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1 Introduction

This notebook analyzes water pump functionality in Tanzania to identify factors influencing failures. By understanding these patterns, we aim to support better decision-making for water infrastructure maintenance.

1.1 Objectives

- Identify key factors affecting water pump functionality.
- Analyze geographic, technical, and managerial influences on failure rates.
- Determine which pump types and water sources are most prone to failure.
- Assess the impact of funding sources and management on well maintenance.
- Develop a predictive model to classify pump status.
- Provide actionable recommendations based on data-driven insights.

1.2 Methodology

1. **Data Exploration & Cleaning** – Handle missing values, outliers, and inconsistencies.
2. **Exploratory Data Analysis (EDA)** – Identify patterns in location, pump type, management, and other features.
3. **Feature Engineering** – Transform relevant attributes for better model performance.
4. **Modeling & Evaluation** – Train machine learning models (e.g., Decision Trees, Random Forest) to predict pump status and assess performance.
5. **Insights & Recommendations** – Use model results to highlight high-risk pumps and suggest preventive actions.

1.3 Importing the neccessary libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from datetime import datetime
import seaborn as sns
import scipy.stats as stats
from sklearn.impute import KNNImputer
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier
from scipy.stats import randint
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import roc_curve, auc
from sklearn import tree
from sklearn.preprocessing import label_binarize
from sklearn.tree import plot_tree
from imblearn.over_sampling import SMOTE
```

2 Data Exploration & Cleaning

2.1 Dataset Description

The dataset contains information on water pumps in Tanzania, including **location, pump type, water source, construction details, and operational status**. The goal is to analyze these factors and predict pump functionality.

📌 **Data Source:** DrivenData – Pump It Up: Data Mining the Water Table (https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/data/)

2.2 Key Features

- **id** – Unique identifier for each pump.
- **date_recorded** – Date when the data was collected.
- **status_group** – Pump functionality status (Functional, Non-functional, or Functional but Needs Repair).
- **funder** – Organization that funded the pump installation.
- **installer** – Company or entity that installed the pump.
- **longitude/latitude** – Geographic coordinates of the pump.

- **basin** – Water basin where the pump is located.
- **region/district** – Administrative location details.
- **extraction_type** – Type of extraction mechanism (e.g., hand pump, submersible).
- **management** – Entity responsible for maintaining the pump.
- **payment_type** – Payment model for water usage (e.g., monthly fees, pay per bucket).
- **quality_group** – Water quality classification.
- **quantity_group** – Water availability classification.
- **source_type** – Origin of the water (e.g., spring, river, groundwater).
- **construction_year** – Year the pump was built.

2.3 Data Size

- **Total Records:** 59400
- **Total Features:** 40

2.4 Data Exploration

In [2]:

```
# the independent variables for the train dataset
X_train_data = pd.read_csv("training set independent TZ.csv")
X_train_data
```

Out[2]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359
...	...	...	...	...	...	...	...	...
59395	60739	10.0	2013-05-03	Germany Republi	1210	CES	37.169807	-3.253847
59396	27263	4700.0	2011-05-07	Cefa-njombe	1212	Cefa	35.249991	-9.070629
59397	37057	0.0	2011-04-11	NaN	0	NaN	34.017087	-8.750434
59398	31282	0.0	2011-03-08	Malec	0	Musa	35.861315	-6.378573
59399	26348	0.0	2011-03-23	World Bank	191	World	38.104048	-6.747464

59400 rows × 40 columns

In [3]:
```
pd.set_option('display.max_columns', None)

X_train_data
```

Out[3]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359
...	...	...	...	...	...	...	...	...
59395	60739	10.0	2013-05-03	Germany Republi	1210	CES	37.169807	-3.253847
59396	27263	4700.0	2011-05-07	Cefa-njombe	1212	Cefa	35.249991	-9.070629
59397	37057	0.0	2011-04-11	NaN	0	NaN	34.017087	-8.750434
59398	31282	0.0	2011-03-08	Malec	0	Musa	35.861315	-6.378573
59399	26348	0.0	2011-03-23	World Bank	191	World	38.104048	-6.747464

59400 rows × 40 columns

In [4]:
```
print(X_train_data['population'].unique())
```

```
[109 280 250 ... 845 976 788]
```

In [5]:
```
print(X_train_data['num_private'].unique())
```

```
[   0   39    5   45    6    3  698   32   15    7   25  102    1   93
   14   34  120   17  213   47    8   41   80  141   20   35  131    4
   22   11   87   61   65  136    2  180   38   62    9   16   23   42
   24   12  668  672   58  150  280  160   50 1776   30   27   10   94
   26  450  240  755   60  111  300   55 1402]
```

In [6]:
```
X_train_data.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
```

In [7]:
```
X_train_data.isnull().sum()
```

Out[7]:
```
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 [8]:
```
num_rows = X_train_data.shape[0]
print(f"Number of rows: {num_rows}")
```

```
Number of rows: 59400
```

In [9]:
```
Y_train_data = pd.read_csv("training set dependent TZ.csv")
Y_train_data
```

Out[9]:

	id	status_group
0	69572	functional
1	8776	functional
2	34310	functional
3	67743	non functional
4	19728	functional
...	...	...
59395	60739	functional
59396	27263	functional
59397	37057	functional
59398	31282	functional
59399	26348	functional

59400 rows × 2 columns

In [10]:
```
test_data = pd.read_csv("test set TZ.csv")
test_data
```

Out[10]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	lat
0	50785	0.0	2013-02-04	Dmdd	1996	DMDD	35.290799	-4.05
1	51630	0.0	2013-02-04	Government Of Tanzania	1569	DWE	36.656709	-3.30
2	17168	0.0	2013-02-01	NaN	1567	NaN	34.767863	-5.00
3	45559	0.0	2013-01-22	Finn Water	267	FINN WATER	38.058046	-9.41
4	49871	500.0	2013-03-27	Bruder	1260	BRUDER	35.006123	-10.95
...	...	...	...	...	...	...	...	
14845	39307	0.0	2011-02-24	Danida	34	Da	38.852669	-6.58
14846	18990	1000.0	2011-03-21	Hiap	0	HIAP	37.451633	-5.35
14847	28749	0.0	2013-03-04	NaN	1476	NaN	34.739804	-4.58
14848	33492	0.0	2013-02-18	Germany	998	DWE	35.432732	-10.58
14849	68707	0.0	2013-02-13	Government Of Tanzania	481	Government	34.765054	-11.22

14850 rows × 40 columns

In [11]:
```
pd.set_option('display.max_columns', None)
test_data = pd.read_csv("test set TZ.csv")
test_data
```

Out[11]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	lat
0	50785	0.0	2013-02-04	Dmdd	1996	DMDD	35.290799	-4.05
1	51630	0.0	2013-02-04	Government Of Tanzania	1569	DWE	36.656709	-3.30
2	17168	0.0	2013-02-01	NaN	1567	NaN	34.767863	-5.00
3	45559	0.0	2013-01-22	Finn Water	267	FINN WATER	38.058046	-9.41
4	49871	500.0	2013-03-27	Bruder	1260	BRUDER	35.006123	-10.95
...	...	...	...	...	...	...	...	
14845	39307	0.0	2011-02-24	Danida	34	Da	38.852669	-6.58
14846	18990	1000.0	2011-03-21	Hiap	0	HIAP	37.451633	-5.35
14847	28749	0.0	2013-03-04	NaN	1476	NaN	34.739804	-4.58
14848	33492	0.0	2013-02-18	Germany	998	DWE	35.432732	-10.58
14849	68707	0.0	2013-02-13	Government Of Tanzania	481	Government	34.765054	-11.22

14850 rows × 40 columns

In [12]:

```
test_data.info()
```

```
 22  permit                 14113 non-null  object
 23  construction_year      14850 non-null  int64
 24  extraction_type        14850 non-null  object
 25  extraction_type_group  14850 non-null  object
 26  extraction_type_class  14850 non-null  object
 27  management             14850 non-null  object
 28  management_group       14850 non-null  object
 29  payment                14850 non-null  object
 30  payment_type           14850 non-null  object
 31  water_quality          14850 non-null  object
 32  quality_group          14850 non-null  object
 33  quantity               14850 non-null  object
 34  quantity_group         14850 non-null  object
 35  source                 14850 non-null  object
 36  source_type            14850 non-null  object
 37  source_class           14850 non-null  object
 38  waterpoint_type        14850 non-null  object
 39  waterpoint_type_group  14850 non-null  object
dtypes: float64(3), int64(7), object(30)
memory usage: 4.5+ MB
```

In [13]:
```
test_data2 = pd.read_csv("test set TZ.csv")
test_data2
```

Out[13]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	lat
0	50785	0.0	2013-02-04	Dmdd	1996	DMDD	35.290799	-4.05
1	51630	0.0	2013-02-04	Government Of Tanzania	1569	DWE	36.656709	-3.30
2	17168	0.0	2013-02-01	NaN	1567	NaN	34.767863	-5.00
3	45559	0.0	2013-01-22	Finn Water	267	FINN WATER	38.058046	-9.41
4	49871	500.0	2013-03-27	Bruder	1260	BRUDER	35.006123	-10.95
...	...	...	...	...	...	...	...	
14845	39307	0.0	2011-02-24	Danida	34	Da	38.852669	-6.58
14846	18990	1000.0	2011-03-21	Hiap	0	HIAP	37.451633	-5.35
14847	28749	0.0	2013-03-04	NaN	1476	NaN	34.739804	-4.58
14848	33492	0.0	2013-02-18	Germany	998	DWE	35.432732	-10.58
14849	68707	0.0	2013-02-13	Government Of Tanzania	481	Government	34.765054	-11.22

14850 rows × 40 columns

In [14]:
```
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14850 entries, 0 to 14849
Data columns (total 40 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     14850 non-null  int64  
 1   amount_tsh             14850 non-null  float64
 2   date_recorded          14850 non-null  object 
 3   funder                 13981 non-null  object 
 4   gps_height             14850 non-null  int64  
 5   installer              13973 non-null  object 
 6   longitude              14850 non-null  float64
 7   latitude               14850 non-null  float64
 8   wpt_name               14850 non-null  object 
 9   num_private            14850 non-null  int64  
 10  basin                  14850 non-null  object 
 11  subvillage             14751 non-null  object 
 12  region                 14850 non-null  object 
 13  region_code            14850 non-null  int64  
 14  district_code          14850 non-null  int64  
 15  lga                    14850 non-null  object 
 16  ward                   14850 non-null  object 
 17  population             14850 non-null  int64  
 18  public_meeting         14029 non-null  object 
 19  recorded_by            14850 non-null  object 
 20  scheme_management      13881 non-null  object 
 21  scheme_name            7758 non-null   object 
 22  permit                 14113 non-null  object 
 23  construction_year      14850 non-null  int64  
 24  extraction_type        14850 non-null  object 
 25  extraction_type_group  14850 non-null  object 
 26  extraction_type_class  14850 non-null  object 
 27  management             14850 non-null  object 
 28  management_group       14850 non-null  object 
 29  payment                14850 non-null  object 
 30  payment_type           14850 non-null  object 
 31  water_quality          14850 non-null  object 
 32  quality_group          14850 non-null  object 
 33  quantity               14850 non-null  object 
 34  quantity_group         14850 non-null  object 
 35  source                 14850 non-null  object 
 36  source_type            14850 non-null  object 
 37  source_class           14850 non-null  object 
 38  waterpoint_type        14850 non-null  object 
 39  waterpoint_type_group  14850 non-null  object 
dtypes: float64(3), int64(7), object(30)
memory usage: 4.5+ MB
```

2.5 Data cleaning

In [15]:
```
# dropping irrelevant columns
X_train_data.drop(["scheme_name","wpt_name"], axis=1, inplace=True)
```

In [16]:
```
# dropping irrelevant columns
X_train_data.drop(["source_type","source","waterpoint_type"], axis=1, inplace
```

In [17]:
```
X_train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 35 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   num_private            59400 non-null  int64  
 9   basin                  59400 non-null  object 
 10  subvillage             59029 non-null  object 
 11  region                 59400 non-null  object 
 12  region_code            59400 non-null  int64  
 13  district_code          59400 non-null  int64  
 14  lga                    59400 non-null  object 
 15  ward                   59400 non-null  object 
 16  population             59400 non-null  int64  
 17  public_meeting         56066 non-null  object 
 18  recorded_by            59400 non-null  object 
 19  scheme_management      55523 non-null  object 
 20  permit                 56344 non-null  object 
 21  construction_year      59400 non-null  int64  
 22  extraction_type        59400 non-null  object 
 23  extraction_type_group  59400 non-null  object 
 24  extraction_type_class  59400 non-null  object 
 25  management             59400 non-null  object 
 26  management_group       59400 non-null  object 
 27  payment                59400 non-null  object 
 28  payment_type           59400 non-null  object 
 29  water_quality          59400 non-null  object 
 30  quality_group          59400 non-null  object 
 31  quantity               59400 non-null  object 
 32  quantity_group         59400 non-null  object 
 33  source_class           59400 non-null  object 
 34  waterpoint_type_group  59400 non-null  object 
dtypes: float64(3), int64(7), object(25)
memory usage: 15.9+ MB
```

In [18]:

```
X_train_data.drop(["water_quality","payment"], axis=1, inplace=True)
```

In [19]:

```
X_train_data.drop(["management","extraction_type"], axis=1, inplace=True)
```

In [20]:

```
X_train_data.drop(["ward","lga","district_code","subvillage"], axis=1, inplac
```

In [21]:

```
X_train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 27 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   num_private            59400 non-null  int64  
 9   basin                  59400 non-null  object 
 10  region                 59400 non-null  object 
 11  region_code            59400 non-null  int64  
 12  population             59400 non-null  int64  
 13  public_meeting         56066 non-null  object 
 14  recorded_by            59400 non-null  object 
 15  scheme_management      55523 non-null  object 
 16  permit                 56344 non-null  object 
 17  construction_year      59400 non-null  int64  
 18  extraction_type_group  59400 non-null  object 
 19  extraction_type_class  59400 non-null  object 
 20  management_group       59400 non-null  object 
 21  payment_type           59400 non-null  object 
 22  quality_group          59400 non-null  object 
 23  quantity               59400 non-null  object 
 24  quantity_group         59400 non-null  object 
 25  source_class           59400 non-null  object 
 26  waterpoint_type_group  59400 non-null  object 
dtypes: float64(3), int64(6), object(18)
memory usage: 12.2+ MB
```

In [22]:
```
tanzania_data = pd.concat([X_train_data, Y_train_data], axis=1)

tanzania_data
```

Out[22]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359
...	...	...	...	...	...	...	...	...
59395	60739	10.0	2013-05-03	Germany Republi	1210	CES	37.169807	-3.253847
59396	27263	4700.0	2011-05-07	Cefa-njombe	1212	Cefa	35.249991	-9.070629
59397	37057	0.0	2011-04-11	NaN	0	NaN	34.017087	-8.750434
59398	31282	0.0	2011-03-08	Malec	0	Musa	35.861315	-6.378573
59399	26348	0.0	2011-03-23	World Bank	191	World	38.104048	-6.747464

59400 rows × 29 columns

In [23]:
```
tanzania_data.isnull().sum()
```

Out[23]:
```
id                          0
amount_tsh                  0
date_recorded               0
funder                   3635
gps_height                  0
installer                3655
longitude                   0
latitude                    0
num_private                 0
basin                       0
region                      0
region_code                 0
population                  0
public_meeting           3334
recorded_by                 0
scheme_management        3877
permit                   3056
construction_year           0
extraction_type_group       0
extraction_type_class       0
management_group            0
payment_type                0
quality_group               0
quantity                    0
quantity_group              0
source_class                0
waterpoint_type_group       0
id                          0
status_group                0
dtype: int64
```

In [24]:
```
tanzania_data.loc[:, "funder"] = tanzania_data["funder"].fillna(tanzania_data
tanzania_data.loc[:, "installer"] = tanzania_data["installer"].fillna(tanzani
tanzania_data["scheme_management"] = tanzania_data.groupby("region")["scheme_
```

In [25]:
```
tanzania_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 29 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                 59400 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              59400 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   num_private            59400 non-null  int64  
 9   basin                  59400 non-null  object 
 10  region                 59400 non-null  object 
 11  region_code            59400 non-null  int64  
 12  population             59400 non-null  int64  
 13  public_meeting         56066 non-null  object 
 14  recorded_by            59400 non-null  object 
 15  scheme_management      59400 non-null  object 
 16  permit                 56344 non-null  object 
 17  construction_year      59400 non-null  int64  
 18  extraction_type_group  59400 non-null  object 
 19  extraction_type_class  59400 non-null  object 
 20  management_group       59400 non-null  object 
 21  payment_type           59400 non-null  object 
 22  quality_group          59400 non-null  object 
 23  quantity               59400 non-null  object 
 24  quantity_group         59400 non-null  object 
 25  source_class           59400 non-null  object 
 26  waterpoint_type_group  59400 non-null  object 
 27  id                     59400 non-null  int64  
 28  status_group           59400 non-null  object 
dtypes: float64(3), int64(7), object(19)
memory usage: 13.1+ MB
```

In [26]:
```
tanzania_data.isnull().sum()
```

Out[26]:
```
id                          0
amount_tsh                  0
date_recorded               0
funder                      0
gps_height                  0
installer                   0
longitude                   0
latitude                    0
num_private                 0
basin                       0
region                      0
region_code                 0
population                  0
public_meeting           3334
recorded_by                 0
scheme_management           0
permit                   3056
construction_year           0
extraction_type_group       0
extraction_type_class       0
management_group            0
payment_type                0
quality_group               0
quantity                    0
quantity_group              0
source_class                0
waterpoint_type_group       0
id                          0
status_group                0
dtype: int64
```

In [27]:
```
test_data.isna().sum()
```

Out[27]:
```
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
```

In [28]:
```
test_data.drop(columns=['waterpoint_type_group'], inplace=True)
```

In [29]:
```
test_data.drop(columns=['management', 'extraction_type', 'recorded_by'], inpl
```

In [30]:
```
test_data.drop(columns=['ward', 'lga', 'district_code',"subvillage"], inplace
```

In [31]:
```
test_data.drop(columns=['extraction_type_group', 'longitude', 'latitude'], ir
```

In [32]:
```
test_data.drop(columns=['wpt_name', 'scheme_name', 'payment'], inplace=True)
```

In [33]:
```
test_data.drop(columns=['water_quality', 'quantity', 'source'], inplace=True)
```

In [34]:
```
test_data['date_recorded'] = pd.to_datetime(test_data['date_recorded']).dt.ye
```

In [35]:
```
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14850 entries, 0 to 14849
Data columns (total 23 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     14850 non-null  int64  
 1   amount_tsh             14850 non-null  float64
 2   date_recorded          14850 non-null  int64  
 3   funder                 13981 non-null  object 
 4   gps_height             14850 non-null  int64  
 5   installer              13973 non-null  object 
 6   num_private            14850 non-null  int64  
 7   basin                  14850 non-null  object 
 8   region                 14850 non-null  object 
 9   region_code            14850 non-null  int64  
 10  population             14850 non-null  int64  
 11  public_meeting         14029 non-null  object 
 12  scheme_management      13881 non-null  object 
 13  permit                 14113 non-null  object 
 14  construction_year      14850 non-null  int64  
 15  extraction_type_class  14850 non-null  object 
 16  management_group       14850 non-null  object 
 17  payment_type           14850 non-null  object 
 18  quality_group          14850 non-null  object 
 19  quantity_group         14850 non-null  object 
 20  source_type            14850 non-null  object 
 21  source_class           14850 non-null  object 
 22  waterpoint_type        14850 non-null  object 
dtypes: float64(1), int64(7), object(15)
memory usage: 2.6+ MB
```

In [36]:
```
tanzania_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 29 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                 59400 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              59400 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   num_private            59400 non-null  int64  
 9   basin                  59400 non-null  object 
 10  region                 59400 non-null  object 
 11  region_code            59400 non-null  int64  
 12  population             59400 non-null  int64  
 13  public_meeting         56066 non-null  object 
 14  recorded_by            59400 non-null  object 
 15  scheme_management      59400 non-null  object 
 16  permit                 56344 non-null  object 
 17  construction_year      59400 non-null  int64  
 18  extraction_type_group  59400 non-null  object 
 19  extraction_type_class  59400 non-null  object 
 20  management_group       59400 non-null  object 
 21  payment_type           59400 non-null  object 
 22  quality_group          59400 non-null  object 
 23  quantity               59400 non-null  object 
 24  quantity_group         59400 non-null  object 
 25  source_class           59400 non-null  object 
 26  waterpoint_type_group  59400 non-null  object 
 27  id                     59400 non-null  int64  
 28  status_group           59400 non-null  object 
dtypes: float64(3), int64(7), object(19)
memory usage: 13.1+ MB
```

In [37]:
```
test_data = test_data.drop(columns=["source_type"])
```

In [38]:
```
tanzania_data = tanzania_data.drop(columns=["id", "extraction_type_group", "c
```

In [39]:
```
tanzania_data
```

Out[39]:

	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	nu
0	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	
1	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	
2	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	
3	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	
4	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	
...	...	...	...	...	...	...	...	
59395	10.0	2013-05-03	Germany Republi	1210	CES	37.169807	-3.253847	
59396	4700.0	2011-05-07	Cefa-njombe	1212	Cefa	35.249991	-9.070629	
59397	0.0	2011-04-11	Government Of Tanzania	0	DWE	34.017087	-8.750434	
59398	0.0	2011-03-08	Malec	0	Musa	35.861315	-6.378573	
59399	0.0	2011-03-23	World Bank	191	World	38.104048	-6.747464	

59400 rows × 24 columns

In [40]:
```
tanzania_data = tanzania_data.drop(columns=[col for col in ['latitude', 'reco
```

3 Feature Engineering

3.1 Pump Age Calculation

In [41]:
```
tanzania_data['date_recorded'] = pd.to_datetime(tanzania_data['date_recorded'
```

In [42]:
```
current_year = datetime.now().year

tanzania_data['pump_age'] = tanzania_data.apply(
    lambda row: (current_year - row['construction_year'])
    if row['construction_year'] > 0 else (current_year - row['date_recorded']
    axis=1)

tanzania_data
```

Out[42]:

	amount_tsh	date_recorded	funder	gps_height	installer	num_private	basin	
0	6000.0	2011	Roman	1390	Roman	0	Lake Nyasa	
1	0.0	2013	Grumeti	1399	GRUMETI	0	Lake Victoria	
2	25.0	2013	Lottery Club	686	World vision	0	Pangani	
3	0.0	2013	Unicef	263	UNICEF	0	Ruvuma / Southern Coast	
4	0.0	2011	Action In A	0	Artisan	0	Lake Victoria	
...	...	...	...	...	...	...	...	
59395	10.0	2013	Germany Republi	1210	CES	0	Pangani	Kil
59396	4700.0	2011	Cefa-njombe	1212	Cefa	0	Rufiji	
59397	0.0	2011	Government Of Tanzania	0	DWE	0	Rufiji	
59398	0.0	2011	Malec	0	Musa	0	Rufiji	
59399	0.0	2011	World Bank	191	World	0	Wami / Ruvu	M

59400 rows × 22 columns

In [43]:
```
print(tanzania_data['pump_age'].unique())
```

```
[26 15 16 39 14 13 38 34 47 33 17 12 51 25 23 21 53 22 45 18 52 40 55 30
 19 63 20 28 29 48 42 41 35 43 49 37 36 50 65 64 27 62 54 31 57 32 24 46
 58 56 44 61 59 60]
```

In [ ]:

3.2 Imputing GPS Height by Region

In [44]:

```
region_medians = tanzania_data.groupby("region")["gps_height"].apply(
    lambda x: np.median(x[x > 0]) if x[x > 0].size > 0 else 0  # Avoid empty
)

tanzania_data.loc[tanzania_data["gps_height"] == 0, "gps_height"] = (
    tanzania_data["region"].map(region_medians)
)
```

In [45]:

```
imputer = KNNImputer(n_neighbors=5)
tanzania_data["gps_height"] = imputer.fit_transform(
    np.array(tanzania_data["gps_height"]).reshape(-1, 1))
```

In [46]:

```
print(tanzania_data["gps_height"].unique())
```

```
[1390. 1399.  686. ...  -90. 2091. 2366.]
```

In [47]:

```
tanzania_data["gps_height"] = tanzania_data.groupby("region")["gps_height"].t
    lambda x: x.replace(0, x[x > 0].median()))
```

In [48]:

```
tanzania_data["gps_height"] = tanzania_data["gps_height"].fillna(0)
```

In [49]:

```
region_means = tanzania_data.groupby('region')['gps_height'].mean()

overall_mean = tanzania_data.loc[tanzania_data['gps_height'] > 0, 'gps_height

tanzania_data['gps_height'] = tanzania_data.apply(
    lambda row: region_means[row['region']] if row['gps_height'] == 0 and reg
                (overall_mean if row['gps_height'] == 0 else row['gps_height'
)
```

In [50]:
```
tanzania_data
```

Out[50]:

	amount_tsh	date_recorded	funder	gps_height	installer	num_private	basin
0	6000.0	2011	Roman	1390.000000	Roman	0	Lake Nyasa
1	0.0	2013	Grumeti	1399.000000	GRUMETI	0	Lake Victoria
2	25.0	2013	Lottery Club	686.000000	World vision	0	Pangani
3	0.0	2013	Unicef	263.000000	UNICEF	0	Ruvuma / Southern Coast
4	0.0	2011	Action In A	1086.967394	Artisan	0	Lake Victoria
...	...	...	...	...	...	...	...
59395	10.0	2013	Germany	1210.000000	CES	0	Pangani

In [51]:
```
region_means = test_data.groupby('region')['gps_height'].mean()

test_data['gps_height'] = test_data.apply(
    lambda row: region_means[row['region']] if row['gps_height'] == 0 else ro
)
```

In [52]:
```
region_means = test_data.groupby('region')['gps_height'].mean()

overall_mean = test_data.loc[test_data['gps_height'] > 0, 'gps_height'].mean(

test_data['gps_height'] = test_data.apply(
    lambda row: region_means[row['region']] if row['gps_height'] == 0 and reg
                (overall_mean if row['gps_height'] == 0 else row['gps_height'
)
```

In [53]:
```
region_means = test_data.groupby('region')['gps_height'].mean()

overall_mean = test_data.loc[test_data['gps_height'] > 0, 'gps_height'].mean(

test_data['gps_height'] = test_data.apply(
    lambda row: region_means[row['region']] if row['gps_height'] == 0 and reg
                (overall_mean if row['gps_height'] == 0 else row['gps_height'
)
```

3.3 Imputing permits

In [54]:
```
tanzania_data.loc[:, "public_meeting"] = tanzania_data["public_meeting"].fill
tanzania_data.loc[:, "permit"] = tanzania_data["permit"].fillna(False)
```

In [55]:
```
test_data['scheme_management'].fillna("Unknown", inplace=True)

def safe_mode(series):
    return series.mode()[0] if not series.mode().empty else False  # Default

permit_modes = test_data.groupby('scheme_management')['permit'].agg(safe_mode

test_data['permit'] = test_data.apply(
    lambda row: permit_modes.get(row['scheme_management'], False) if pd.isna(
)
```

3.4 imputing installer

In [56]:
```
test_data['installer'] = test_data.groupby('region')['installer'].transform(
    lambda x: x.fillna(x.mode()[0] if not x.mode().empty else "Unknown")
)
```

In [57]:
```
test_data['scheme_management'] = test_data.groupby('region')['scheme_manageme
    lambda x: x.fillna(x.mode()[0] if not x.mode().empty else "Unknown")
)
```

3.5 Imputing funder

In [58]:
```
test_data['funder'] = test_data.groupby('region')['funder'].transform(
    lambda x: x.fillna(x.mode()[0] if not x.mode().empty else "Unknown")
)
```

3.6 Imputing public meeting

In [59]:
```
test_data["public_meeting"] = test_data.groupby("scheme_management")["public_
    lambda x: x.fillna(x.mode()[0] if not x.mode().empty else np.nan))
```

4 Exploratory Data Analysis

4.1 Univariate analysis.

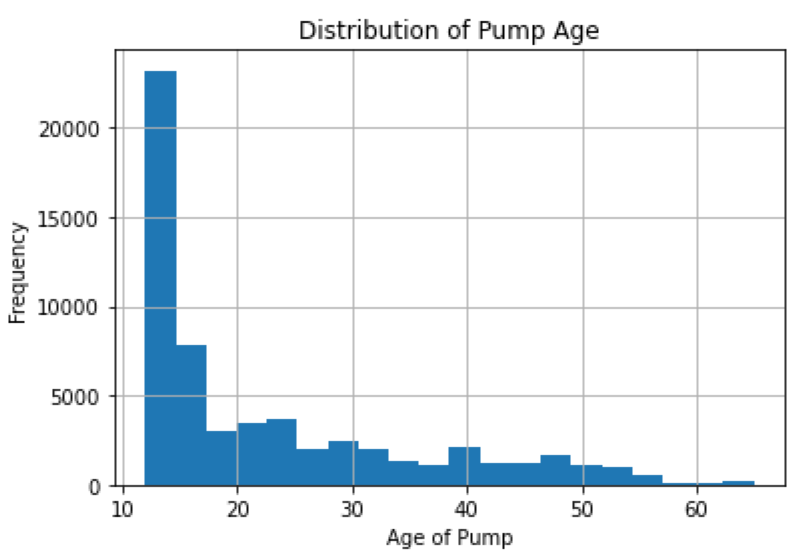
In [60]:
```
tanzania_data.describe()
```

Out[60]:

	amount_tsh	date_recorded	gps_height	num_private	region_code	population	c
count	59400.000000	59400.000000	59400.000000	59400.000000	59400.000000	59400.000000	
mean	317.650385	2011.921667	1059.088383	0.474141	15.297003	179.909983	
std	2997.574558	0.958758	511.076441	12.236230	17.587406	471.482176	
min	0.000000	2002.000000	-90.000000	0.000000	1.000000	0.000000	
25%	0.000000	2011.000000	836.000000	0.000000	5.000000	0.000000	
50%	0.000000	2012.000000	1086.967394	0.000000	12.000000	25.000000	
75%	20.000000	2013.000000	1350.500000	0.000000	17.000000	215.000000	
max	350000.000000	2013.000000	2770.000000	1776.000000	99.000000	30500.000000	

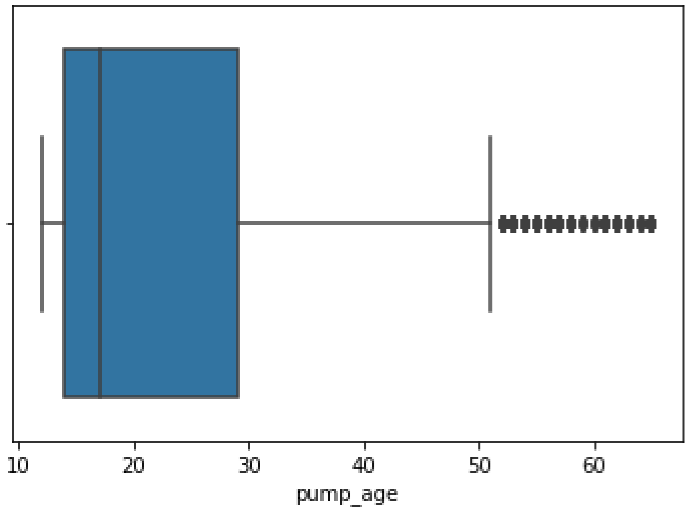
4.1.1 Checking the pump age

In [61]:
```
tanzania_data['pump_age'].hist(bins=20)
plt.title('Distribution of Pump Age')
plt.xlabel('Age of Pump')
plt.ylabel('Frequency')
plt.show()
```



In [62]:
```python
sns.boxplot(x=tanzania_data['pump_age'])
```

Out[62]: <AxesSubplot:xlabel='pump_age'>



In [63]:
```python
common_age = tanzania_data['pump_age'].mode()[0]
common_age
```

Out[63]: 14

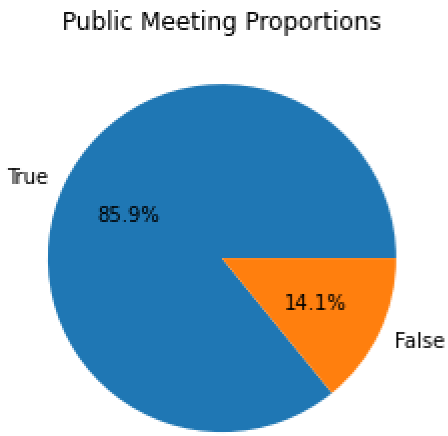
In [64]:
```python
tanzania_data["pump_age"].unique()
```

Out[64]:
```
array([26, 15, 16, 39, 14, 13, 38, 34, 47, 33, 17, 12, 51, 25, 23, 21, 53,
       22, 45, 18, 52, 40, 55, 30, 19, 63, 20, 28, 29, 48, 42, 41, 35, 43,
       49, 37, 36, 50, 65, 64, 27, 62, 54, 31, 57, 32, 24, 46, 58, 56, 44,
       61, 59, 60], dtype=int64)
```

The pumps in the dataset range from 12 to 65 years old, with 14 years being the most common age. This distribution provides insights into the aging infrastructure and potential maintenance needs. Understanding pump age helps assess functionality trends and predict failure risks over time.

4.1.2 Checking wether public meetings were held?

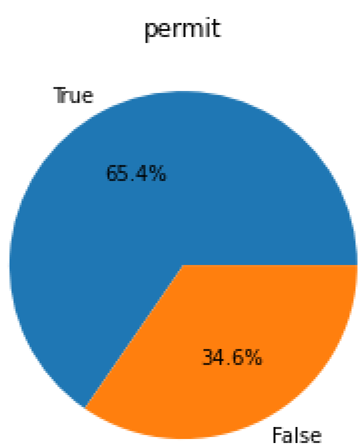
In [65]:
```
tanzania_data['public_meeting'].value_counts().plot(kind='pie', autopct='%1.1
plt.title('Public Meeting Proportions')
plt.ylabel('')
plt.show()
```



Public meetings were held to discuss pump management, with 85.9% attendance. However, 14.1% of region lacked participation, which may affect maintenance and sustainabilit

4.1.3 Checking wether permits were handed out?

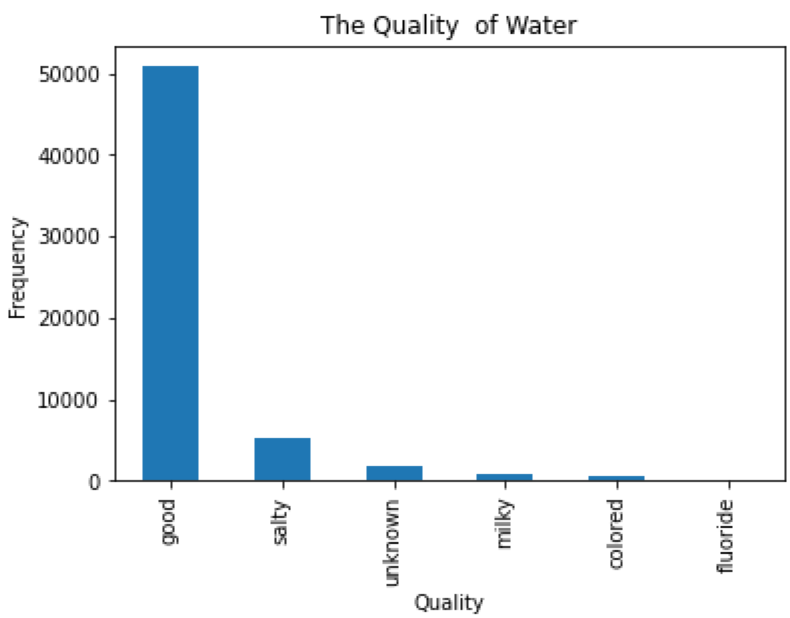
In [66]:
```
#checking wether they were attending the public meetings.
tanzania_data['permit'].value_counts().plot(kind='pie', autopct='%1.1f%%')
plt.title('permit')
plt.ylabel('')
plt.show()
```



Permits were issued for 65.4% of wells, ensuring regulated installation and oversight. However, 34.6% operated without permits, which could impact compliance, maintenance, and long-term functionality.

4.1.4 Checking the water quality?

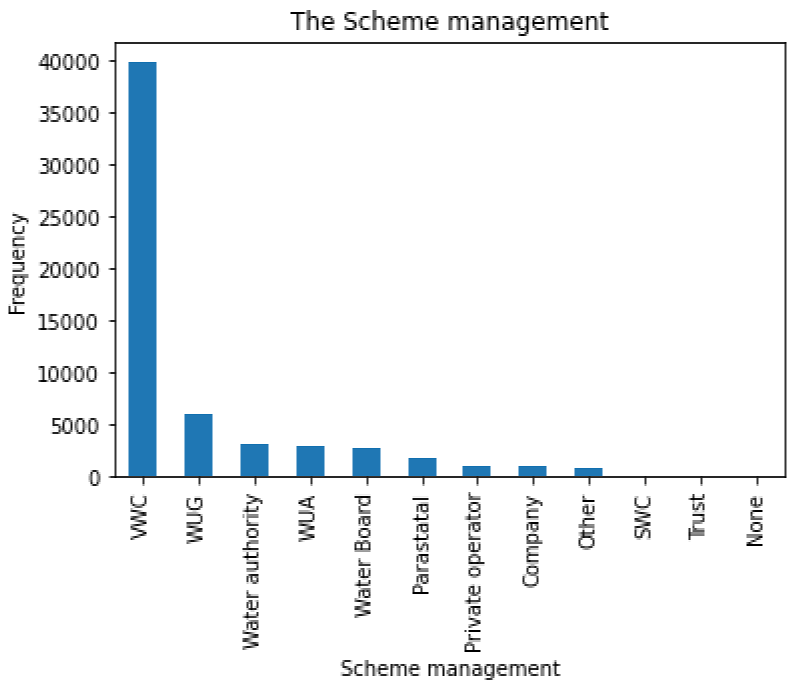
In [67]:
```
tanzania_data['quality_group'].value_counts().plot(kind='bar')
plt.title('The Quality  of Water')
plt.xlabel('Quality')
plt.ylabel('Frequency')
plt.show()
```



Most wells had good water quality, ensuring safe usage. However, a few showed signs of slight salinity or milky appearance, which could affect usability and treatment needs

4.1.5 Which scheme management runs most of the pumps?

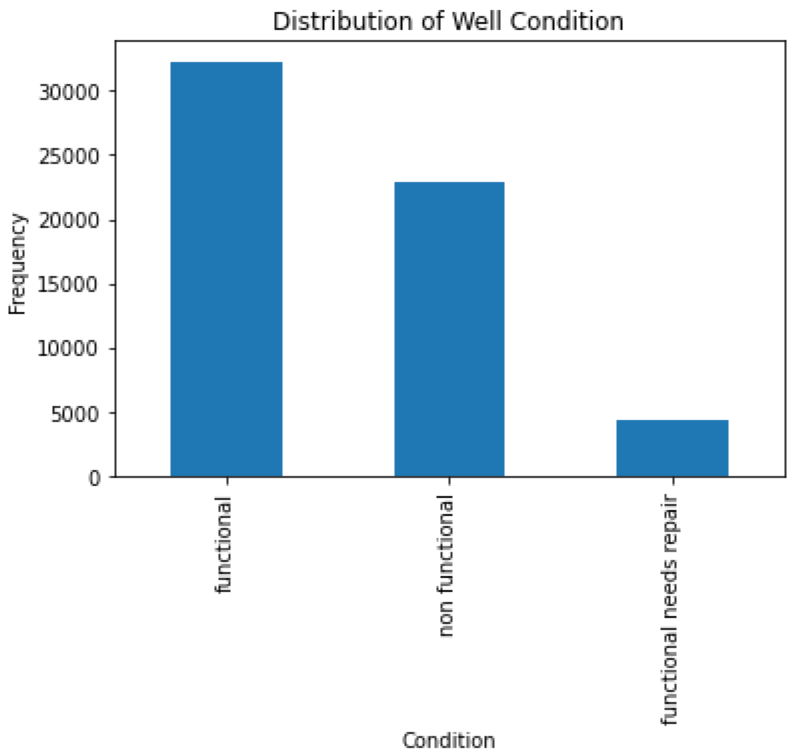
In [68]:
```
tanzania_data['scheme_management'].value_counts().plot(kind='bar')
plt.title('The Scheme management')
plt.xlabel('Scheme management')
plt.ylabel('Frequency')
plt.show()
```



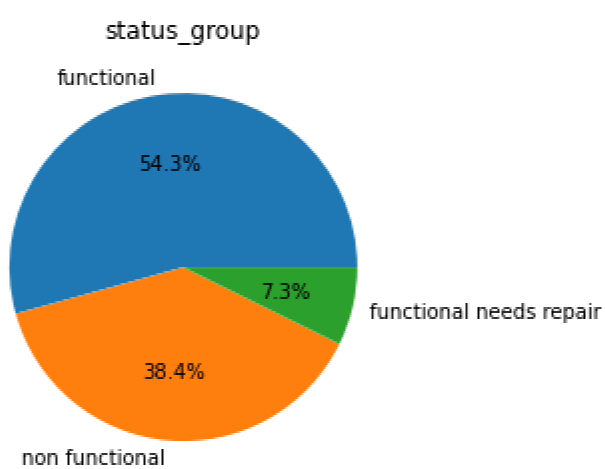
Most water wells were managed by WWC scheme management, followed by WUG in second place, the water authority in third, the water board in fourth, and parastatals in fifth.

4.1.6 Status of most of the water pumps

In [69]:
```
tanzania_data['status_group'].value_counts().plot(kind='bar')
plt.title('Distribution of Well Condition')
plt.xlabel('Condition')
plt.ylabel('Frequency')
plt.show()
```



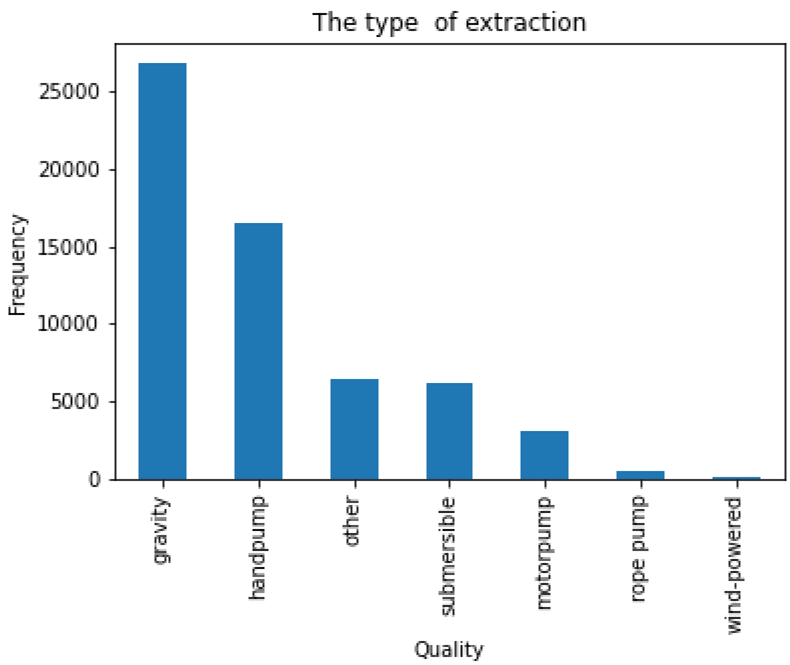
In [70]:
```
tanzania_data['status_group'].value_counts().plot(kind='pie', autopct='%1.1f%
plt.title('status_group')
plt.ylabel('')
plt.show()
```



The majority of wells (**54.4%**) were **fully functional**, providing reliable water access. **7.3%** were **functional but needed repairs**, indicating potential maintenance issues. Meanwhile, **38.4%** were **non-functional**, highlighting significant challenges in water accessibility and infrastructure upkeep.

4.1.7 Which extraction type are most of the wells running on?

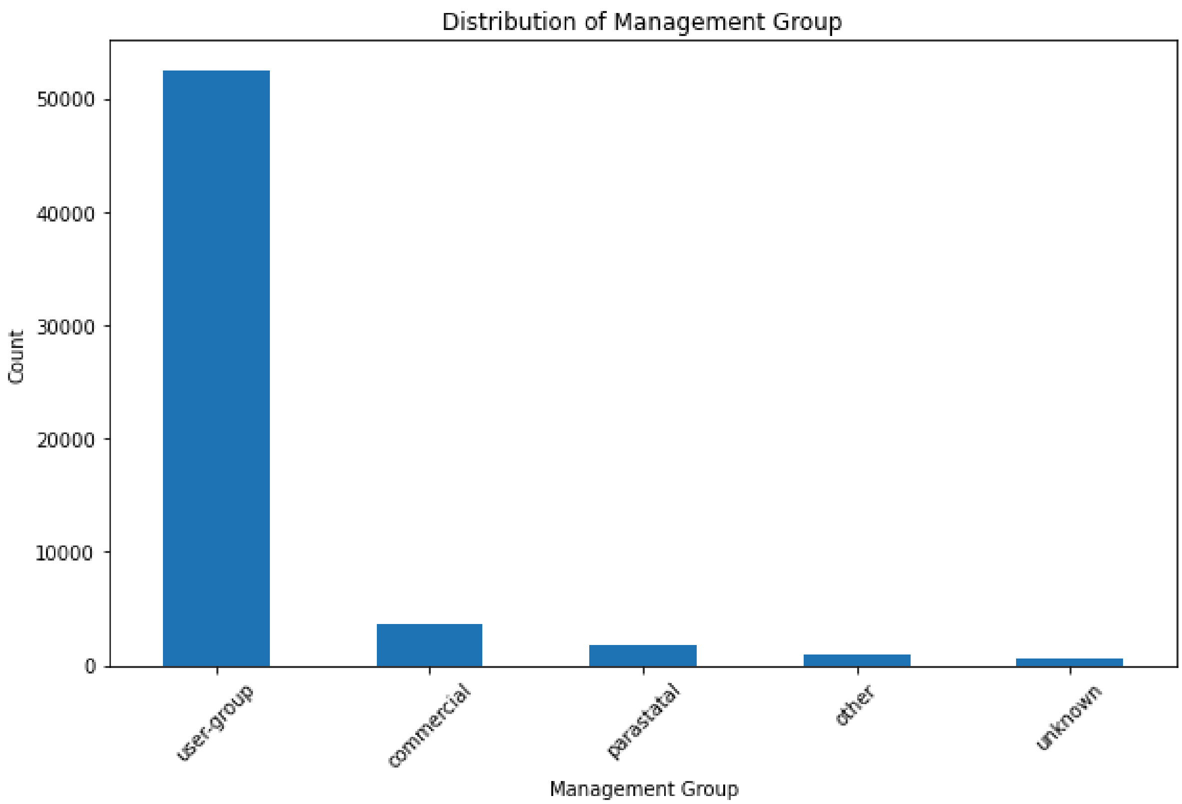
In [71]:
```
tanzania_data['extraction_type_class'].value_counts().plot(kind='bar')
plt.title('The type  of extraction')
plt.xlabel('Quality')
plt.ylabel('Frequency')
plt.show()
```



Most wells use **gravity extraction**, allowing water to flow naturally without mechanical assistance. Other common methods include **hand pumps**, **submersible pumps**, and **rope pumps**, each varying in efficiency and suitability based on location and infrastructure.

4.1.8 Which management group runs most wells?

In [72]:
```
tanzania_data['management_group'].value_counts().plot(kind='bar', figsize=(10
plt.title('Distribution of Management Group')
plt.xlabel('Management Group')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



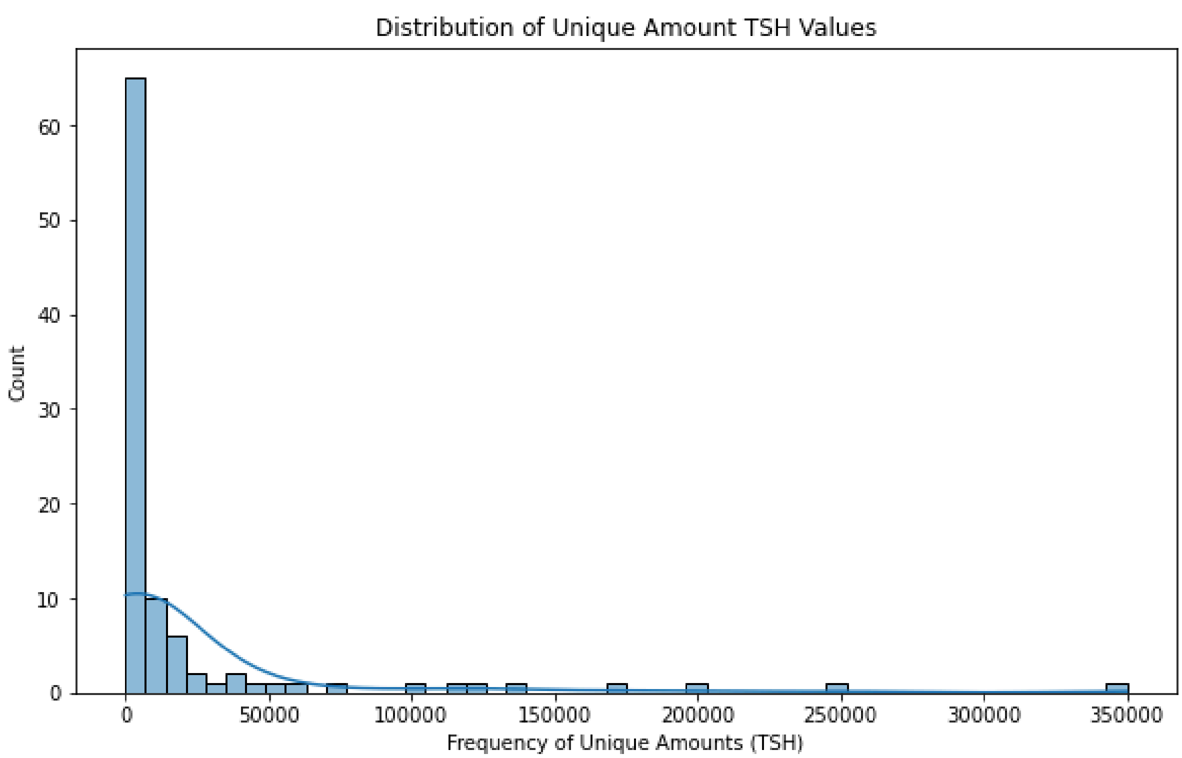
Most of the management groups were user-managed, followed by commercial management, and then parastatals

4.1.9 Ammount that the users pay.

In [73]:
```
np.set_printoptions(suppress=True)  # Disable scientific notation

unique_values = tanzania_data["amount_tsh"].unique()
print(unique_values)
```

```
[  6000.        0.       25.       20.      200.      500.       50.
   4000.     1500.        6.      250.       10.     1000.      100.
     30.     2000.      400.     1200.       40.      300.    25000.
    750.     5000.      600.     7200.     2400.        5.     3600.
    450.    40000.    12000.     3000.        7.    20000.     2800.
   2200.       70.     5500.    10000.     2500.     6500.      550.
     33.     8000.     4700.     7000.    14000.     1300.   100000.
    700.        1.       60.      350.        0.2      35.      306.
   8500.   117000.     3500.      520.       15.     6300.     9000.
    150.   120000.   138000.   350000.     4500.    13000.    45000.
      2.    15000.    11000.    50000.     7500.    16300.      800.
  16000.    30000.       53.     5400.    70000.   250000.   200000.
  26000.    18000.       26.      590.      900.        9.     1400.
 170000.      220.    38000.        0.25     12.    60000.       59.   ]
```

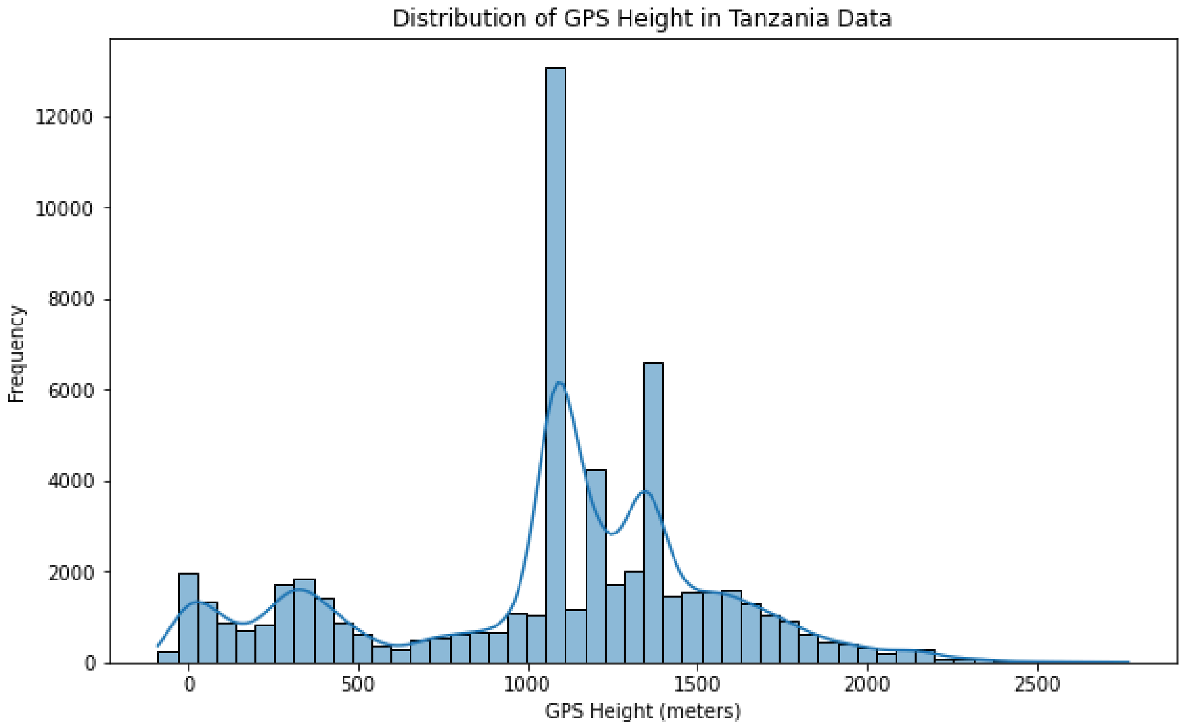
In [74]:
```
plt.figure(figsize=(10, 6))
sns.histplot(unique_values, bins=50, kde=True)

plt.xlabel("Frequency of Unique Amounts (TSH)")
plt.ylabel("Count")
plt.title("Distribution of Unique Amount TSH Values")

plt.show()
```



Most users access the wells for free, but some pay between **50,000 TSH and 350,000 TSH** for water usage.

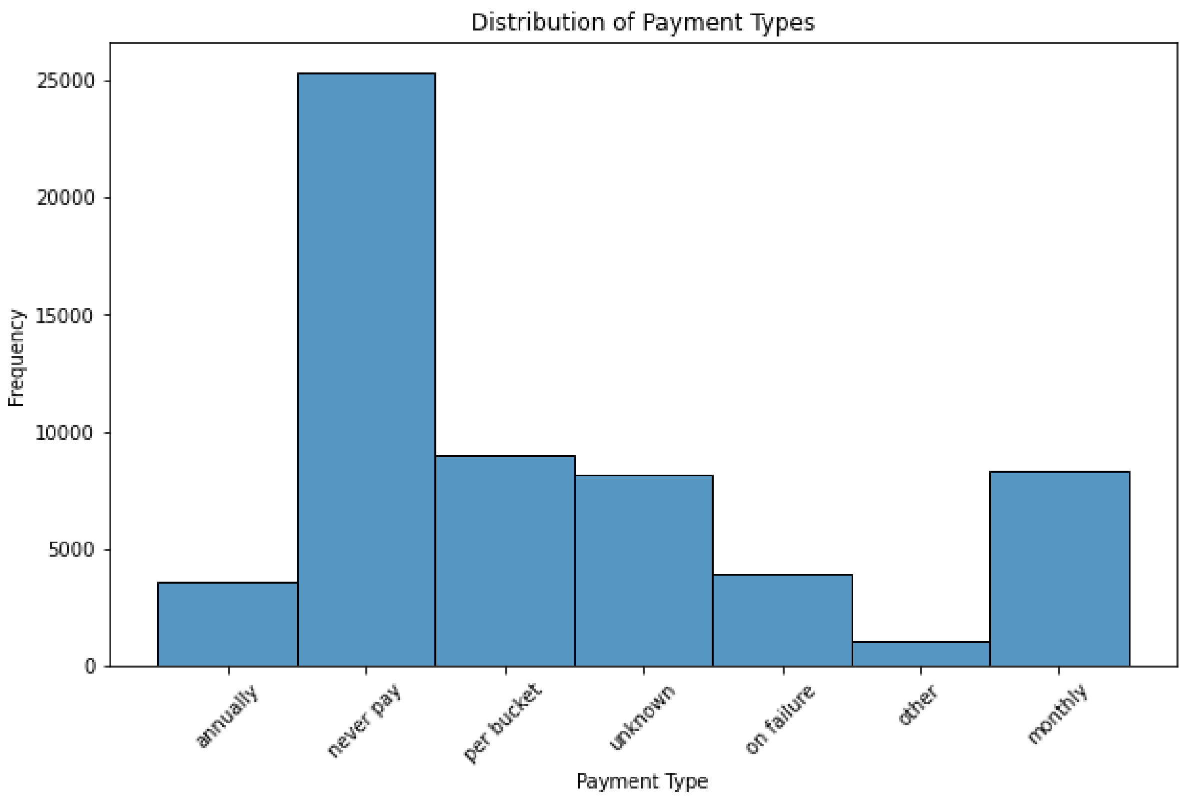
4.1.10 distribution of the gps height

In [75]:
```
plt.figure(figsize=(10, 6))
sns.histplot(tanzania_data["gps_height"], bins=50, kde=True)
plt.xlabel("GPS Height (meters)")
plt.ylabel("Frequency")
plt.title("Distribution of GPS Height in Tanzania Data")
plt.show()
```



4.1.11 how did most users pay?

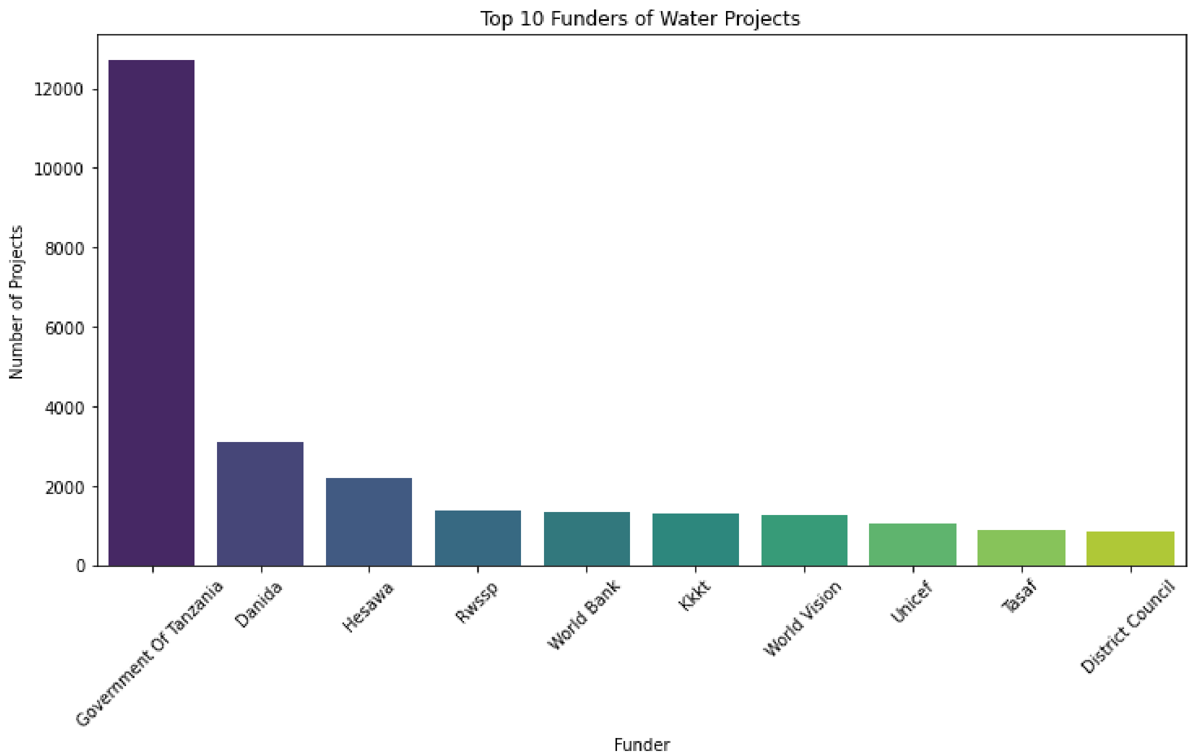
In [76]:
```
plt.figure(figsize=(10, 6))
sns.histplot(tanzania_data["payment_type"], bins=len(tanzania_data["payment_t

plt.xlabel("Payment Type")
plt.ylabel("Frequency")
plt.title("Distribution of Payment Types")
plt.xticks(rotation=45)
plt.show()
```



Most wells operate without a payment system, providing free access to water. However, some communities use pay-per-bucket models, while others opt for monthly or annual payments to support maintenance and sustainability.

4.1.12 who are the top 10 funders?

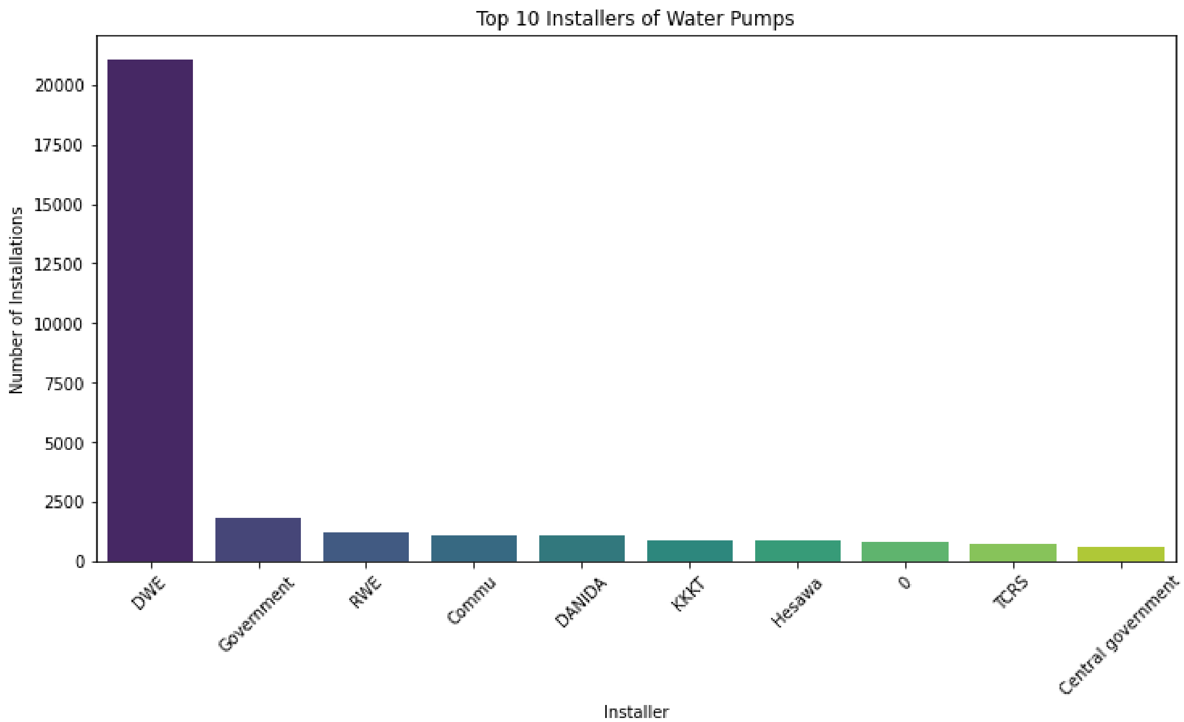
In [77]:
```
top_funders = tanzania_data["funder"].value_counts().head(10)

plt.figure(figsize=(12, 6))
sns.barplot(x=top_funders.index, y=top_funders.values, palette="viridis")
plt.xlabel("Funder")
plt.ylabel("Number of Projects")
plt.title("Top 10 Funders of Water Projects")
plt.xticks(rotation=45)
plt.show()
```



The Government of Tanzania is the leading funder of water wells, playing a major role in infrastructure development. Other key contributors include DANIDA, HESAWA, RWSSP, World Bank, KKT, World Vision, UNICEF, TASAF, and District Councils, highlighting the involvement of both international and local organizations in improving water access.

4.1.13 top 10 installers

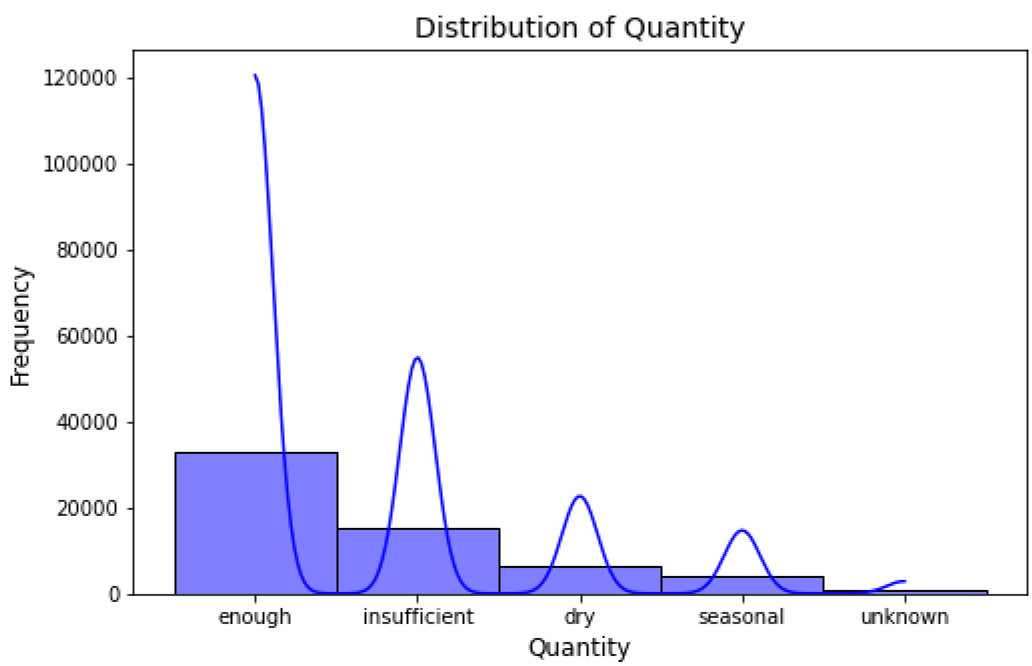
In [78]:
```
top_installers = tanzania_data["installer"].value_counts().head(10)
plt.figure(figsize=(12, 6))
sns.barplot(x=top_installers.index, y=top_installers.values, palette="viridis
plt.xlabel("Installer")
plt.ylabel("Number of Installations")
plt.title("Top 10 Installers of Water Pumps")
plt.xticks(rotation=45)
plt.show()
```



The majority of wells were installed by **DWE (District Water Engineers)**, followed by the **Government of Tanzania**. Other key installers include **RWE (Regional Water Engineers)** and local **community-led initiatives**, reflecting a mix of institutional and grassroots efforts in water infrastructure development.

4.1.14 how much is the quantity of water coming from the wells

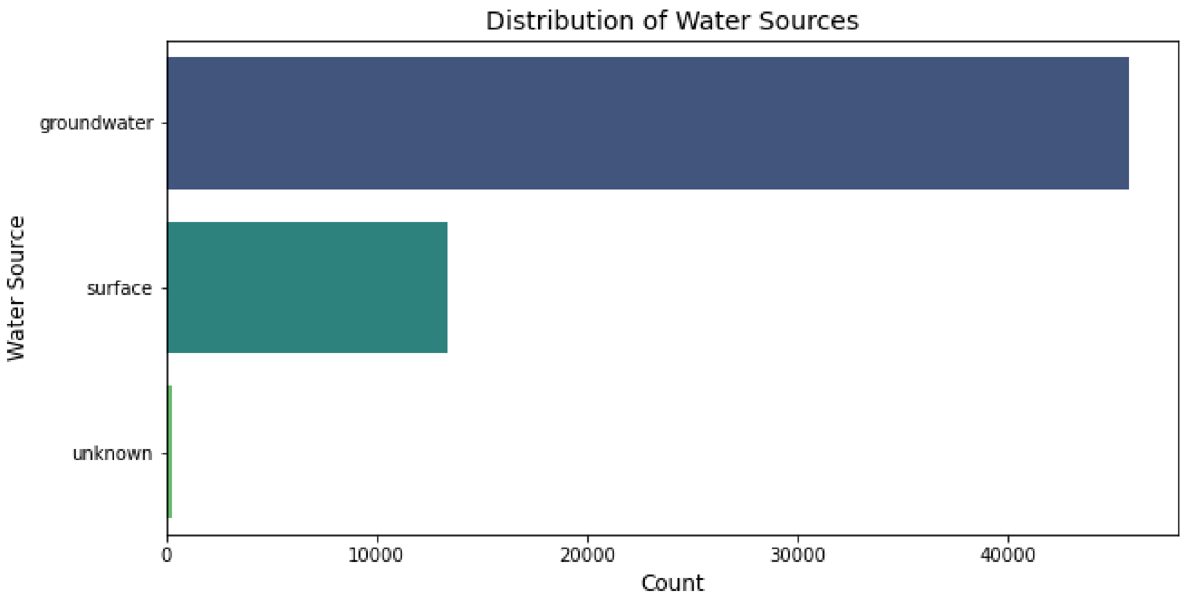
In [79]:
```
plt.figure(figsize=(8, 5))
sns.histplot(tanzania_data["quantity_group"], bins=10, kde=True, color="blue"
plt.xlabel("Quantity", fontsize=12)
plt.ylabel("Frequency", fontsize=12)
plt.title("Distribution of Quantity", fontsize=14)
plt.show()
```



Most wells provided **enough water** to meet community needs, while some were classified as **sufficient** but not abundant. A few wells were **dry**, others had **seasonal water availability**, and some had **unknown water quantity**, indicating gaps in data or inconsistent supply.

4.1.15 what is the source class of the water from the well??

In [80]:
```
plt.figure(figsize=(10, 5))
sns.countplot(y=tanzania_data["source_class"], order=tanzania_data["source_cl
plt.xlabel("Count", fontsize=12)
plt.ylabel("Water Source", fontsize=12)
plt.title("Distribution of Water Sources", fontsize=14)
plt.show()
```



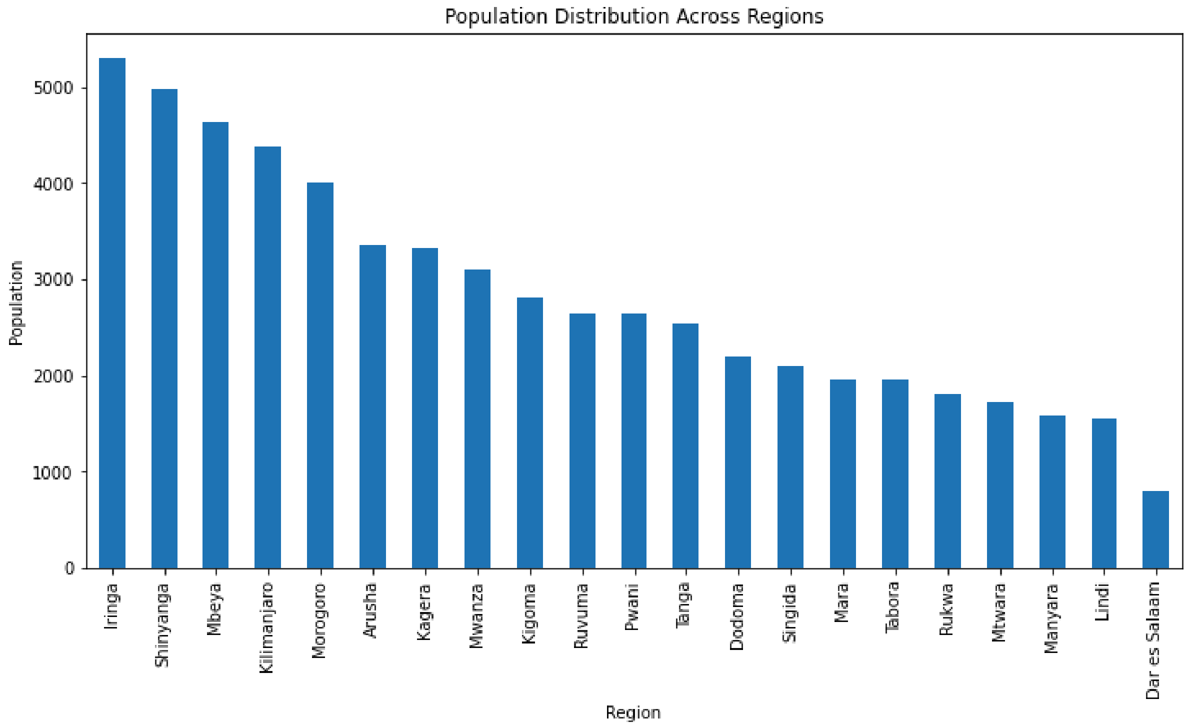
Most of the water sources are from groundwater, while a smaller portion comes from surface water sources.

4.2 bivariate analysis

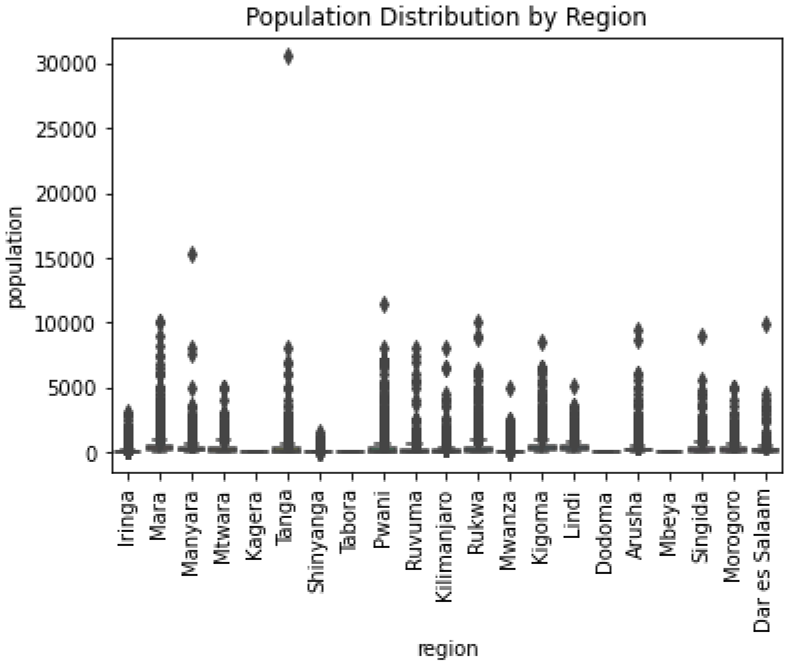
4.2.1 checking the population distribution per region

In [81]:

```
tanzania_data['region'].value_counts().plot(kind='bar', figsize=(12, 6))
plt.title('Population Distribution Across Regions')
plt.xlabel('Region')
plt.ylabel('Population')
plt.show()
```



In [82]:
```
sns.boxplot(x='region', y='population', data=tanzania_data)
plt.xticks(rotation=90)
plt.title('Population Distribution by Region')
plt.show()
```

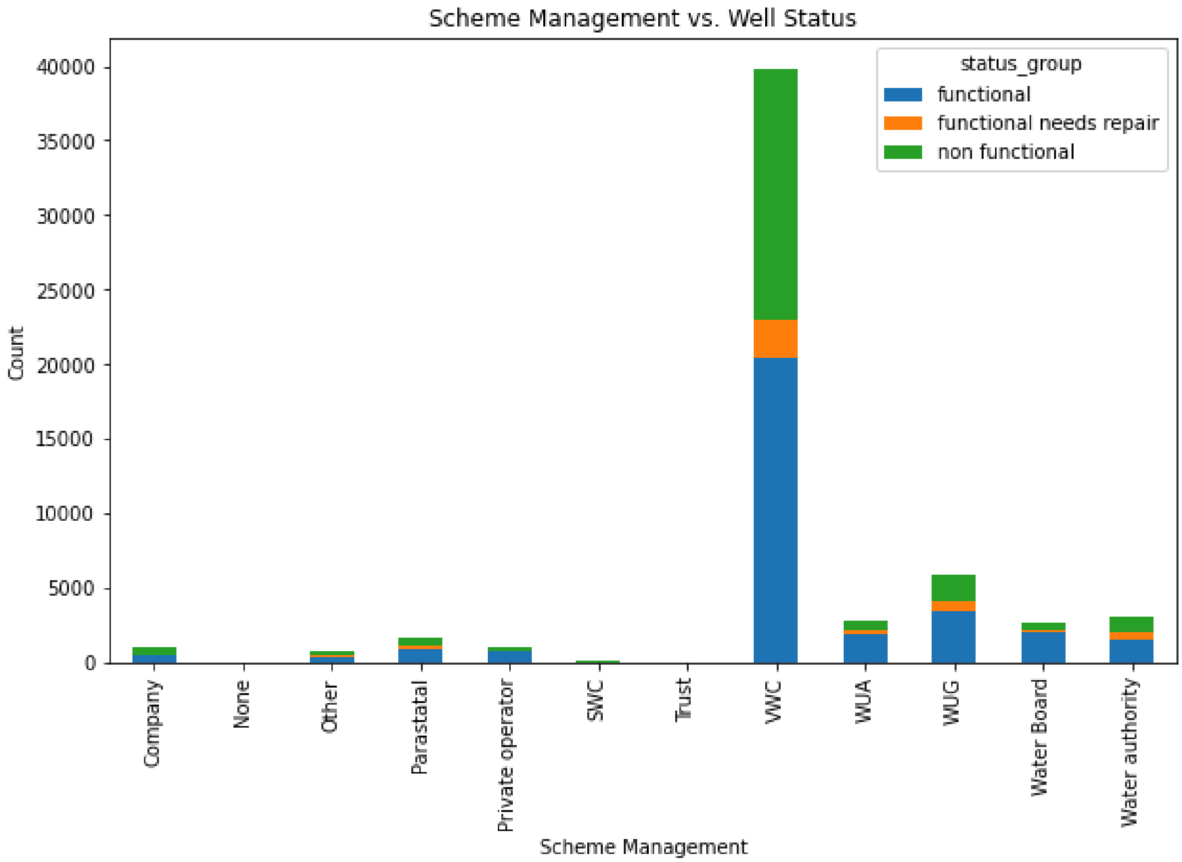


The regions with the highest populations include **Iringa, Shinyanga, Mbeya, Kilimanjaro, Morogoro, Arusha, Kagera, Mwanza, Kigoma, Ruvuma, and Pwani**. These areas have a higher demand for water, making well functionality and maintenance critical for community sustainability.

4.2.2 comparing the scheme management vs the status of the pumps

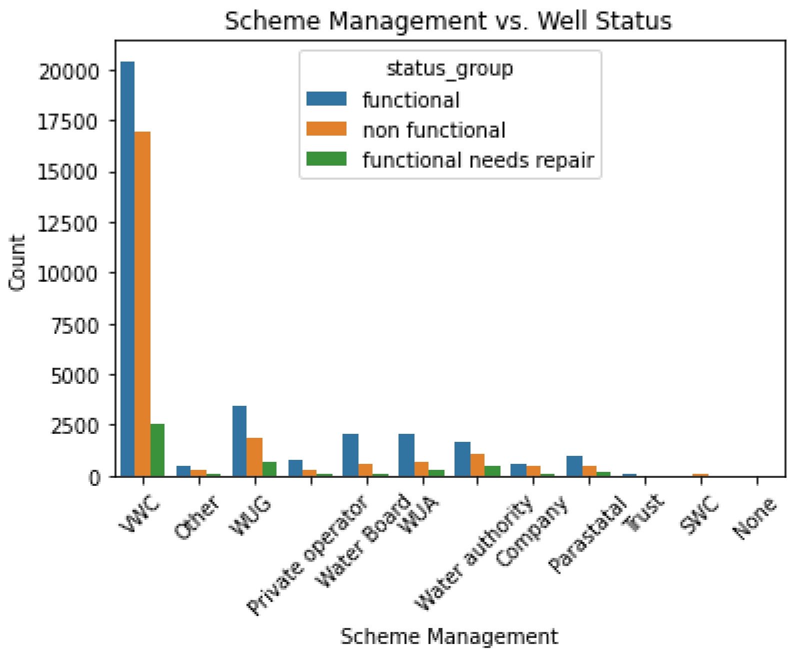
In [83]:

```
tanzania_data.groupby(['scheme_management', 'status_group']).size().unstack()
plt.title('Scheme Management vs. Well Status')
plt.ylabel('Count')
plt.xlabel('Scheme Management')
plt.show()
```



In [84]:

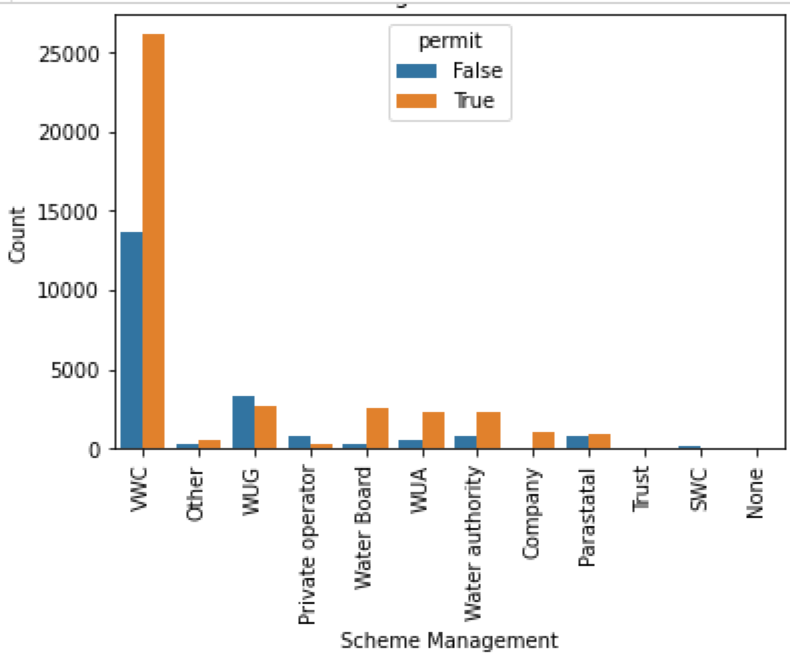
```
sns.countplot(x='scheme_management', hue='status_group', data=tanzania_data)
plt.title('Scheme Management vs. Well Status')
plt.xlabel('Scheme Management')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



Wells under the **VMC scheme** had the highest number of **functional** wells, followed by **non-functional** ones, with only a few requiring **repairs**. This trend was similar across other schemes, indicating that while many wells remain operational, maintenance challenges persist.

4.2.3 checking wether the scheme management were issued permits

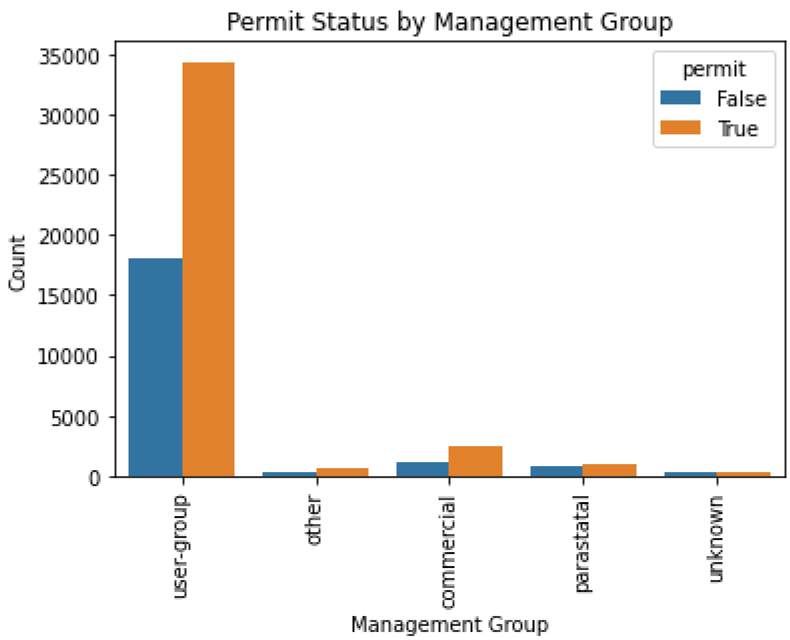
In [85]:
```
sns.countplot(x='scheme_management', hue='permit', data=tanzania_data)
plt.title('Scheme Management vs. Well Status')
plt.xlabel('Scheme Management')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.show()
```



The **VMC scheme** had permits for most of its wells, ensuring regulatory compliance. However, a few wells operated **without permits**. This pattern was consistent across other schemes, highlighting both adherence to regulations and instances of unpermitted installations.

4.2.4 checking wether the management groups have permit

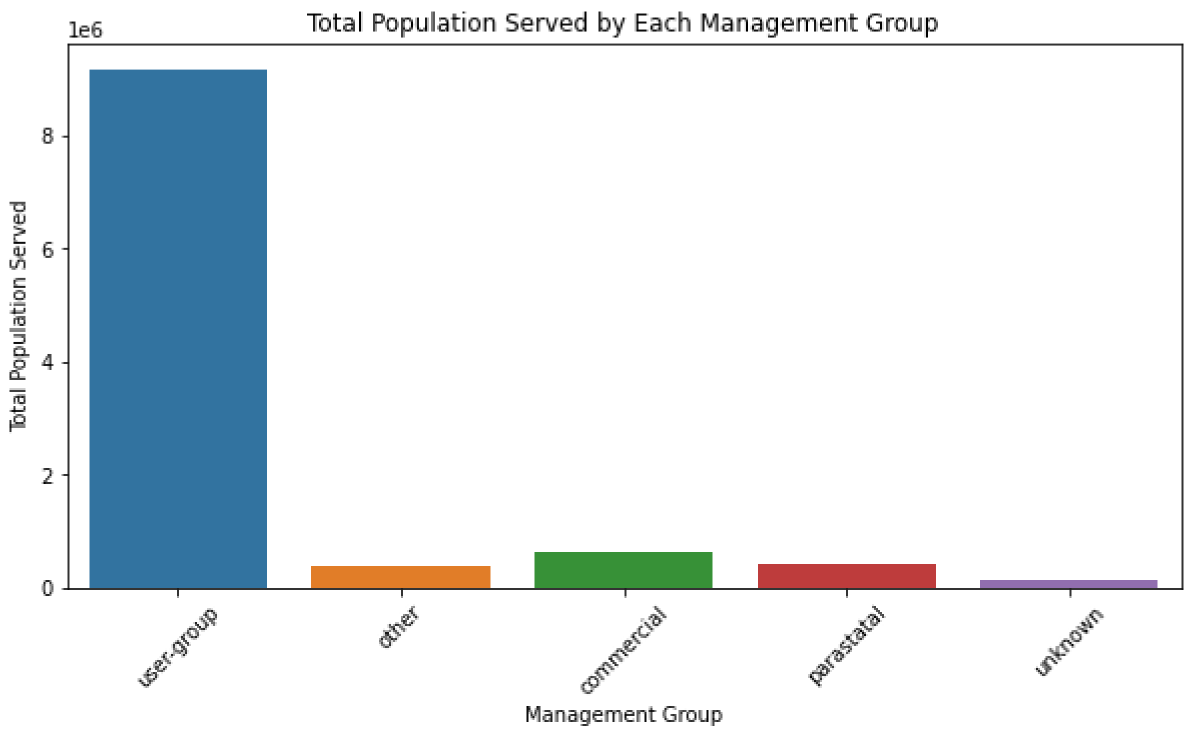
In [86]:
```
sns.countplot(x='management_group', hue='permit', data=tanzania_data)
plt.title('Permit Status by Management Group')
plt.xlabel('Management Group')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.show()
```



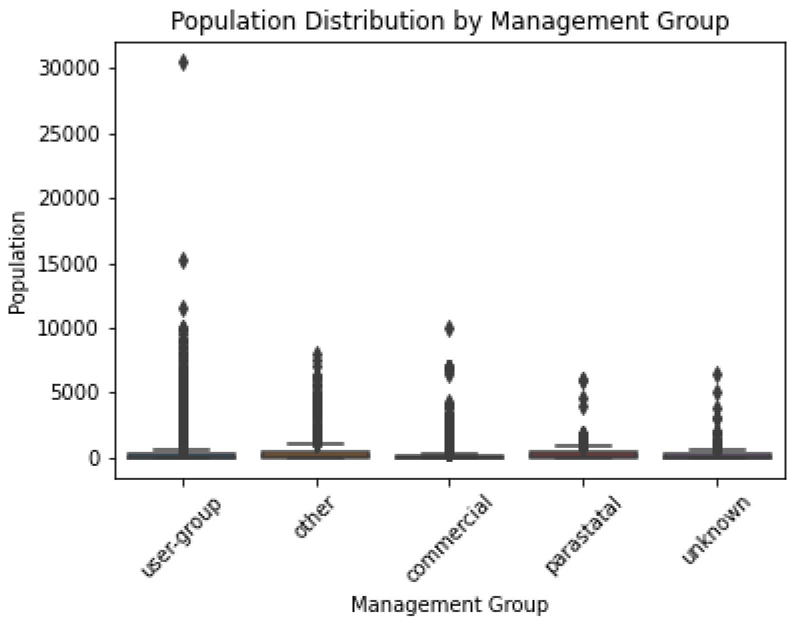
Wells managed by user groups had permits for most installations, though a few lacked them. Similarly, commercial and parastatal-managed wells followed the same trend, with most being permitted but some operating without official approval.

4.2.5 population by management group

In [87]:
```
plt.figure(figsize=(10, 5))
sns.barplot(x="management_group", y="population", data=tanzania_data, estimat
plt.xticks(rotation=45)
plt.ylabel("Total Population Served")
plt.xlabel("Management Group")
plt.title("Total Population Served by Each Management Group")
plt.show()
```



In [88]:
```
sns.boxplot(x='management_group', y='population', data=tanzania_data)
plt.title('Population Distribution by Management Group')
plt.xlabel('Management Group')
plt.ylabel('Population')
plt.xticks(rotation=45)
plt.show()
```

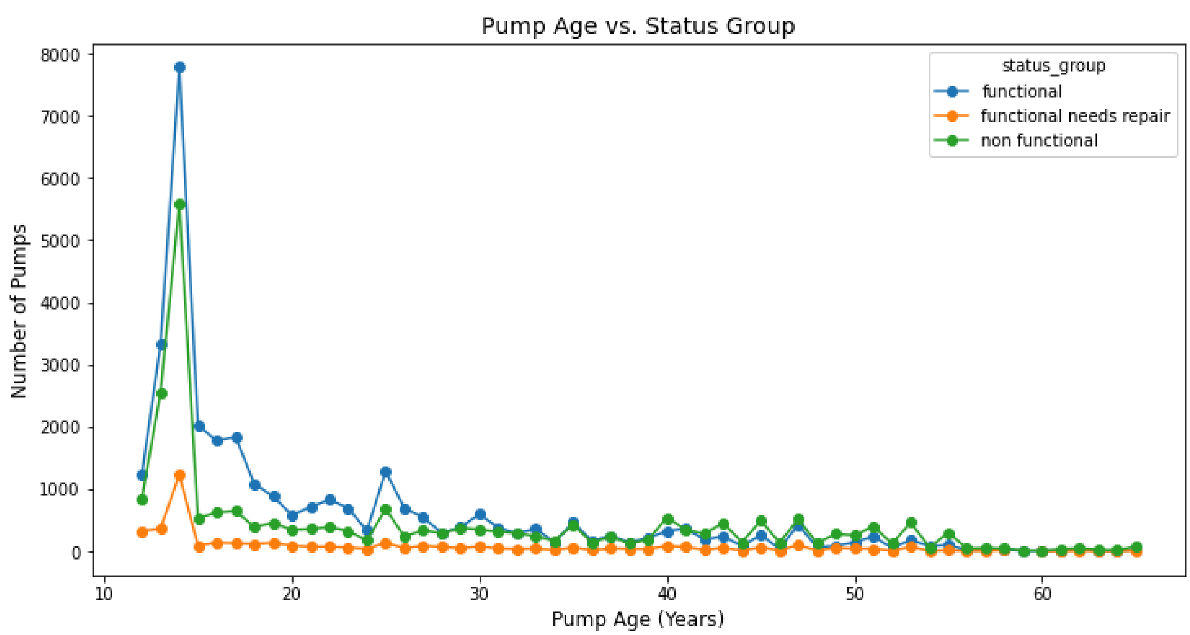


Most of the population relied on wells managed by user groups, ensuring community oversight. Others were managed by commercial entities and parastatals, playing a role in regulated water distribution and maintenance.

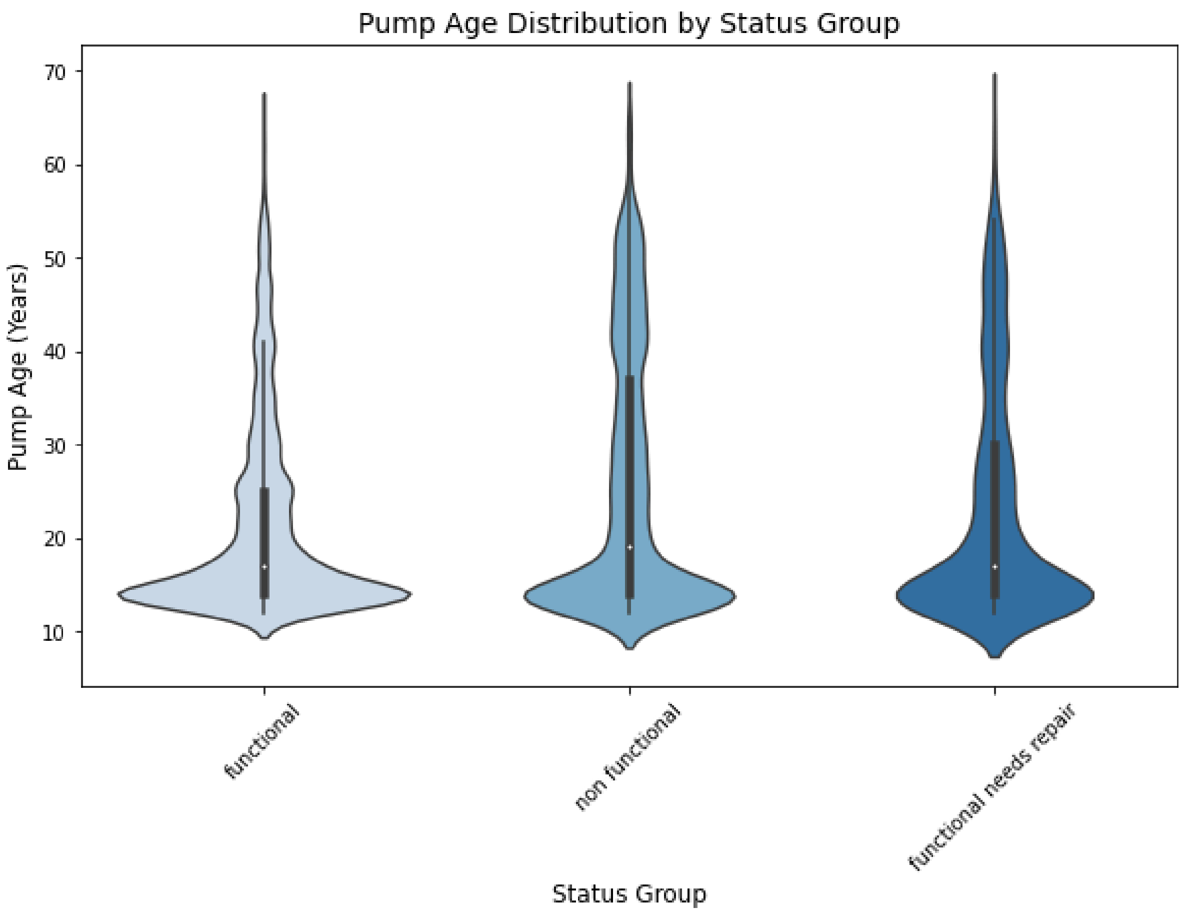
4.2.6 checking the trend across the age and status group

In [89]:
```
plt.figure(figsize=(12, 6))
tanzania_data.groupby(["pump_age", "status_group"]).size().unstack().plot(kir

plt.xlabel("Pump Age (Years)", fontsize=12)
plt.ylabel("Number of Pumps", fontsize=12)
plt.title("Pump Age vs. Status Group", fontsize=14)
plt.show()
```

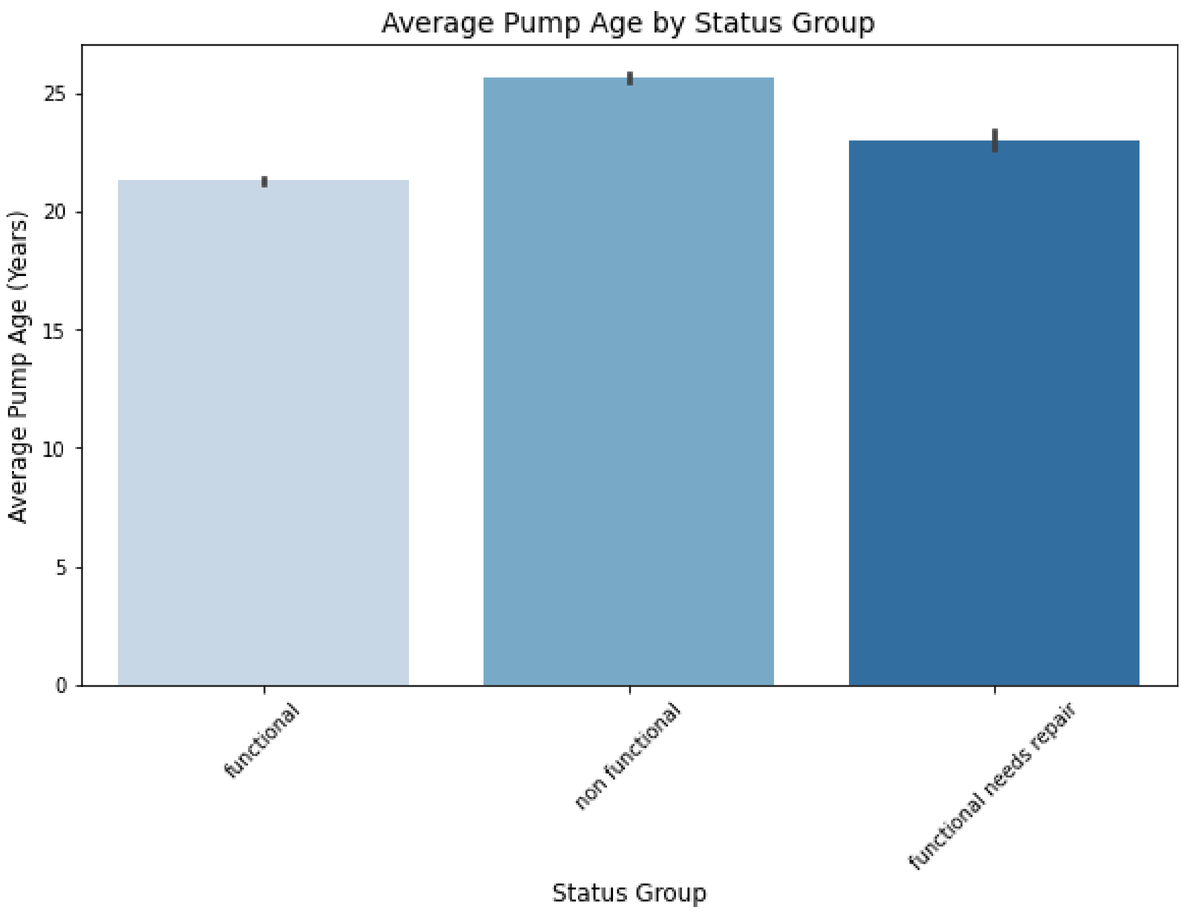
```
<Figure size 864x432 with 0 Axes>
```



In [90]:
```
plt.figure(figsize=(10, 6))
sns.violinplot(x="status_group", y="pump_age", data=tanzania_data, palette="B

plt.xlabel("Status Group", fontsize=12)
plt.ylabel("Pump Age (Years)", fontsize=12)
plt.title("Pump Age Distribution by Status Group", fontsize=14)
plt.xticks(rotation=45)
plt.show()
```

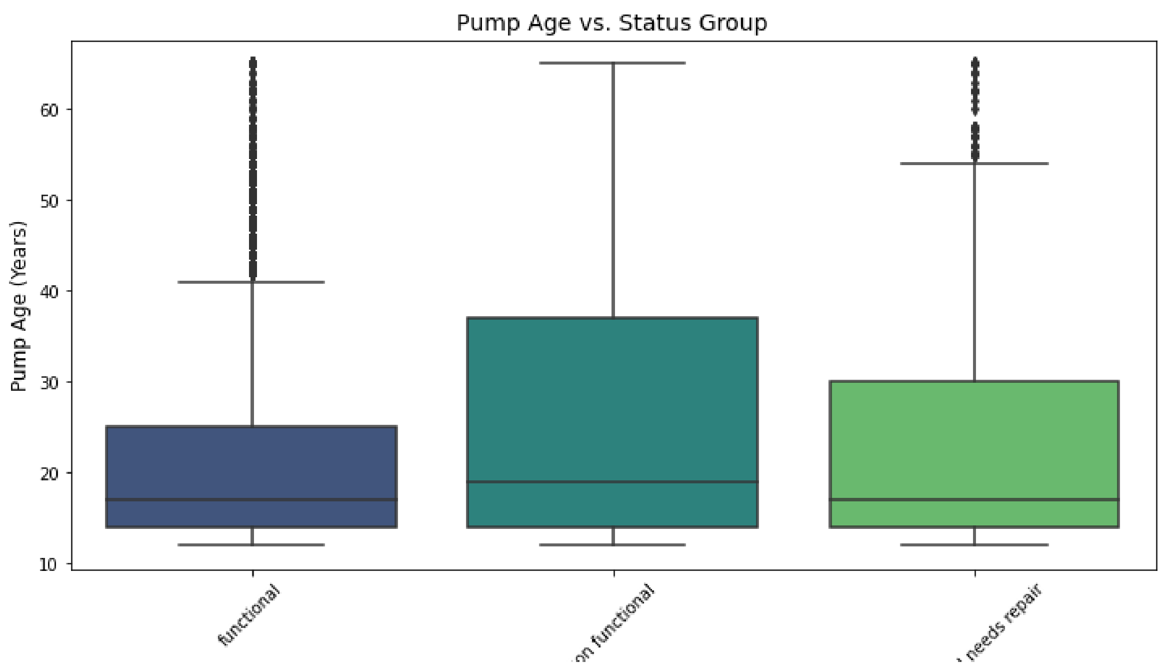


In [91]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x="status_group", y="pump_age", data=tanzania_data, estimator=lam

plt.xlabel("Status Group", fontsize=12)
plt.ylabel("Average Pump Age (Years)", fontsize=12)
plt.title("Average Pump Age by Status Group", fontsize=14)
plt.xticks(rotation=45)
plt.show()
```



In [92]:

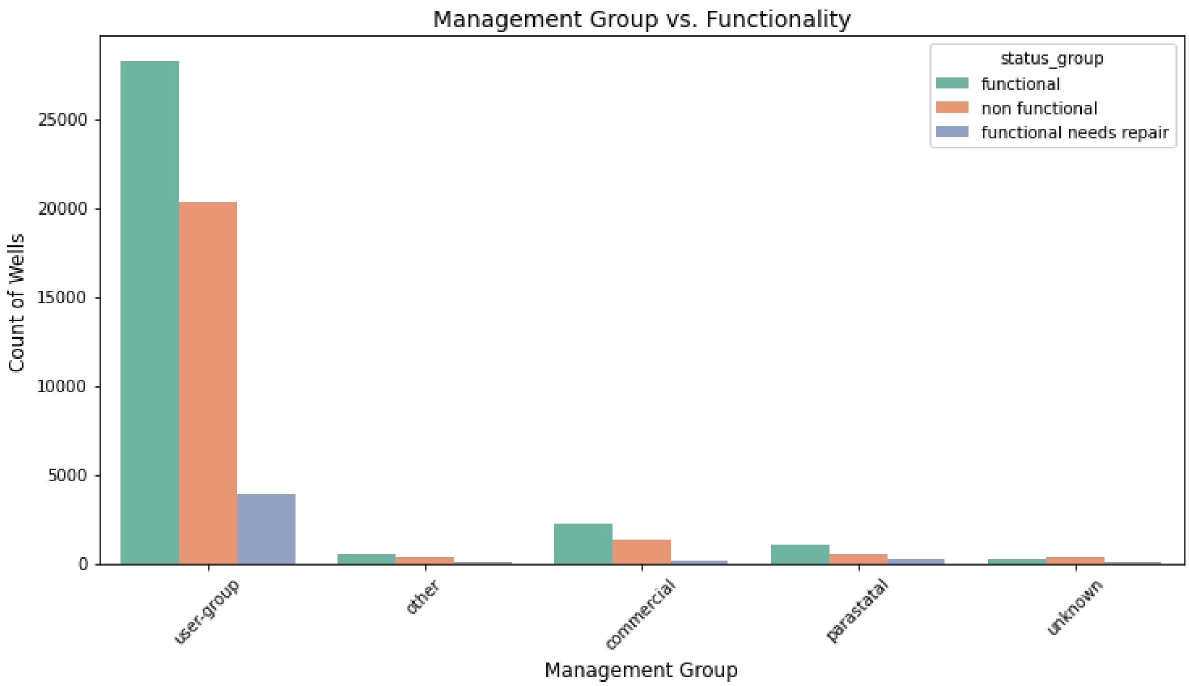
```
plt.figure(figsize=(12, 6))
sns.boxplot(x="status_group", y="pump_age", data=tanzania_data, palette="viri

plt.xlabel("Status Group", fontsize=12)
plt.ylabel("Pump Age (Years)", fontsize=12)
plt.title("Pump Age vs. Status Group", fontsize=14)
plt.xticks(rotation=45)
plt.show()
```



Younger pumps are performing well, with fewer issues and consistent functionality. However, older pumps are more prone to failure, requiring frequent maintenance or replacement due to wear and aging infrastructure.

4.2.7 checking well management vs functionality

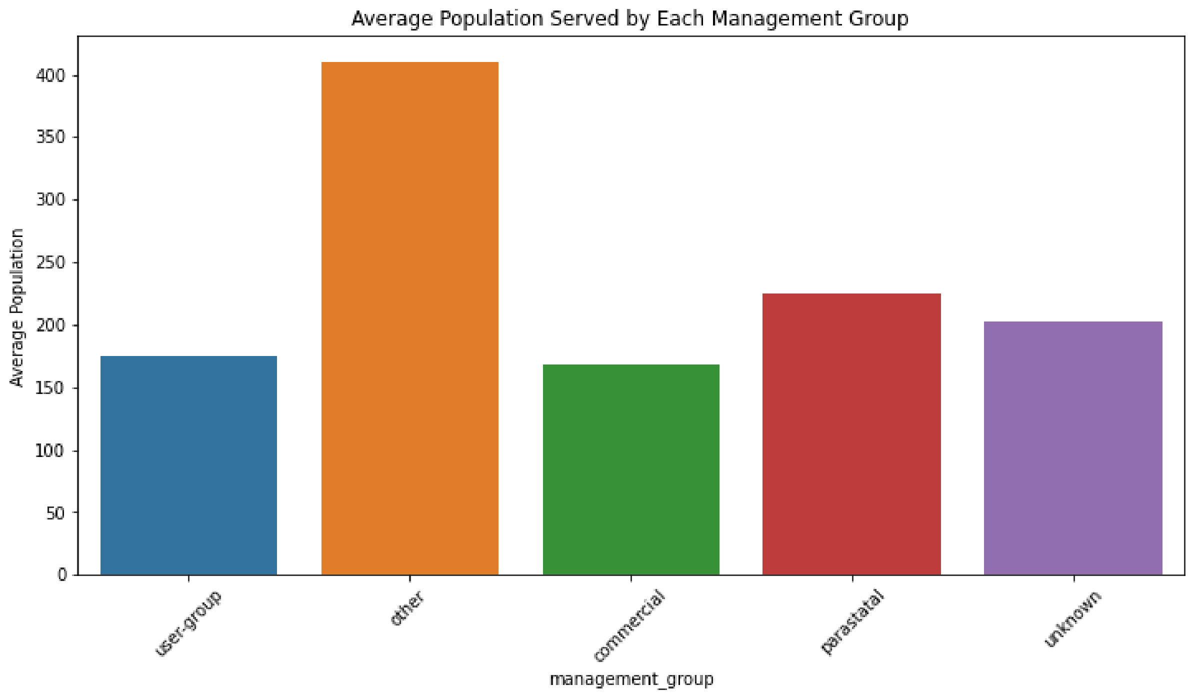
In [93]:
```
plt.figure(figsize=(12, 6))
sns.countplot(x="management_group", hue="status_group", data=tanzania_data, p

plt.xlabel("Management Group", fontsize=12)
plt.ylabel("Count of Wells", fontsize=12)
plt.title("Management Group vs. Functionality", fontsize=14)
plt.xticks(rotation=45)
plt.show()
```



Most wells, whether user group, commercial, or parastatal-managed, were functional, though some failed, and a few required repairs, following a consistent trend across all management types.

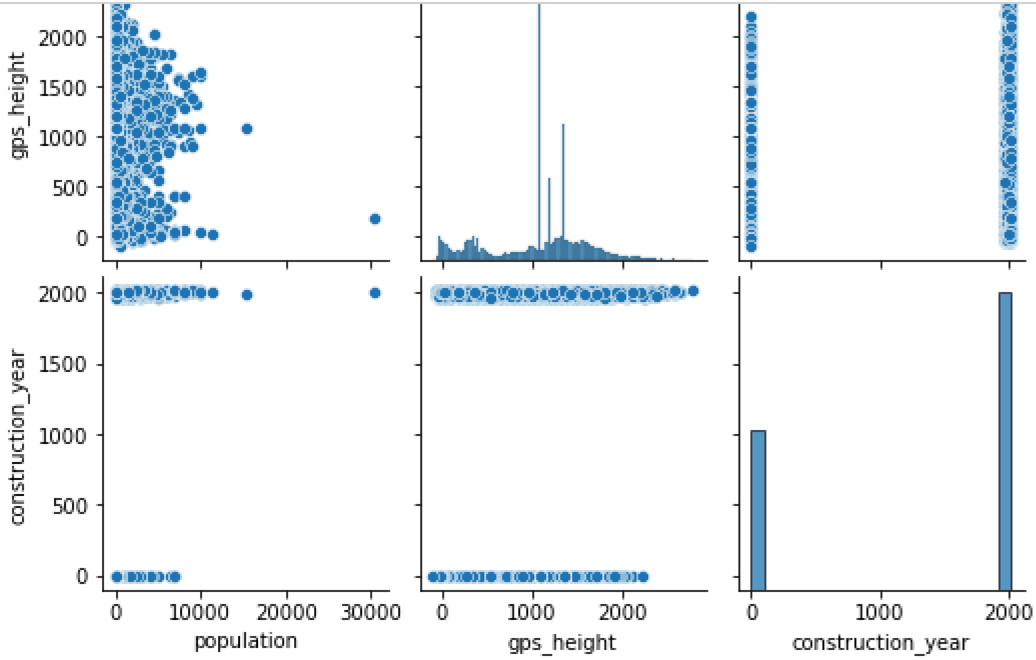
4.2.8 population by management group

In [94]:
```
plt.figure(figsize=(12,6))
sns.barplot(x="management_group", y="population", data=tanzania_data, estimat
plt.xticks(rotation=45)
plt.ylabel("Average Population")
plt.title("Average Population Served by Each Management Group")
plt.show()
```



4.3 Multivariate analysis

In [95]:
```
sns.pairplot(tanzania_data[['population', 'gps_height', 'construction_year']]
plt.show()
```



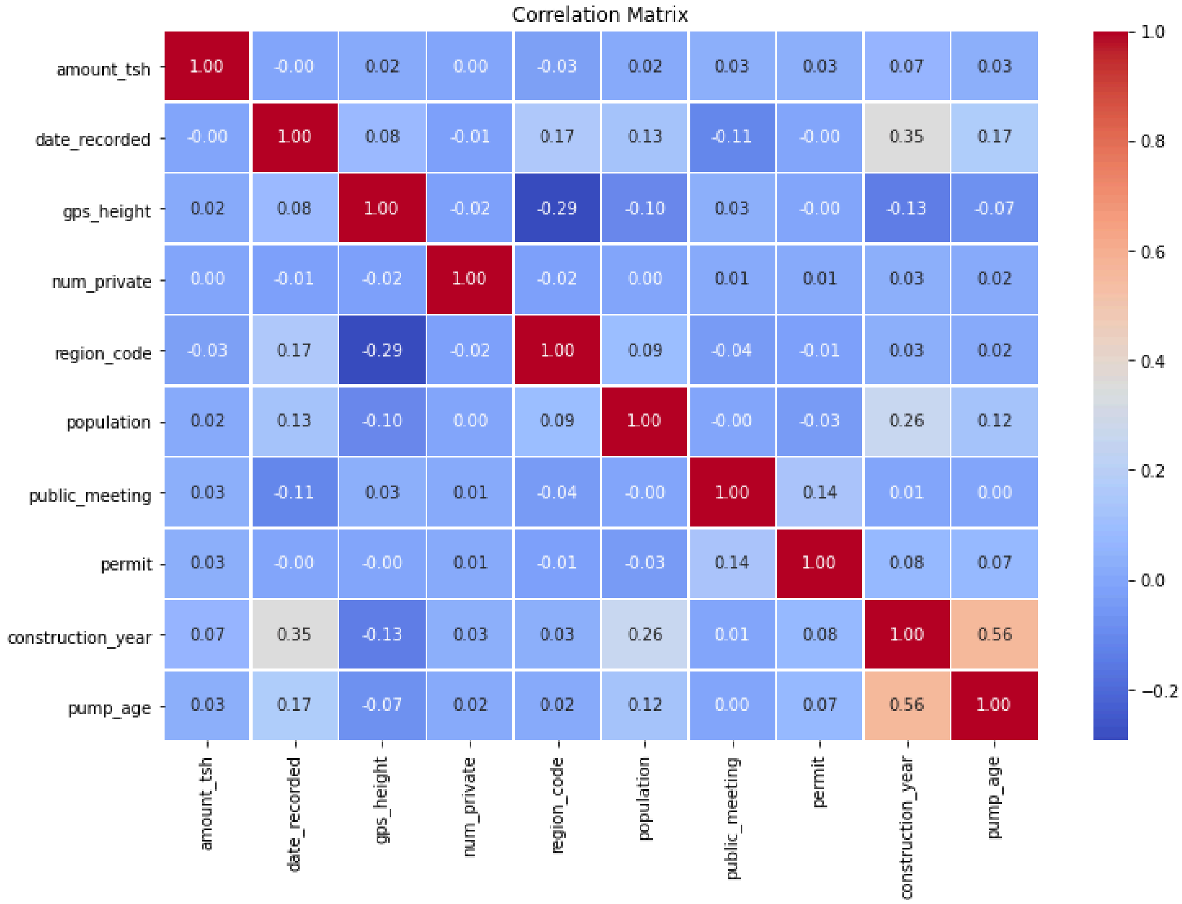
In [96]:
```
tanzania_data.corr()
```

Out[96]:

	amount_tsh	date_recorded	gps_height	num_private	region_code	population
amount_tsh	1.000000	-0.004743	0.023743	0.002944	-0.026813	0.016288
date_recorded	-0.004743	1.000000	0.081006	-0.013816	0.165532	0.131747
gps_height	0.023743	0.081006	1.000000	-0.018274	-0.293706	-0.100316
num_private	0.002944	-0.013816	-0.018274	1.000000	-0.020377	0.003818
region_code	-0.026813	0.165532	-0.293706	-0.020377	1.000000	0.094088
population	0.016288	0.131747	-0.100316	0.003818	0.094088	1.000000
public_meeting	0.025683	-0.111386	0.028689	0.011230	-0.044806	-0.000398
permit	0.025042	-0.003344	-0.000484	0.011962	-0.010835	-0.034684
construction_year	0.067915	0.354792	-0.132223	0.026056	0.031724	0.260910
pump_age	0.033813	0.174573	-0.070436	0.017523	0.024029	0.122728

In [97]:

```
correlation_matrix = tanzania_data.corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linew
plt.title('Correlation Matrix')
plt.show()
```



4.3.1 Chi-square

In [98]:

```
contingency_table = pd.crosstab(tanzania_data["management_group"], tanzania_d

chi2, p, dof, expected = stats.chi2_contingency(contingency_table)

print(f"Chi-Square Value: {chi2}")
print(f"P-Value: {p}")

if p < 0.05:
    print("There is a significant relationship between management group and s
else:
    print("No significant relationship found.")
```

```
Chi-Square Value: 287.65157783580787
P-Value: 1.744626138526002e-57
There is a significant relationship between management group and status grou
p.
```

This means that the **management group** (user group, commercial, parastatal, etc.) has a **significant impact** on the **functionality status** of the wells (**functional, non-functional, or needs repair**).

Since the **Chi-square value is high** (287.65) and the **p-value is extremely low** (1.74e-57, much smaller than 0.05), we reject the null hypothesis, confirming that **well management is strongly associated with whether a well is functional or not**.

5 Feature Selection.

In [99]:
```
tanzania_data
```

Out[99]:

	amount_tsh	date_recorded	funder	gps_height	installer	num_private	basin	
0	6000.0	2011	Roman	1390.000000	Roman	0	Lake Nyasa	
1	0.0	2013	Grumeti	1399.000000	GRUMETI	0	Lake Victoria	
2	25.0	2013	Lottery Club	686.000000	World vision	0	Pangani	
3	0.0	2013	Unicef	263.000000	UNICEF	0	Ruvuma / Southern Coast	
4	0.0	2011	Action In A	1086.967394	Artisan	0	Lake Victoria	
...	...	...	...	...	...	...	...	
59395	10.0	2013	Germany Republi	1210.000000	CES	0	Pangani	K
59396	4700.0	2011	Cefa-njombe	1212.000000	Cefa	0	Rufiji	
59397	0.0	2011	Government Of Tanzania	1086.967394	DWE	0	Rufiji	
59398	0.0	2011	Malec	1086.967394	Musa	0	Rufiji	
59399	0.0	2011	World Bank	191.000000	World	0	Wami / Ruvu	

59400 rows × 22 columns

5.1 defining features and target

In [100]:
```
X = tanzania_data.drop(columns=["date_recorded","scheme_management","status_g
X
```

Out[100]:

	amount_tsh	gps_height	region_code	population	public_meeting	permit	construction_y
0	6000.0	1390.000000	11	109	True	False	1!
1	0.0	1399.000000	20	280	False	True	2(
2	25.0	686.000000	21	250	True	True	2(
3	0.0	263.000000	90	58	True	True	1!
4	0.0	1086.967394	18	0	True	True	
...	...	...	...	...	...	...	
59395	10.0	1210.000000	3	125	True	True	1!
59396	4700.0	1212.000000	11	56	True	True	1!
59397	0.0	1086.967394	12	0	True	False	
59398	0.0	1086.967394	1	0	True	True	
59399	0.0	191.000000	5	150	True	True	2(

59400 rows × 14 columns

In [101]:
```
y = tanzania_data["status_group"]
y
```

Out[101]:
```
0            functional
1            functional
2            functional
3        non functional
4            functional
              ...
59395        functional
59396        functional
59397        functional
59398        functional
59399        functional
Name: status_group, Length: 59400, dtype: object
```

5.2 Encoding categorical values

In [102]:
```
le = LabelEncoder()
y_encoded = le.fit_transform(y)
```

In [103]:
```python
label_mapping = dict(zip(le.classes_, le.transform(le.classes_)))
print("Label Encoding Mapping:", label_mapping)
```

```
Label Encoding Mapping: {'functional': 0, 'functional needs repair': 1, 'non
functional': 2}
```

In [104]:
```python
y_encoded
```

Out[104]:
```
array([0, 0, 0, ..., 0, 0, 0])
```

In [105]:
```python
encoder = LabelEncoder()

X["permit"] = encoder.fit_transform(X["permit"])
X["public_meeting"] = encoder.fit_transform(X["public_meeting"])
```

In [106]:
```python
X
```

Out[106]:

	amount_tsh	gps_height	region_code	population	public_meeting	permit	construction_y
0	6000.0	1390.000000	11	109	1	0	1
1	0.0	1399.000000	20	280	0	1	2
2	25.0	686.000000	21	250	1	1	2
3	0.0	263.000000	90	58	1	1	1
4	0.0	1086.967394	18	0	1	1	
...	...	...	...	...	...	...	
59395	10.0	1210.000000	3	125	1	1	1
59396	4700.0	1212.000000	11	56	1	1	1
59397	0.0	1086.967394	12	0	1	0	
59398	0.0	1086.967394	1	0	1	1	
59399	0.0	191.000000	5	150	1	1	2

59400 rows × 14 columns

In [107]:
```python
X["quality_group"] = le.fit_transform(X["quality_group"])
X["quantity_group"] = le.fit_transform(X["quantity_group"])
X["management_group"] = le.fit_transform(X["management_group"])
X["payment_type"] = le.fit_transform(X["payment_type"])
X["quality_group"] = le.fit_transform(X["quality_group"])
X["extraction_type_class"] = le.fit_transform(X["extraction_type_class"])
X["source_class"] = le.fit_transform(X["source_class"])
```

5.3 Scaling the numeric features.

In [108]:
```
scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)
```

In [109]:
```
X_scaled
```

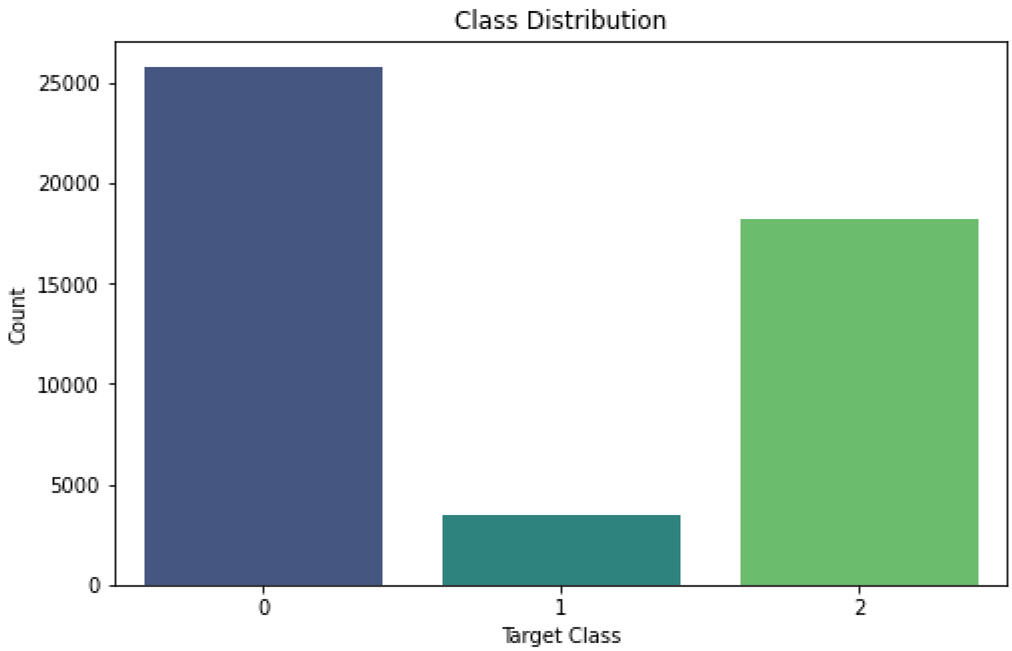
Out[109]:
```
array([[ 1.89566509,  0.64748514, -0.2443248 , ..., -0.40530054,
        -0.53841035,  0.2382332 ],
       [-0.10597003,  0.66509518,  0.26740931, ...,  0.83887787,
         1.76507387, -0.65937589],
       [-0.09762988, -0.7300112 ,  0.32426866, ..., -0.40530054,
         1.76507387, -0.57777506],
       ...,
       [-0.10597003,  0.05455005, -0.18746545, ..., -0.40530054,
        -0.53841035, -0.74097672],
       [-0.10597003,  0.05455005, -0.81291826, ...,  0.83887787,
        -0.53841035, -0.74097672],
       [-0.10597003, -1.69856331, -0.58548087, ..., -0.40530054,
        -0.53841035, -0.00656928]])
```

5.4 Stratified sampling

In [110]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y_encoded, test_size=0.2, stratify=y, random_state=42)
```

5.5 Class imbalance

In [111]:
```
plt.figure(figsize=(8,5))
sns.countplot(x=y_train, palette="viridis")
plt.title("Class Distribution")
plt.xlabel("Target Class")
plt.ylabel("Count")
plt.show()
```



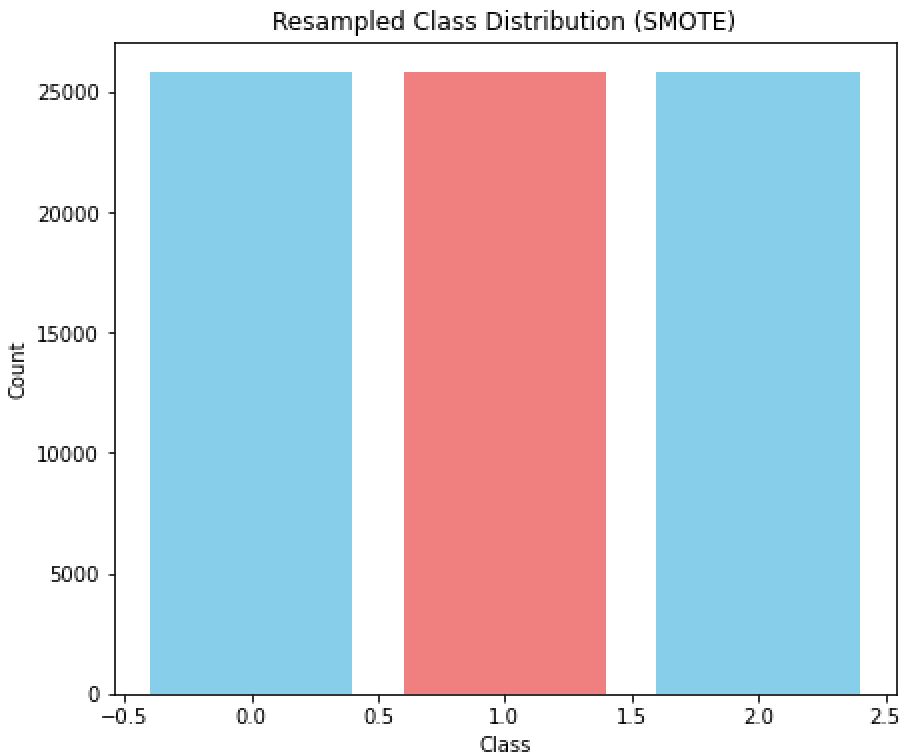
In [112]:
```
smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
```

In [113]:
```
y_train = pd.Series(y_train)
y_train_res = pd.Series(y_train_res)
```

In [114]:
```
print("Original class distribution:")
print(y_train.value_counts())

print("Resampled class distribution:")
print(y_train_res.value_counts())
```

```
Original class distribution:
0    25807
2    18259
1     3454
dtype: int64
Resampled class distribution:
2    25807
1    25807
0    25807
dtype: int64
```

In [115]:
```
plt.figure(figsize=(7, 6))
plt.bar(y_train_res.value_counts().index, y_train_res.value_counts().values,
plt.title('Resampled Class Distribution (SMOTE)')
plt.xlabel('Class')
plt.ylabel('Count')
plt.show()
```



6 Modelling & Evaluation.

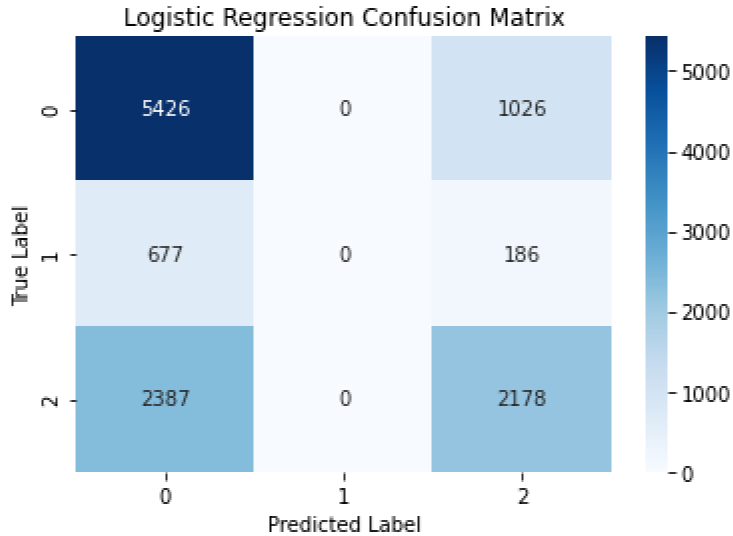
6.1 Baseline logistic model

In [116]:
```
baseline_lr = LogisticRegression(max_iter=1000, random_state=42)

baseline_lr.fit(X_train, y_train)

y_pred_baseline = baseline_lr.predict(X_test)

baseline_accuracy = accuracy_score(y_test, y_pred_baseline)
print(f"Baseline Logistic Regression Accuracy: {baseline_accuracy:.4f}")
```

```
Baseline Logistic Regression Accuracy: 0.6401
```

In [117]:

```
cm = confusion_matrix(y_test, y_pred_baseline)

plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=baseline_lr.cl
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Logistic Regression Confusion Matrix")
plt.show()
```

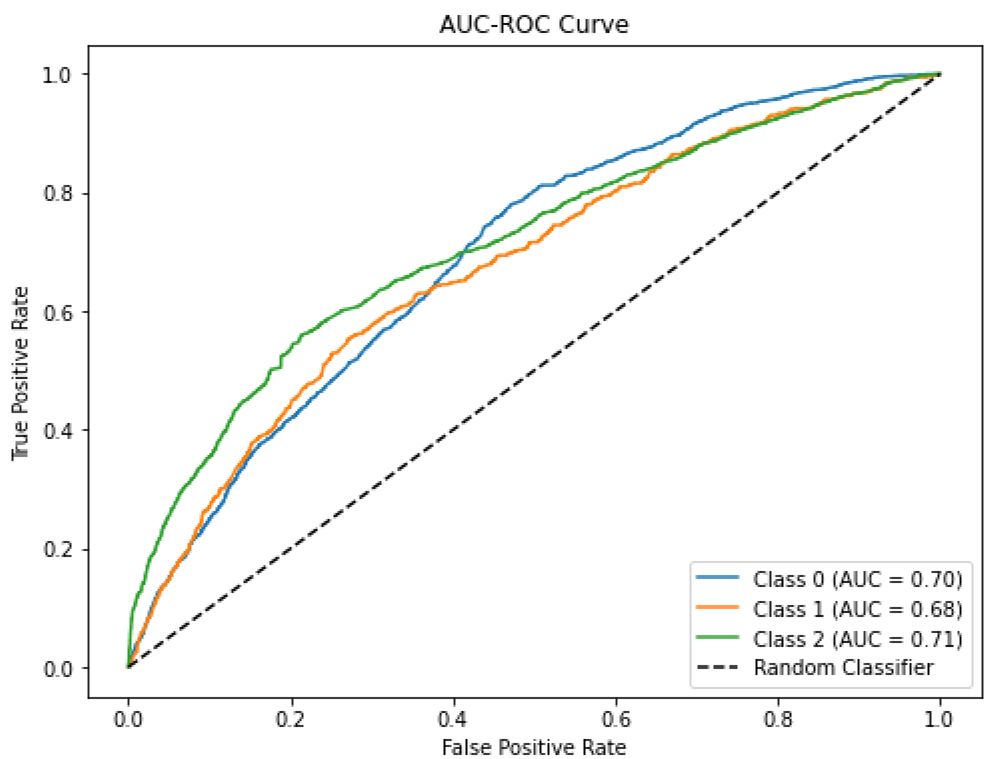


In [118]:

```
report = classification_report(y_test, y_pred_baseline, zero_division=1)

print(report)
```

```
              precision    recall  f1-score   support

           0       0.64      0.84      0.73      6452
           1       1.00      0.00      0.00       863
           2       0.64      0.48      0.55      4565

    accuracy                           0.64     11880
   macro avg       0.76      0.44      0.42     11880
weighted avg       0.67      0.64      0.60     11880
```

In [119]:
```
y_test_binarized = label_binarize(y_test, classes=baseline_lr.classes_)

y_score = baseline_lr.predict_proba(X_test)

plt.figure(figsize=(8, 6))

for i in range(y_test_binarized.shape[1]):
    fpr, tpr, _ = roc_curve(y_test_binarized[:, i], y_score[:, i])
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f'Class {baseline_lr.classes_[i]} (AUC = {roc_au

plt.plot([0, 1], [0, 1], 'k--', label="Random Classifier")

plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("AUC-ROC Curve")
plt.legend(loc="lower right")
plt.show()
```



6.2 Desicion tree.

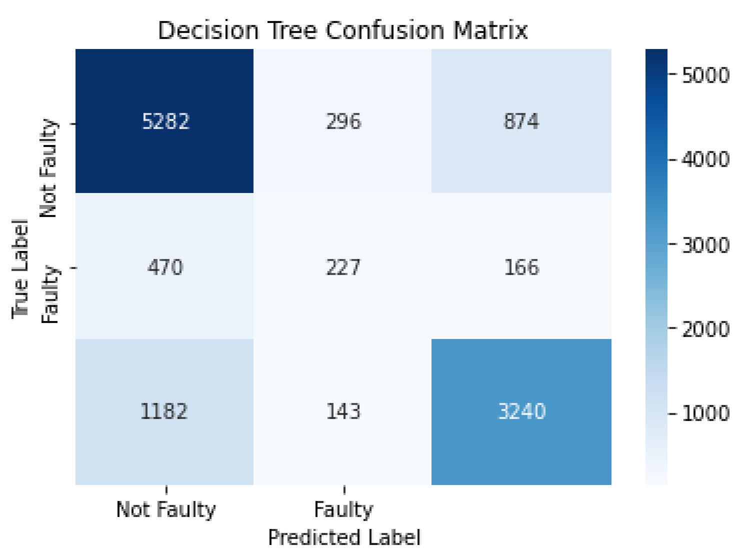
In [120]:
```
dt_model = DecisionTreeClassifier(random_state=42)

dt_model.fit(X_train, y_train)

y_pred_dt = dt_model.predict(X_test)

dt_accuracy = accuracy_score(y_test, y_pred_dt)
print(f"Decision Tree Accuracy: {dt_accuracy:.4f}")
```

```
Decision Tree Accuracy: 0.7364
```

In [121]:
```
cm_dt = confusion_matrix(y_test, y_pred_dt)
print("Confusion Matrix:")
print(cm_dt)
```

```
Confusion Matrix:
[[5282  296  874]
 [ 470  227  166]
 [1182  143 3240]]
```

In [122]:
```
plt.figure(figsize=(6, 4))
sns.heatmap(cm_dt, annot=True, fmt="d", cmap="Blues", xticklabels=["Not Fault
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Decision Tree Confusion Matrix")
plt.show()
```



In [123]:
```python
print("Classification Report:")
print(classification_report(y_test, y_pred_dt))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.76      0.82      0.79      6452
           1       0.34      0.26      0.30       863
           2       0.76      0.71      0.73      4565

    accuracy                           0.74     11880
   macro avg       0.62      0.60      0.61     11880
weighted avg       0.73      0.74      0.73     11880
```

In [124]:
```python
dt_gini = DecisionTreeClassifier(criterion="gini", random_state=42)

dt_gini.fit(X_train, y_train)

y_pred_gini = dt_gini.predict(X_test)

gini_accuracy = accuracy_score(y_test, y_pred_gini)
print(f"Decision Tree (Gini) Accuracy: {gini_accuracy:.4f}")
```

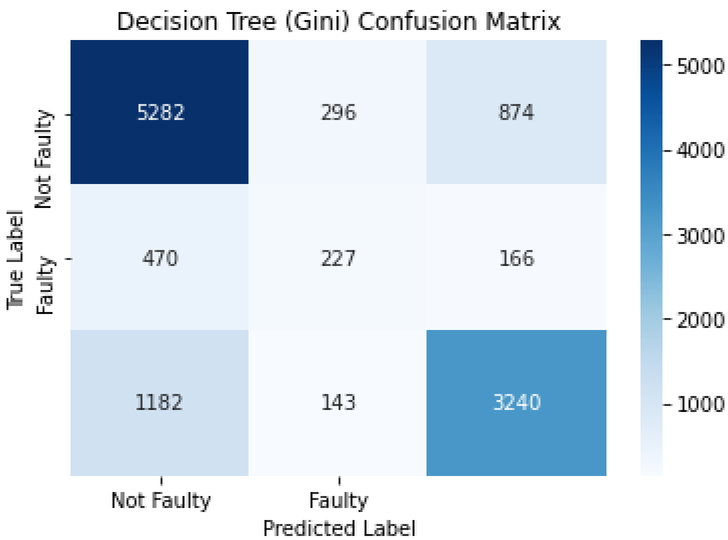
```
Decision Tree (Gini) Accuracy: 0.7364
```

In [125]:
```python
dt_model = DecisionTreeClassifier(criterion="gini", max_depth=10, min_samples
dt_model.fit(X_train, y_train)

y_pred = dt_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Decision Tree Accuracy: {accuracy:.4f}")
```

```
Decision Tree Accuracy: 0.7392
```

In [126]:

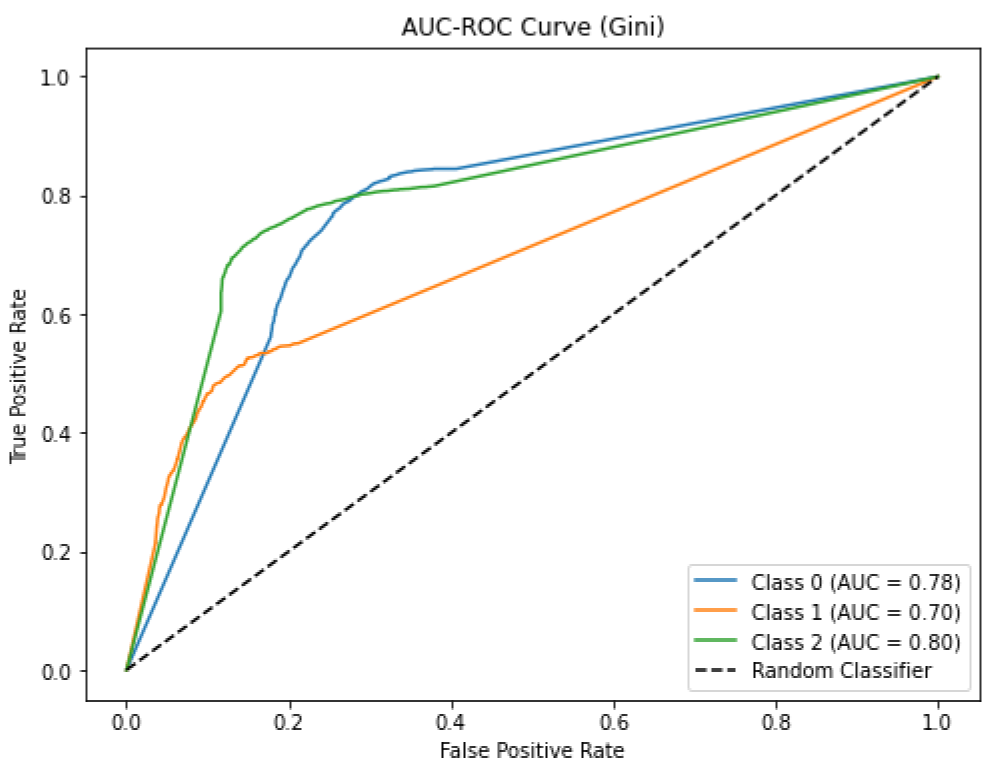
```python
y_pred_gini = dt_gini.predict(X_test)

cm_gini = confusion_matrix(y_test, y_pred_gini)
plt.figure(figsize=(6, 4))
sns.heatmap(cm_gini, annot=True, fmt="d", cmap="Blues", xticklabels=["Not Fau
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Decision Tree (Gini) Confusion Matrix")
plt.show()

print("Classification Report:")
print(classification_report(y_test, y_pred_gini))
```




```
Classification Report:
              precision    recall  f1-score   support

           0       0.76      0.82      0.79      6452
           1       0.34      0.26      0.30       863
           2       0.76      0.71      0.73      4565

    accuracy                           0.74     11880
   macro avg       0.62      0.60      0.61     11880
weighted avg       0.73      0.74      0.73     11880
```

In [127]:

```
y_test_binarized = label_binarize(y_test, classes=dt_gini.classes_)

y_score = dt_gini.predict_proba(X_test)

plt.figure(figsize=(8, 6))

for i in range(y_test_binarized.shape[1]):
    fpr, tpr, _ = roc_curve(y_test_binarized[:, i], y_score[:, i])
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f'Class {dt_gini.classes_[i]} (AUC = {roc_auc:.2

plt.plot([0, 1], [0, 1], 'k--', label="Random Classifier")

plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("AUC-ROC Curve (Gini)")
plt.legend(loc="lower right")
plt.show()
```



In [128]:

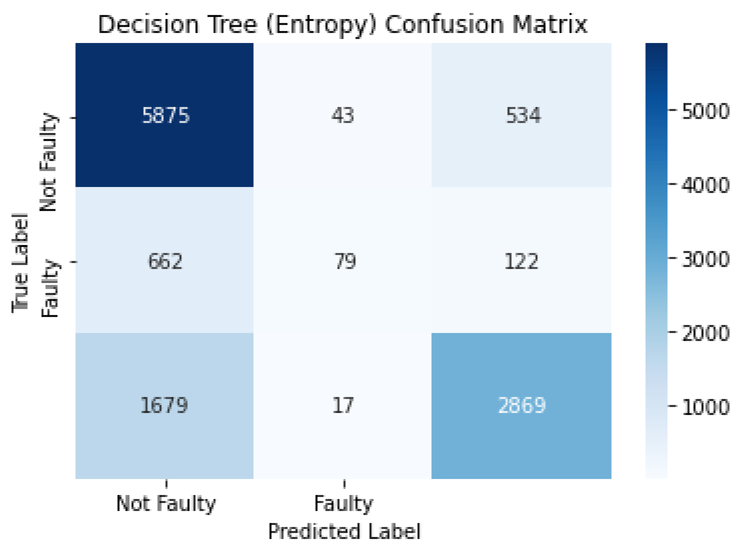
```
dt_entropy = DecisionTreeClassifier(criterion="entropy", random_state=42)

dt_entropy.fit(X_train, y_train)

y_pred_entropy = dt_entropy.predict(X_test)

entropy_accuracy = accuracy_score(y_test, y_pred_entropy)
print(f"Decision Tree (Entropy) Accuracy: {entropy_accuracy:.4f}")
```

```
Decision Tree (Entropy) Accuracy: 0.7391
```

In [129]:
```
dt_model_entropy = DecisionTreeClassifier(criterion="entropy", max_depth=10,
dt_model_entropy.fit(X_train, y_train)

y_pred_entropy = dt_model_entropy.predict(X_test)

accuracy_entropy = accuracy_score(y_test, y_pred_entropy)
print(f"Decision Tree (Entropy) Accuracy: {accuracy_entropy:.4f}")
```

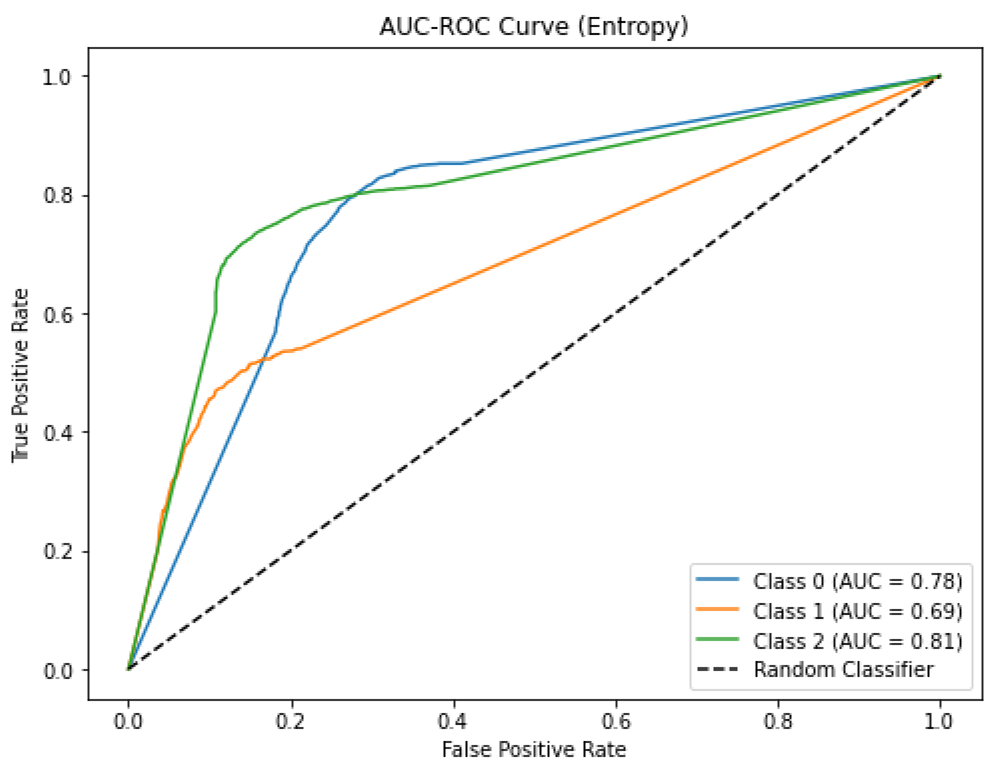
```
Decision Tree (Entropy) Accuracy: 0.7427
```

In [130]:
```
y_pred_entropy = dt_model_entropy.predict(X_test)

cm_entropy = confusion_matrix(y_test, y_pred_entropy)
plt.figure(figsize=(6, 4))
sns.heatmap(cm_entropy, annot=True, fmt="d", cmap="Blues", xticklabels=["Not
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Decision Tree (Entropy) Confusion Matrix")
plt.show()

print("Classification Report:")
print(classification_report(y_test, y_pred_entropy))
```




```
Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.91      0.80      6452
           1       0.57      0.09      0.16       863
           2       0.81      0.63      0.71      4565

    accuracy                           0.74     11880
   macro avg       0.70      0.54      0.56     11880
weighted avg       0.74      0.74      0.72     11880
```

```
In [131]: y_test_binarized = label_binarize(y_test, classes=dt_entropy.classes_)
          y_score_entropy = dt_entropy.predict_proba(X_test)

          plt.figure(figsize=(8, 6))

          for i in range(y_test_binarized.shape[1]):
              fpr, tpr, _ = roc_curve(y_test_binarized[:, i], y_score_entropy[:, i])
              roc_auc = auc(fpr, tpr)
              plt.plot(fpr, tpr, label=f'Class {dt_entropy.classes_[i]} (AUC = {roc_auc

          plt.plot([0, 1], [0, 1], 'k--', label="Random Classifier")
          plt.xlabel("False Positive Rate")
          plt.ylabel("True Positive Rate")
          plt.title("AUC-ROC Curve (Entropy)")
          plt.legend(loc="lower right")
          plt.show()
```



6.2.1 Hyperparameter tuning

In [132]:
```
param_dist = {
    'criterion': ['gini', 'entropy'],
    'max_depth': np.arange(3, 20),
    'min_samples_split': np.arange(2, 10),
    'min_samples_leaf': np.arange(1, 10)
}

dt = DecisionTreeClassifier(random_state=42)

random_search = RandomizedSearchCV(dt, param_distributions=param_dist,
                                   n_iter=50, scoring='accuracy',
                                   cv=5, random_state=42, n_jobs=-1)

random_search.fit(X_train, y_train)

best_model = random_search.best_estimator_
print("Best Parameters:", random_search.best_params_)
print("Best Score:", random_search.best_score_)
```

```
Best Parameters: {'min_samples_split': 4, 'min_samples_leaf': 5, 'max_depth':
13, 'criterion': 'entropy'}
Best Score: 0.75128367003367
```

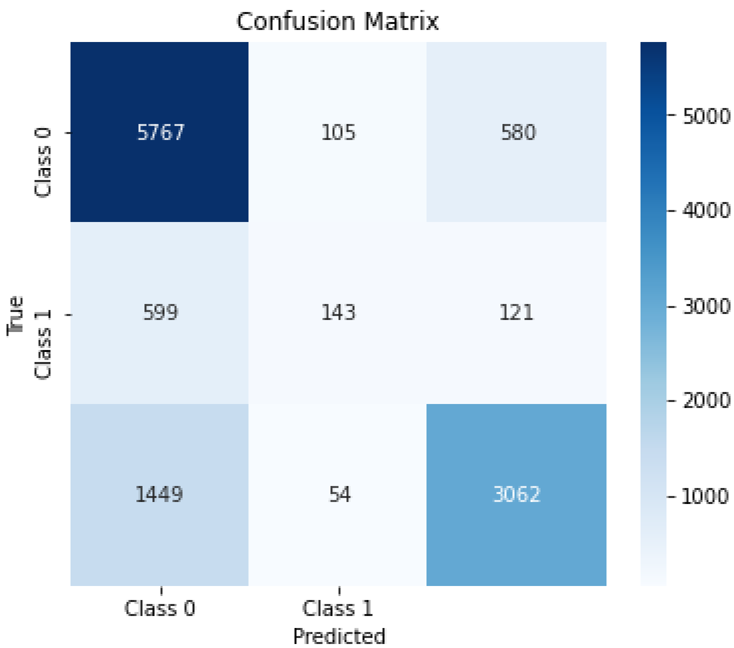
In [133]:
```
best_model = random_search.best_estimator_

y_pred = best_model.predict(X_test)

print("Test Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Test Accuracy: 0.7552188552188552

Classification Report:
               precision    recall  f1-score   support

           0       0.74      0.89      0.81      6452
           1       0.47      0.17      0.25       863
           2       0.81      0.67      0.74      4565

    accuracy                           0.76     11880
   macro avg       0.68      0.58      0.60     11880
weighted avg       0.75      0.76      0.74     11880
```

In [134]:
```
conf_matrix = confusion_matrix(y_test, y_pred)
```

In [135]:

```
plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Cla
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



6.3 Random forest

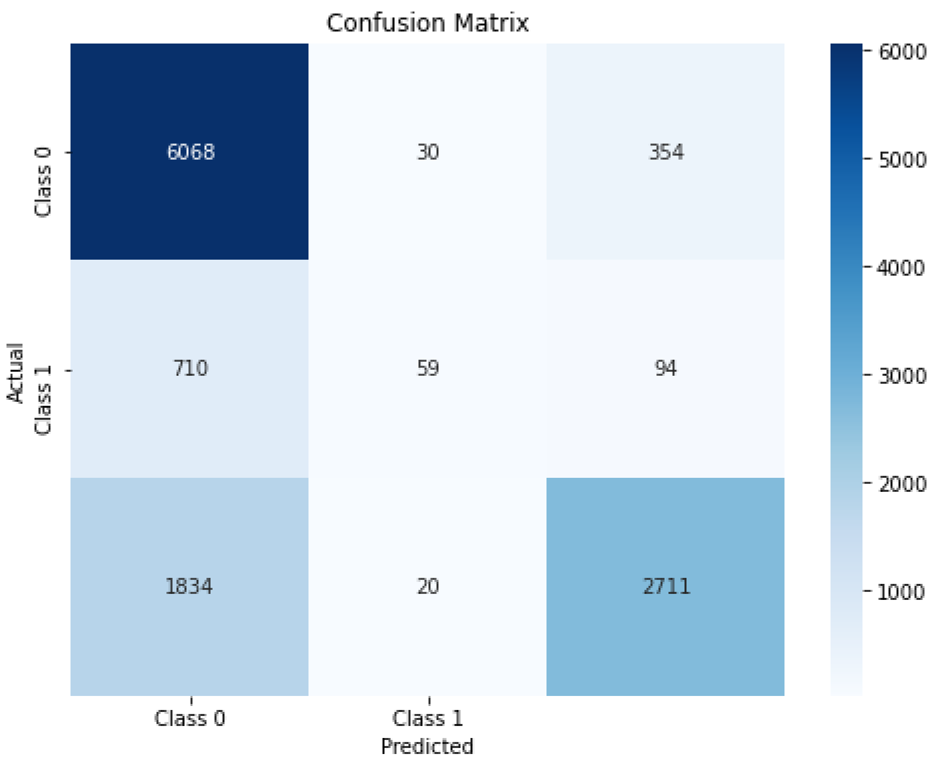
In [136]:

```
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

scaler = StandardScaler()
X_train_resampled = scaler.fit_transform(X_train_resampled)
X_test = scaler.transform(X_test)

rf = RandomForestClassifier(random_state=42, n_jobs=-1)
rf.fit(X_train_resampled, y_train_resampled)

y_pred = rf.predict(X_test)

print("Test Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

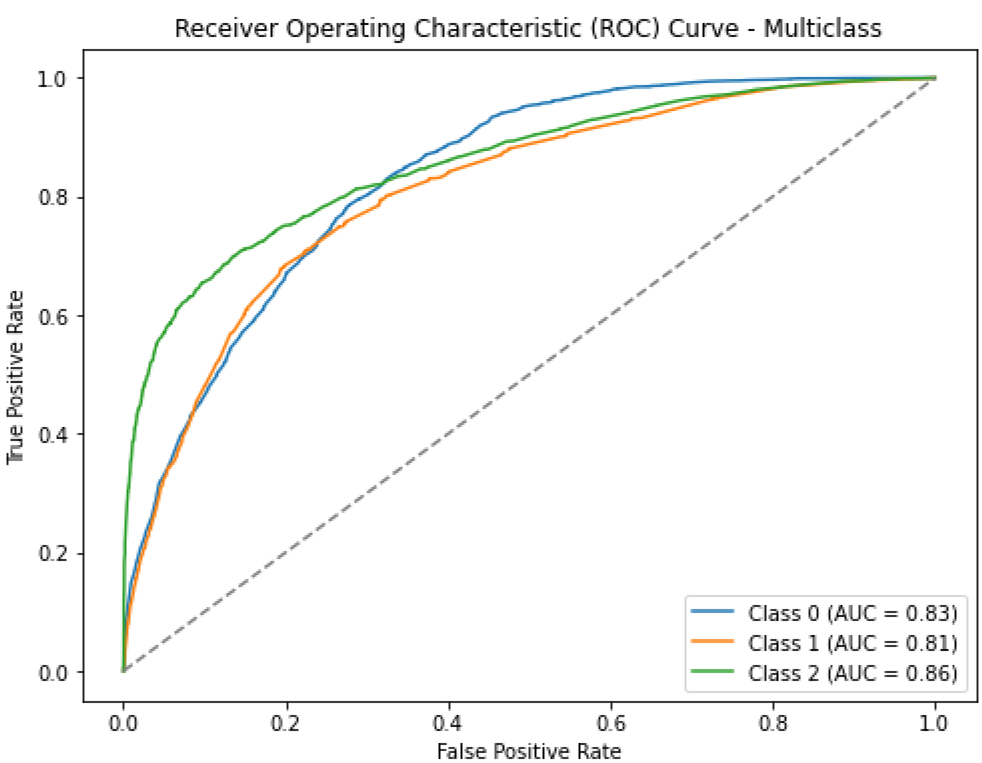
```
Test Accuracy: 0.7387205387205387

Classification Report:
               precision    recall  f1-score   support

           0       0.81      0.76      0.79      6452
           1       0.28      0.51      0.36       863
           2       0.81      0.75      0.78      4565

    accuracy                           0.74     11880
   macro avg       0.63      0.67      0.64     11880
weighted avg       0.77      0.74      0.75     11880
```

In [137]:

```
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)

y_pred = rf.predict(X_test)

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='g', cmap='Blues', xticklabels=['Class 0', 'C
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



In [138]:
```
n_classes = len(set(y_test))
y_test_bin = label_binarize(y_test, classes=[0, 1, 2])
y_prob = rf.predict_proba(X_test)

fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

plt.figure(figsize=(8, 6))
for i in range(n_classes):
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.title('Receiver Operating Characteristic (ROC) Curve - Multiclass')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.show()
```



6.3.1 Hyper parameter tuning

In [ ]:

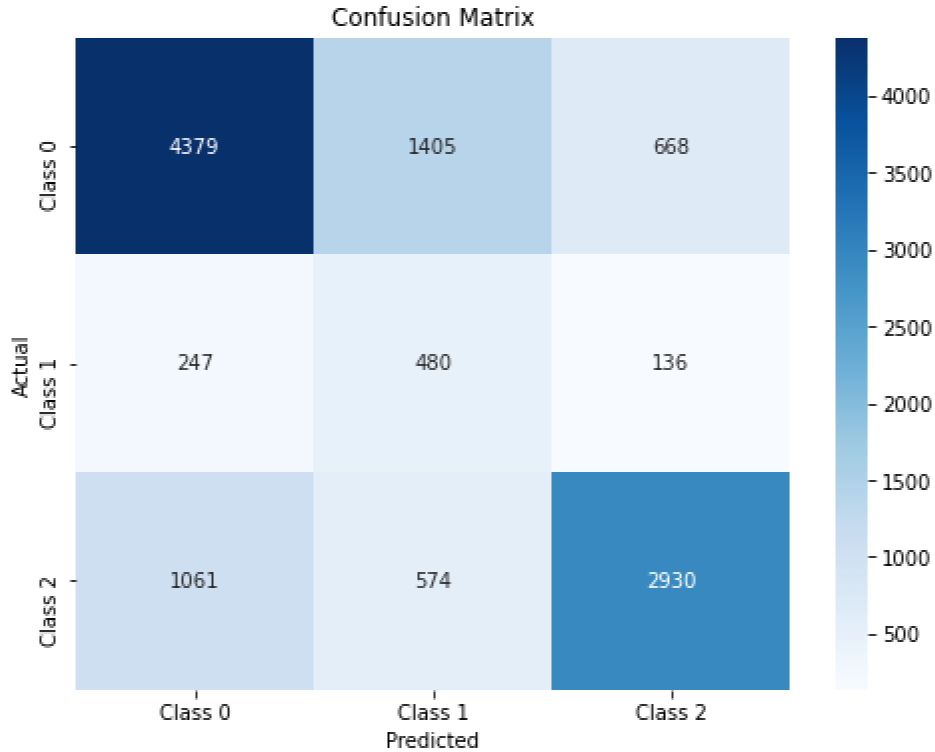
6.4 Gradient boosting

In [139]:
```
gb = GradientBoostingClassifier(random_state=42)
gb.fit(X_train_resampled, y_train_resampled)

y_pred = gb.predict(X_test)

print("Test Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Test Accuracy: 0.6556397306397307

Classification Report:
               precision    recall  f1-score   support

           0       0.77      0.68      0.72      6452
           1       0.20      0.56      0.29       863
           2       0.78      0.64      0.71      4565

    accuracy                           0.66     11880
   macro avg       0.58      0.63      0.57     11880
weighted avg       0.73      0.66      0.68     11880
```

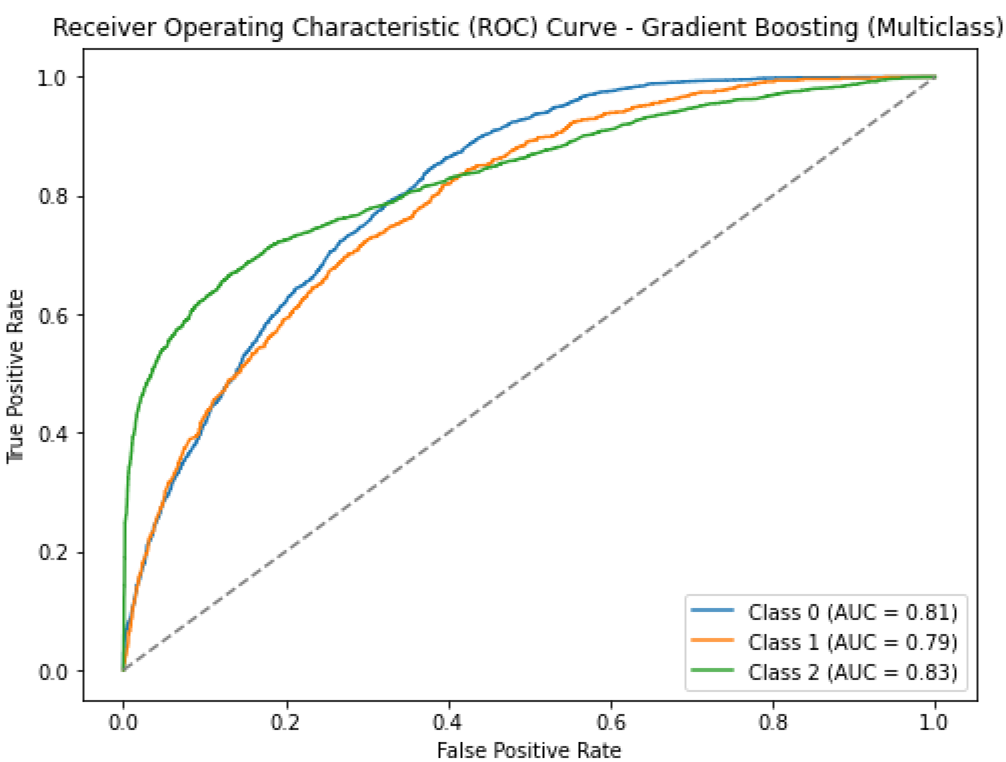
In [140]:

```
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["Class 0", "C
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



In [141]:

```python
y_test_bin = label_binarize(y_test, classes=[0, 1, 2])
y_prob = gb.predict_proba(X_test)

fpr = dict()
tpr = dict()
roc_auc = dict()

n_classes = len(set(y_test))

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

plt.figure(figsize=(8, 6))
for i in range(n_classes):
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.title('Receiver Operating Characteristic (ROC) Curve - Gradient Boosting
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.show()
```



6.4.1 Early stopping

In [142]:
```
gb = GradientBoostingClassifier(n_estimators=1000,
                                learning_rate=0.1,
                                random_state=42,
                                warm_start=True,
                                validation_fraction=0.1,
                                n_iter_no_change=10)

gb.fit(X_train_resampled, y_train_resampled)

y_pred = gb.predict(X_test)

print("Test Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Test Accuracy: 0.7073232323232324

Classification Report:
               precision    recall  f1-score   support

           0       0.78      0.75      0.76      6452
           1       0.26      0.52      0.35       863
           2       0.80      0.68      0.73      4565

    accuracy                           0.71     11880
   macro avg       0.61      0.65      0.61     11880
weighted avg       0.75      0.71      0.72     11880
```

6.4.2 cross - validation

In [144]:
```
from sklearn.model_selection import cross_val_score

gb = GradientBoostingClassifier(n_estimators=100, random_state=42)

cv_scores = cross_val_score(gb, X_train_resampled, y_train_resampled, cv=5, s

print(f'Cross-validation scores: {cv_scores}')
print(f'Mean CV score: {cv_scores.mean()}')
print(f'Standard Deviation of CV scores: {cv_scores.std()}')
```

```
Cross-validation scores: [0.65243784 0.6914234  0.69265048 0.70065874 0.69161
715]
Mean CV score: 0.6857575246984878
Standard Deviation of CV scores: 0.017007044322297608
```

In [145]:

```
gb.fit(X_train_resampled, y_train_resampled)


y_pred = gb.predict(X_test)

test_accuracy = accuracy_score(y_test, y_pred)
print(f'Test Set Accuracy: {test_accuracy}')
```

```
Test Set Accuracy: 0.3293771043771044
```

6.4.3 Light GBM

In [143]:

```
import lightgbm as lgb

smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)

scaler = StandardScaler()
X_train_res = scaler.fit_transform(X_train_res)
X_test = scaler.transform(X_test)

lgbm = lgb.LGBMClassifier(n_estimators=100, random_state=42)
lgbm.fit(X_train_res, y_train_res)

y_pred = lgbm.predict(X_test)

print("Test Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of tes
ting was 0.070104 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 2850
[LightGBM] [Info] Number of data points in the train set: 77421, number of us
ed features: 14
[LightGBM] [Info] Start training from score -1.098612
[LightGBM] [Info] Start training from score -1.098612
[LightGBM] [Info] Start training from score -1.098612
Test Accuracy: 0.27154882154882154

Classification Report:
               precision    recall  f1-score   support

           0       0.96      0.01      0.02      6452
           1       0.10      0.91      0.18       863
           2       0.61      0.52      0.56      4565

    accuracy                           0.27     11880
   macro avg       0.56      0.48      0.25     11880
weighted avg       0.76      0.27      0.24     11880
```