:
```
best_parameters = {'C': 0.014495162994032825, 'class_weight': None, 'l1_ratio': 1,
                   'penalty': 'none', 'solver': 'newton-cg'}
final_xgb_classifier = XGBClassifier(
    objective='multi:softmax',
    num_class=len(np.unique(y_train)),
    use_label_encoder=False,
    eval_metric='mlogloss',
    random_state=42,
    **best_parameters
)

# Train the XGBoost model
final_xgb_classifier.fit(X_resampled, y_resampled)

# Make predictions on the processed test data
y_pred_xgb_smote = final_xgb_classifier.predict(X_test_processed)

# Calculate and print the accuracy
accuracy_xgb = accuracy_score(y_test, y_pred_xgb_smote) * 100
print(f"XGBoost Model Accuracy: {accuracy_xgb:.2f}%")

# Generate and print the classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred_xgb_smote))
```

```
[00:25:56] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\learner.cc:516:
Parameters: { C, l1_ratio, penalty, solver, use_label_encoder } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


XGBoost Model Accuracy: 74.74%

Classification Report:
                         precision    recall  f1-score   support

             functional       0.81      0.78      0.79      2180
functional needs repair       0.34      0.54      0.42       350
         non functional       0.82      0.75      0.78      1448

               accuracy                           0.75      3978
              macro avg       0.66      0.69      0.66      3978
           weighted avg       0.77      0.75      0.76      3978
```

Overall Performance Accuracy (75%): The model correctly classified the state of a well 75% of the time. While this seems good, it can be misleading, especially when one class is much smaller than the others.

Performance by Class Functional: The model does very well here. With a precision of 0.81, when it predicts a well is functional, it's correct 81% of the time. The recall of 0.78 means it successfully identifies 78% of all truly functional wells.

Non Functional: The performance is also strong for this class. It has a high precision of 0.82, correctly identifying 82% of the wells it predicts as non-functional. Its recall is 0.75, meaning it finds 75% of all non-functional wells.

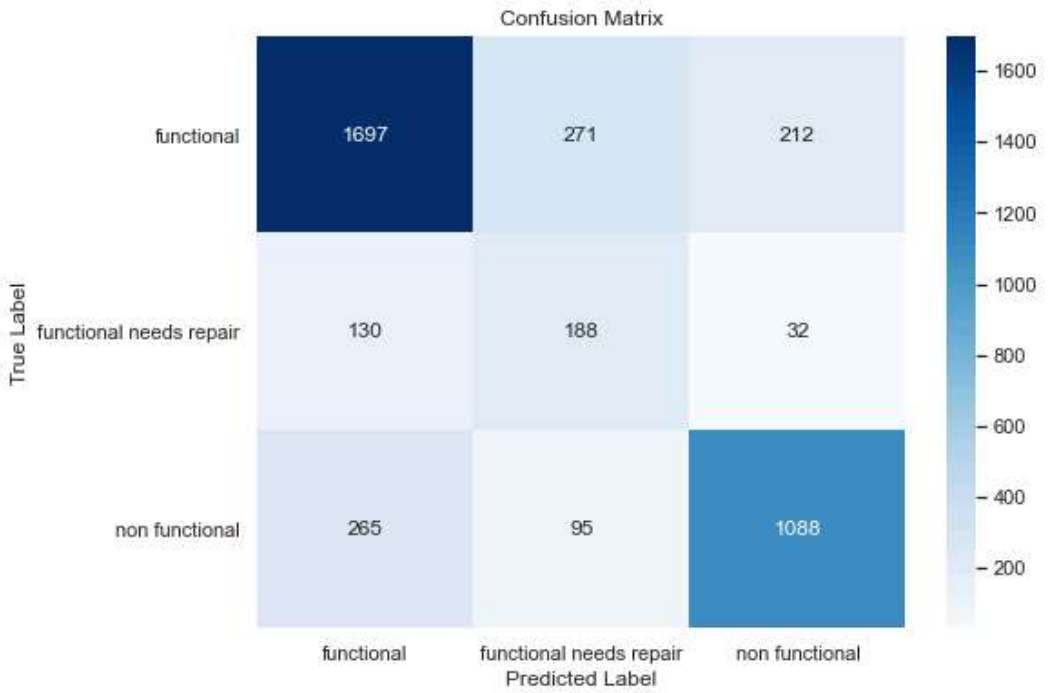
Functional Needs Repair: This is the model's main weakness. The recall of 0.54 means it only correctly identifies about half of the wells that actually need repair. Even worse, the precision is only 0.34, meaning that when the model predicts a well needs repair, it is correct just 34% of the time. This suggests a high number of false positives for this class. The F1-score of 0.42 is very low, confirming the poor performance on this class.

The Tuned XGBoost was better at distinguishing between the Pump classes than the and Random Forestand logistic regression.

In [182]:

```
#1. Generate the Confusion Matrix
cm = confusion_matrix(y_test, y_pred_xgb_smote)

# 2. Print the confusion matrix
print("Confusion Matrix:")
print(cm)

# 3. (Optional) Visualize the Confusion Matrix for better readability
# Get the unique class labels from the test data to label the axes
labels = np.unique(y_test)

plt.figure(figsize=(8, 6))
sns.heatmap(
    cm,
    annot=True,
    fmt='d',
    cmap='Blues',
    xticklabels=labels,
    yticklabels=labels
)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Confusion Matrix:
[[1697  271  212]
 [ 130  188   32]
 [ 265   95 1088]]
```



Overall Insights and Conclusion Strong Performance on Extreme Classes: The model does a very good job of correctly identifying the "functional" (1697/2180) and "non-functional" (1088/1448) pumps. The diagonal values for these classes are the highest in their respective rows.

6. Conclusion

The project successfully built a machine learning model to predict the functional status of water pumps in Tanzania. The final model, an optimized XGBoost Classifier, provides a more reliable and realistic measure of its expected performance on new, unseen data. This tuned model is the one recommended for deployment, as it is more robust and better aligned with the ultimate goal of accurate and dependable prediction in practical applications.

7. Recommendation

To significantly improve the predictive accuracy of the model, especially for the "functional needs repair" class, future data collection efforts should focus on enriching the dataset with additional, more detailed features. Incorporating details such as:

The last service date of the well.

The types of repairs that were performed.

A list of specific parts that were replaced or repaired.

These would provide invaluable information for more robust model predictions.