BUSINESS UNDERSTANDING

PROBLEM STATEMENT

In Tanzania, water wells become non-functional due to various factors such as quantity of water available in the wells, the source of the water feeding the well and their management among others. Identifying non-functional wells will help prioritize maintenance efforts and improve water infrastructure planning. This analysis aims to develop a machine learning classifier that predicts the condition of water wells based on features like water point type, construction year, and other factors. The model will categorize wells as functional or non-functional.

BUSINESS OBJECTIVES

1. Develop a classification model to predict whether a well is functional or non-functional using historical data.
2. Implement and compare multiple algorithms to identify the most effective model for well functionality prediction.
3. Improve prediction accuracy through feature selection, hyperparameter tuning, and handling class imbalances.

BUSINESS QUESTIONS

This exploratory part of this analysis aims to answer the following questions:

1. What factors contribute most to well failures?
2. Which regions have the highest concentration of non-functional wells?
3. How does the construction year affect well failure rates?

SUCCESS CRITERIA

1. A highly accurate and reliable model that effectively classifies water wells as functional or non-functional, ensuring strong performance in accuracy, recall, and F1-score.
2. Identification of high-risk regions in Tanzania where wells require more attention and maintenance efforts.
3. Understanding the impact of construction year on well functionality to support strategic planning and scheduling of maintenance based on well age.
4. Identifying features that highly impact well functionality for strategic allocation of resources during future constructions.

What about this problem makes it a candidate for Machine Learning?

- This dataset includes both categorical and numerical variables. ML models can naturally handle both with minimal preprocessing while regression models are best suited for continuous data
- If the dataset has more functional than non-functional wells, ML models can be adjusted to account for this, whereas standard regression models might struggle with imbalanced data, leading to biased predictions toward the majority class unless special techniques like weighting or resampling are applied.
- The goal is not just to analyze existing wells but to predict the functionality of future wells, making ML a great choice, whereas traditional regression models focus more on explaining relationships between variables rather than making highly accurate classifications.
- Since we have a dataset with known well statuses, we can train a model to find patterns and make accurate predictions, whereas regression models might miss complex, non-linear

DATA UNDERSTANDING

SOURCE AND BRIEF DESCRIPTION

The source of the data sets used in this analysis are from [http://taarifa.org/ (http://taarifa.org/)](http://taarifa.org/) and [http://maji.go.tz/ (http://maji.go.tz/)](http://maji.go.tz/). They contain attributes pertaining to water points supplying clean and potable water across Tanzania. The data was split into three - training set values, test set values and training set labels - for the purpose of an online competition. For the scope of this analysis, the training set and its labels will be merged into a single dataset, allowing for greater control over the direction of the investigation. The test data will not be used as its values for the status of well are missing.

CONDITION OF THE DATA

Loading the data before checking its condition:

In [300]:
```python
# Importing Libraries
import pandas as pd
import geopandas as gpd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [301]:
```python
# Reading the datasets
label_df = pd.read_csv('0bf8bc6e-30d0-4c50-956a-603fc693d966.csv')
test_df = pd.read_csv('702ddfc5-68cd-4d1d-a0de-f5f566f76d91.csv')
train_df = pd.read_csv('4910797b-ee55-40a7-8668-10efd5c1b960.csv')
```

In [302]:
```
label_df.head()
```

Out[302]:

	id	status_group
0	69572	functional
1	8776	functional
2	34310	functional
3	67743	non functional
4	19728	functional

In [303]:
```
label_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   id            59400 non-null  int64 
 1   status_group  59400 non-null  object
dtypes: int64(1), object(1)
memory usage: 928.2+ KB
```

In [304]:
```
label_df.describe()
```

Out[304]:

	id
count	59400.000000
mean	37115.131768
std	21453.128371
min	0.000000
25%	18519.750000
50%	37061.500000
75%	55656.500000
max	74247.000000

In [305]:
```
label_df.shape
```

Out[305]: (59400, 2)

In [306]:
```
test_df.shape
```

Out[306]: (14850, 40)

In [307]:
```
train_df.head()
```

Out[307]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_na
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	r
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zaha
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Mah
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	Zaha Nanyu
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	Shu

5 rows × 40 columns

In [308]:
```
train_df.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 [309]:
```
train_df.describe()
```

Out[309]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	regi
count	59400.000000	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.000000	5940
mean	37115.131768	317.650385	668.297239	34.077427	-5.706033e+00	0.474141	1
std	21453.128371	2997.574558	693.116350	6.567432	2.946019e+00	12.236230	1
min	0.000000	0.000000	-90.000000	0.000000	-1.164944e+01	0.000000	
25%	18519.750000	0.000000	0.000000	33.090347	-8.540621e+00	0.000000	
50%	37061.500000	0.000000	369.000000	34.908743	-5.021597e+00	0.000000	1
75%	55656.500000	20.000000	1319.250000	37.178387	-3.326156e+00	0.000000	1
max	74247.000000	350000.000000	2770.000000	40.345193	-2.000000e-08	1776.000000	9

In [310]:
```
train_df.shape
```

Out[310]:
```
(59400, 40)
```

In [311]:
```
train_df.columns
```

Out[311]:
```
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')
```

From the above, there is uniformity in the three data sets in that all have 40 columns. The columns in train_df are similar to those in test_df. Promising features that could contribute to answering our business questions include 'construction_year','extraction_type','management','water_quality' and 'quantity'. From the shapes, the initial dataset was split using the ratio 80%:20%

DATA PREPARATION

MERGING

We shall start by merging the train_df with its corresponding labels. This way, when we drop rows with null values, the corresponding labels will also be removed, ensuring that our data and labels remain aligned.

In [312]:
```python
# Merging the train_df and label datasets
train_df = pd.merge(train_df, label_df, on='id')
train_df.head()
```

Out[312]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_na
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	r
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zaha
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Mah
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	Zaha Nanyu
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	Shu

5 rows × 41 columns

DATA CLEANING

In [313]:
```
# From the data head, we spot some redundant columns i.e quantity and quantity gr
# To investigate this, let us narrow them down into their own dataframe
redundant_cols = ['region', 'region_code', 'district_code', 'extraction_type', 'e
                  'payment', 'payment_type','water_quality', 'quality_group', 'q
                  'source_type', 'source_class', 'waterpoint_type', 'waterpoint_
redundant_cols_df = train_df[redundant_cols]
redundant_cols_df.head(20)
```

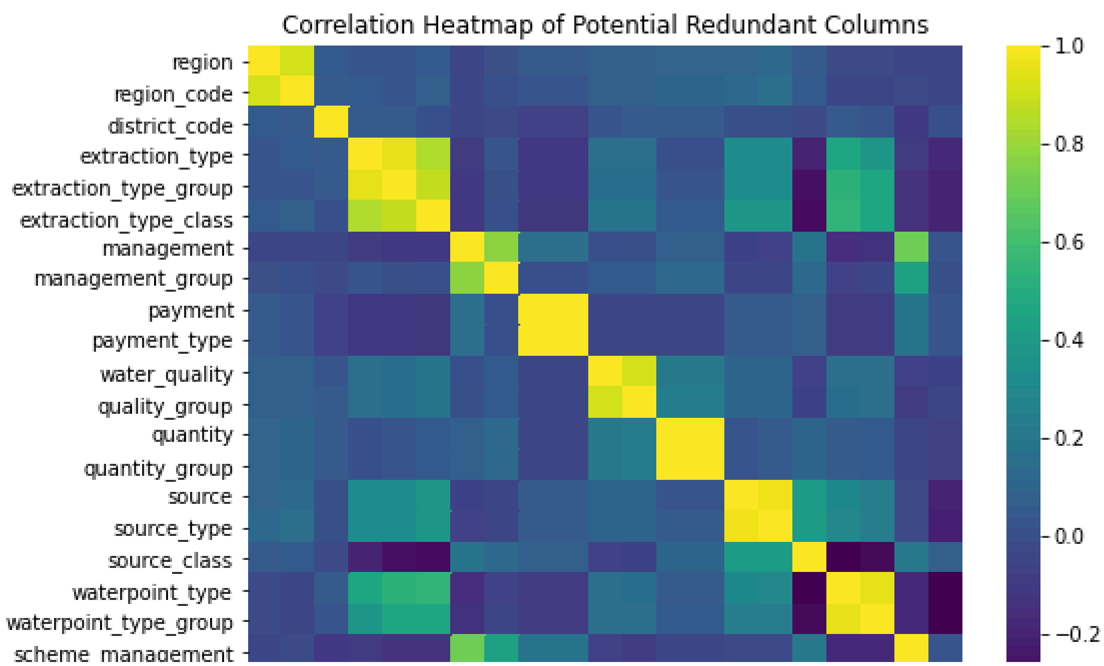
Out[313]:

	region	region_code	district_code	extraction_type	extraction_type_group	extraction_type_cl
0	Iringa	11	5	gravity	gravity	gra
1	Mara	20	2	gravity	gravity	gra
2	Manyara	21	4	gravity	gravity	gra
3	Mtwara	90	63	submersible	submersible	submers
4	Kagera	18	1	gravity	gravity	gra
5	Tanga	4	8	submersible	submersible	submers
6	Shinyanga	17	3	swn 80	swn 80	handpu
7	Shinyanga	17	3	nira/tanira	nira/tanira	handpu
8	Tabora	14	6	india mark ii	india mark ii	handpu
9	Kagera	18	1	nira/tanira	nira/tanira	handpu
10	Pwani	60	43	submersible	submersible	submers
11	Ruvuma	10	5	swn 80	swn 80	handpu
12	Shinyanga	17	2	nira/tanira	nira/tanira	handpu
13	Kilimanjaro	3	7	gravity	gravity	gra
14	Shinyanga	17	6	nira/tanira	nira/tanira	handpu
15	Rukwa	15	2	swn 80	swn 80	handpu
16	Iringa	11	4	gravity	gravity	gra
17	Iringa	11	4	gravity	gravity	gra
18	Mwanza	19	1	other	other	o
19	Iringa	11	5	gravity	gravity	gra

20 rows × 21 columns

From the above, we can tell that the columns are giving pretty much the same information. Let us solidify this futher by checking the correlation between the columns

In [314]:
```
# Plotting a heat map
plt.figure(figsize=(8,6))
sns.heatmap(train_df[redundant_cols].apply(lambda x: pd.factorize(x)[0]).corr(),
plt.title("Correlation Heatmap of Potential Redundant Columns")
plt.show()
```



From the above, we can clearly tell that the suspected columns are very highly correlated with each other. We will therefore drop one of each column.

In [315]:
```
# Dropping duplicated columns
train_df.drop(columns=['region_code', 'district_code', 'extraction_type_group',
                        'quantity_group', 'source_type', 'source_class', 'waterpo
```

In [316]:
```
# Majority of the data in the num_private column is 0.
train_df['num_private'].value_counts()
```

Out[316]:
```
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 [317]:
```
# As a result, we will drop this column
train_df.drop(columns='num_private', inplace=True)
```

In [318]:
```
train_df.columns
```

Out[318]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'wpt_name', 'basin', 'subvillage',
       'region', 'lga', 'ward', 'population', 'public_meeting', 'recorded_by',
       'scheme_management', 'scheme_name', 'permit', 'construction_year',
       'extraction_type', 'management_group', 'payment_type', 'water_quality',
       'quantity', 'source', 'waterpoint_type', 'status_group'],
      dtype='object')
```

In [319]:
```
# Dropping columns that will not contribute to this analysis
train_df.drop(columns=['id', 'date_recorded', 'gps_height', 'wpt_name', 'recordec
```

In [320]:
```
train_df.shape
```

Out[320]:
```
(59400, 24)
```

In [321]:
```
# Checking for missing values
train_df.isnull().sum()
```

Out[321]:
```
amount_tsh               0
funder                3635
installer             3655
longitude                0
latitude                 0
basin                    0
subvillage             371
region                   0
lga                      0
ward                     0
population               0
public_meeting        3334
scheme_management     3877
scheme_name          28166
permit                3056
construction_year        0
extraction_type          0
management_group         0
payment_type             0
water_quality            0
quantity                 0
source                   0
waterpoint_type          0
status_group             0
dtype: int64
```

In [322]:
```
# Printing unique values for each column
for i in train_df.columns:
  print(f' Unique values for {i}')
  print(f' N-unique values for {i} is {train_df[i].nunique()}')
  print(list(train_df[i].unique())) # sort to identify duplicates within column
  print('')
```

```
arekani', 'Regina Group', 'Snv-swash', 'Seram', 'Lcdg', 'Adap', 'Laizer', 'Af
rican Barrick Gold', 'Salehe', 'Jumanne', 'Masai Land', 'Jipa', 'S. Kumar',
'Hpa', 'Mp Mzeru', 'W.D &', 'Wafidhi Wa Ziwa T', 'Matimbwa Sec', "Lee Kang Py
ung's Family", 'Rwsssp', 'Rural Drinking Water Supply', 'Mhoranzi', 'Woyege',
'Quick Win Project', 'Muslimu Society(shia)', 'Morovian Church', 'Grazie Fran
co Lucchini', 'Pankrasi', 'Irevea Sister Water', 'Unesco', 'Iucn', 'Kdc', 'Ja
pan Embassy', 'Jacobin', 'Greinaker', 'Totoland', 'Bahresa', 'Mwalimu Muhenz
a', 'Handeni Trunk Main(', 'Cefa/rcchurch', 'Quick Win', 'Prince Medium Schoo
l', 'Mtibwa S', 'Stansilaus', 'Sakwidi', 'Seleman Masoud', 'Rc Mission', 'Wua
And Ded', 'Ardhi Instute', 'Japan Food Aid', 'D Ct', 'Diocese Of Mount Kilima
njaro', 'Health  Ministry', 'Vickfis', 'Isf / Tasaff', 'Serian', 'Roman Catho
ric', 'Chacha Issame', 'Villege Council', 'Kilimarondo Parish', 'Tempo', 'Mbo
ni Salehe', 'Koica And Tanzania Government', 'Simavi', 'Water Sector Developm
ent', 'Rural Water Supply', 'Cgi', 'Nrwssp', 'Htm', 'Bruder', 'Redcross', 'Sa
id Hashim', 'Tlc/nyengesa Masanja', 'Miomb', 'Staford Higima', 'Makanga', 'Gr
azie Grouppo Padre Fiorentin', 'Waheke', 'Bridge North', 'Magutu Maro', 'Lion
s', 'Icf', 'Villagers Mpi', 'Lions C', 'Misheni', 'Maswi Drilling Co. Ltd',
'Drv Na Idara', 'Vodacom', 'Friends Of Kibara Foundation', 'Missionary', 'Buk
wang Church Saints', 'Lisa', 'Sengerema District Council', 'Msikiti Masji',
```

From the above, aside from null values we can see that some columns have 'unknown' values and 'other' values. For all of these cases, we shall call these values 'unknown' for uniformity.

In [323]:
```
# Replacing the values known as 'other' with 'Unknown'
train_df['scheme_name'].replace('other', 'unknown', inplace=True)
train_df['scheme_management'].replace('other', 'unknown', inplace=True)
train_df['extraction_type'].replace('other', 'unknown', inplace=True)
train_df['management_group'].replace('other', 'unknown', inplace=True)
train_df['payment_type'].replace('other', 'unknown', inplace=True)
train_df['source'].replace('other', 'unknown', inplace=True)
train_df['waterpoint_type'].replace('other', 'unknown', inplace=True)
```

In [324]:
```
# Inspecting 'funder' column
train_df['funder'].value_counts().head(10)
```

Out[324]:
```
Government Of Tanzania    9084
Danida                    3114
Hesawa                    2202
Rwssp                     1374
World Bank                1349
Kkkt                      1287
World Vision              1246
Unicef                    1057
Tasaf                      877
District Council           843
Name: funder, dtype: int64
```

In [325]:
```
# Inspecting 'installer' column
train_df['installer'].value_counts().head(10)
```

Out[325]:
```
DWE                   17402
Government             1825
RWE                    1206
Commu                  1060
DANIDA                 1050
KKKT                    898
Hesawa                  840
0                       777
TCRS                    707
Central government      622
Name: installer, dtype: int64
```

In [326]:
```
# Since we cannot predict unknown values for 'funder' and 'installer' column, we
train_df['funder'].fillna('Unknown', inplace=True)
train_df['installer'].fillna('Unknown', inplace=True)
train_df.isnull().sum()
```

Out[326]:
```
amount_tsh               0
funder                   0
installer                0
longitude                0
latitude                 0
basin                    0
subvillage             371
region                   0
lga                      0
ward                     0
population               0
public_meeting        3334
scheme_management     3877
scheme_name          28166
permit                3056
construction_year        0
extraction_type          0
management_group         0
payment_type             0
water_quality            0
quantity                 0
source                   0
waterpoint_type          0
status_group             0
dtype: int64
```

In [327]:
```
# Inspecting 'subvillage' column
train_df['subvillage'].value_counts()
```

Out[327]:
```
Madukani        508
Shuleni         506
Majengo         502
Kati            373
Mtakuja         262
               ...
Njia Tatu         1
Chini Dukani      1
Mabwe Matitu      1
Machinjiono       1
Ishingiasha B     1
Name: subvillage, Length: 19287, dtype: int64
```

From the above, there is no subvillage that stands out as an outlier. Therefore, we cannot make any meaningful assumptions. This means that we have to drop the missing values.There is also a subvillage that has a value of 'M', which appears to be an anomaly. However, the frequency of its occurrence suggests that it may actually represent a legitimate subvillage, thus we will not remove it.

In [328]:
```
# Dropping null values
train_df = train_df.dropna(subset=['subvillage'])
```

In [329]:
```
# Inpecting the 'population' column
train_df['population'].value_counts()
```

Out[329]:
```
0       21020
1        7024
200      1940
150      1892
250      1681
        ...
3241        1
1960        1
1685        1
2248        1
1439        1
Name: population, Length: 1049, dtype: int64
```

We can see that a third of the data is zero for population. Since it does not contribute much to this analysis, we will drop this column.

In [330]:
```
# Dropping the 'population' column
train_df.drop(columns='population', inplace=True)
```

In [331]:
```
# Inspecting 'public_meeting' column
train_df['public_meeting'].value_counts()
```

Out[331]:
```
True     50642
False     5054
Name: public_meeting, dtype: int64
```

In [332]:
```
# 'public_meeting' is a boolean column heavily dominated by True. Since we can no
train_df = train_df.dropna(subset=['public_meeting'])
```

In [333]:
```
# Inspecting 'scheme_management' column
train_df['scheme_management'].value_counts()
```

Out[333]:
```
VWC                 35207
WUG                  4392
Water authority      3124
WUA                  2862
Water Board          2709
Parastatal           1468
Company              1057
Private operator      817
Other                 434
SWC                    97
Trust                  72
None                    1
Name: scheme_management, dtype: int64
```

In [334]:
```
# Inspecting 'scheme_name' column
train_df['scheme_name'].value_counts()
```

Out[334]:
```
K                        676
None                     643
Borehole                 546
Chalinze wate            404
M                        345
                        ...
villagers                  1
BL Siha Sec                1
Mafuriko Water Suppl       1
Wisi                       1
Mlima wa Nyasho            1
Name: scheme_name, Length: 2617, dtype: int64
```

In [335]:
```
# Since we cannot predict unknown values for 'scheme_name' and 'scheme_management
train_df['scheme_name'].fillna('unknown', inplace=True)
train_df['scheme_management'].fillna('unknown', inplace=True)
train_df.isnull().sum()
```

Out[335]:
```
amount_tsh               0
funder                   0
installer                0
longitude                0
latitude                 0
basin                    0
subvillage               0
region                   0
lga                      0
ward                     0
public_meeting           0
scheme_management        0
scheme_name              0
permit                2785
construction_year        0
extraction_type          0
management_group         0
payment_type             0
water_quality            0
quantity                 0
source                   0
waterpoint_type          0
status_group             0
dtype: int64
```

In [336]:
```
# Inspecting 'permit' column
train_df['permit'].value_counts()
```

Out[336]:
```
True     36996
False    15915
Name: permit, dtype: int64
```

In [337]:
```
# Since 'permit' is a boolean column, we can not accurately predict unknown value
train_df = train_df.dropna(subset=['permit'])
```

In [338]:
```
# Inspecting 'quality' column
train_df['water_quality'].value_counts()
```

Out[338]:
```
soft                  46013
salty                  4164
unknown                1087
milky                   733
coloured                478
salty abandoned         237
fluoride                183
fluoride abandoned       16
Name: water_quality, dtype: int64
```

In [339]:
```
# Combining salty and salty abandoned, and fluoride and fluoride abandoned
train_df['water_quality'] = train_df['water_quality'].replace(['salty', 'salty ab
train_df['water_quality'] = train_df['water_quality'].replace(['fluoride', 'fluor
train_df['water_quality'].value_counts()
```

Out[339]:
```
soft        46013
salty        4401
unknown      1087
milky         733
coloured      478
fluoride      199
Name: water_quality, dtype: int64
```

In [340]:
```
train_df.isnull().sum()
```

Out[340]:
```
amount_tsh           0
funder               0
installer            0
longitude            0
latitude             0
basin                0
subvillage           0
region               0
lga                  0
ward                 0
public_meeting       0
scheme_management    0
scheme_name          0
permit               0
construction_year    0
extraction_type      0
management_group     0
payment_type         0
water_quality        0
quantity             0
source               0
waterpoint_type      0
status_group         0
dtype: int64
```

There are no more missing values.

In [341]:
```
train_df.shape

# We lost 10% of the data by dropping the missing values while cleaning.
```

Out[341]:
```
(52911, 23)
```

In [342]:
```
# Checking for duplicates
train_df.duplicated().sum()
```

Out[342]:
```
114
```

In [343]:
```
# Listing the duplicated rows
train_df[train_df.duplicated(keep=False)]
```

Out[343]:

	amount_tsh	funder	installer	longitude	latitude	basin	subvillage	r
168	0.0	Wvt	WVT	0.000000	-2.000000e-08	Lake Victoria	Ilula	Shin
301	0.0	Government Of Tanzania	Government	0.000000	-2.000000e-08	Lake Victoria	Nyanza	Mv
326	0.0	Government Of Tanzania	Government	0.000000	-2.000000e-08	Lake Victoria	Nyanza	Mv
370	0.0	Government Of Tanzania	Government	0.000000	-2.000000e-08	Lake Victoria	Nyanza	Mv
965	0.0	Government Of Tanzania	DWE	0.000000	-2.000000e-08	Lake Victoria	K/Center	Mv
...	...	...	...	...	...	...	...	
56899	0.0	Government Of Tanzania	Government	0.000000	-2.000000e-08	Lake Victoria	Sweya	Mv
57285	0.0	Hesawa	DWE	0.000000	-2.000000e-08	Lake Tanganyika	Sozibuye	Mv
57423	0.0	W.D & I.	RWE	37.540901	-6.959749e+00	Wami / Ruvu	Majengo	Mor
57807	0.0	Government Of Tanzania	Government	0.000000	-2.000000e-08	Lake Victoria	C/Center	Mv
57824	1000.0	Nethalan	RWE	37.375717	-7.056372e+00	Wami / Ruvu	Mission	Mor

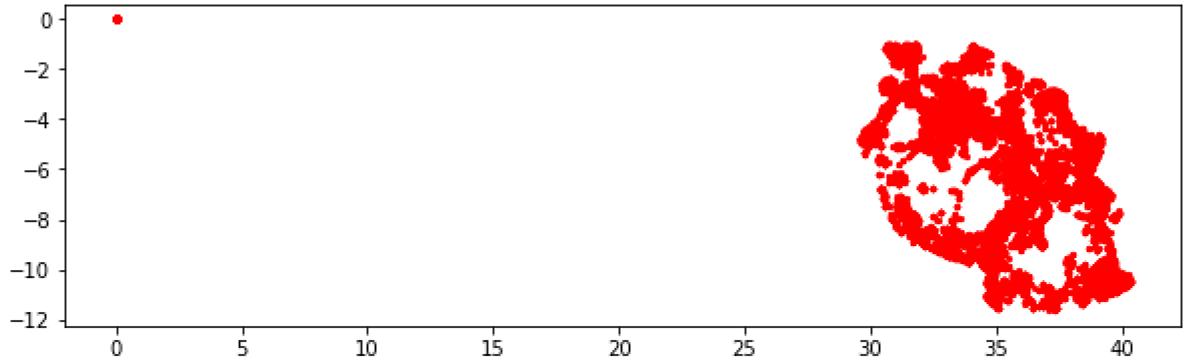
204 rows × 23 columns

From the above, we can see that the data are near duplicates and not necessarily exact duplicates. To eliminate redundancy, we shall drop the duplicated values

In [344]:
```
train_df = train_df.drop_duplicates()
train_df.shape
```

Out[344]: (52797, 23)

In [345]:
```
# Checking for outliers in the Longitude and Latitude columns
# Convert DataFrame to GeoDataFrame
gdf = gpd.GeoDataFrame(train_df, geometry=gpd.points_from_xy(train_df.longitude,
# Plot
gdf.plot(figsize=(10,6), marker='o', color='red', markersize=5)
plt.show()
```



We can see that there is an outlier with coordinates 0,0. We can remove this point.

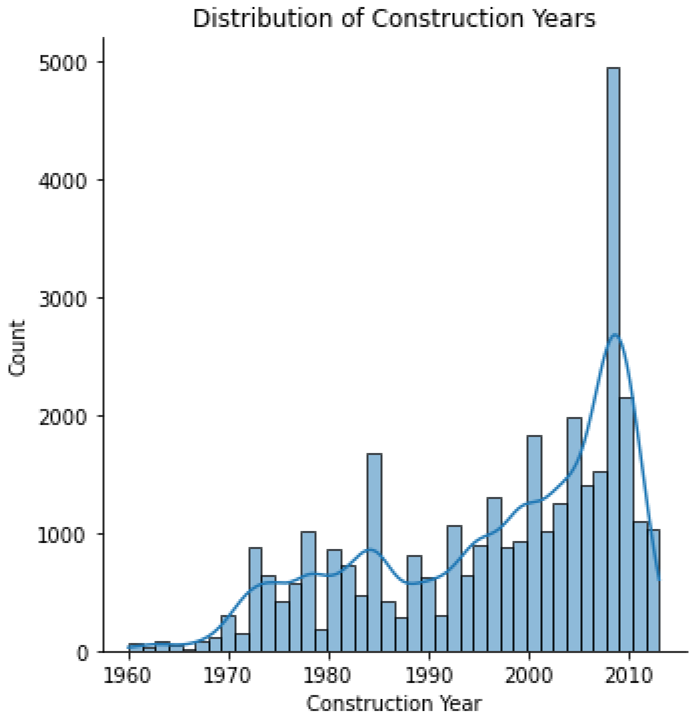
In [346]:
```
# Dropping columns with latitude and longitude = 0
train_df = train_df[train_df['latitude'] != 0]
train_df = train_df[train_df['longitude'] != 0]
train_df.shape
```

Out[346]:
```
(51434, 23)
```

In [347]:
```
# Checking for outliers in the construction year column
train_df['construction_year'].value_counts().sort_index().head()
```

Out[347]:
```
0       16764
1960       38
1961       20
1962       28
1963       84
Name: construction_year, dtype: int64
```

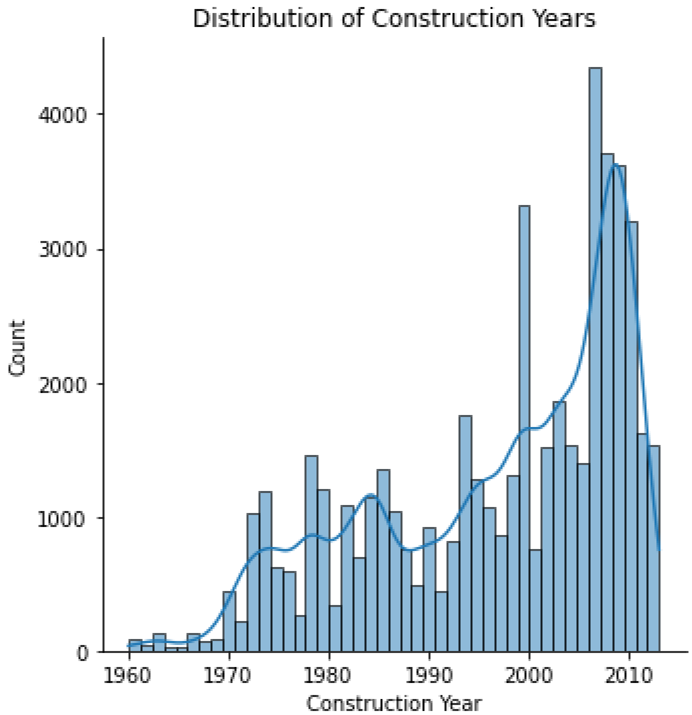
In [348]:
```
# Checking on the distribution of the construction years excluding year 0
construction_year_df = train_df[train_df['construction_year'] != 0]
sns.displot(construction_year_df['construction_year'], kde=True)
plt.xlabel('Construction Year')
plt.title('Distribution of Construction Years')
plt.show()
```



Since almost 30% of the data in the construction_year column are 0, replacing the zero values with a single value like median or mode will significantly shift the distribution of the dataset. We shall prioritize the distribution of the data by random sampling from the non-zero values.

In [349]:
```
# Filtering out non-zero construction years
non_zero_years = train_df[train_df['construction_year'] > 0]['construction_year']
# Randomly sampling replacement from non-zero construction years and replacing ze
train_df.loc[train_df['construction_year'] == 0, 'construction_year'] = np.randor
```

In [350]:
```
# Checking on the distribution of the construction years after replacement
sns.displot(train_df['construction_year'], kde=True)
plt.xlabel('Construction Year')
plt.title('Distribution of Construction Years')
plt.show()
```



From the graph, we have been able to maintain the distribution of the original dataset without dropping any values.

In [351]:
```
# investigating the distribution of the amount_tsh column
train_df['amount_tsh'].value_counts().sort_index()
```

Out[351]:
```
0.0         34582
0.2             3
1.0             3
2.0            13
5.0           375
            ...
117000.0        7
138000.0        1
170000.0        1
200000.0        1
250000.0        1
Name: amount_tsh, Length: 91, dtype: int64
```

The column amount_tsh has a lot of zero values, which doesnt make sense. We will replace the 0s with the mode of the entire dataset, as the mode represents what well construction usually costs.

In [352]:
```
# First calculating the mode for amount_tsh excluding zeros
mode_amount_tsh = train_df[train_df['amount_tsh'] != 0]['amount_tsh'].mode()[0]
mode_count = (train_df['amount_tsh'] == mode_amount_tsh).sum()
print(f"Mode Value: {mode_amount_tsh}, Count: {mode_count}")
```

```
Mode Value: 500.0, Count: 3028
```

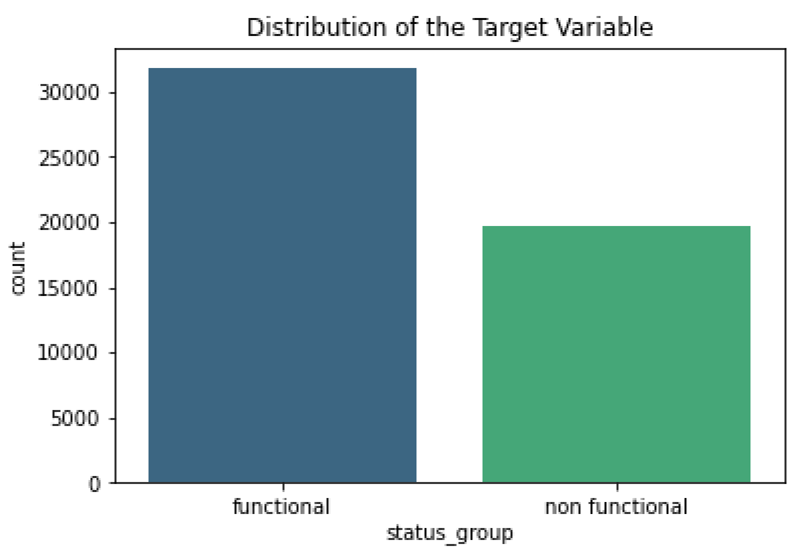
In [353]:
```
# Replacing zeros with the mode
train_df['amount_tsh'] = train_df['amount_tsh'].replace(0, mode_amount_tsh)
```

EXPLORATORY DATA ANALYSIS

In [354]:
```
# Combining the functional and functional needs repair values in the status_group
train_df['status_group'] = train_df['status_group'].replace(['functional needs re
train_df['status_group'].value_counts()
```

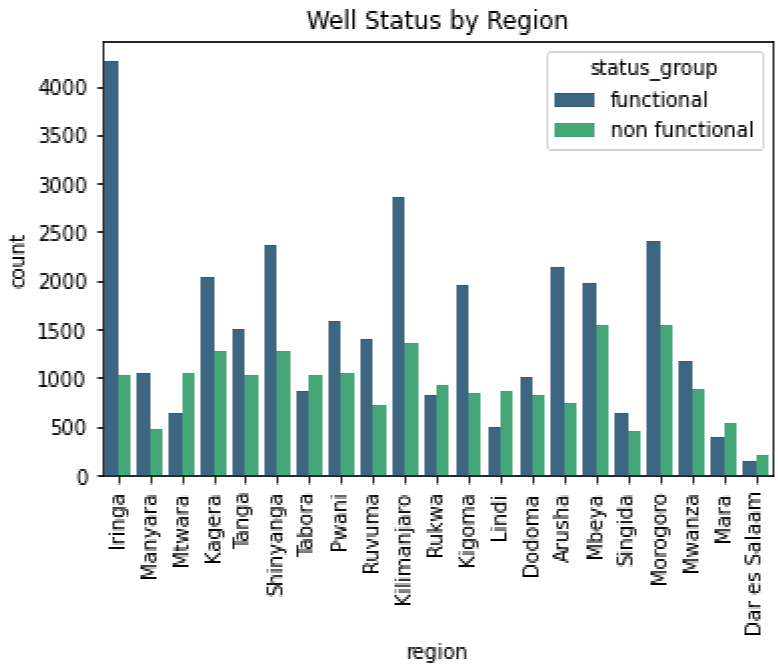
Out[354]:
```
functional        31735
non functional    19699
Name: status_group, dtype: int64
```

In [355]:
```
# Using a bar graph, we can check the distribution of the target variable
sns.countplot(x='status_group', data=train_df, palette='viridis')
plt.title('Distribution of the Target Variable')
plt.show()
```



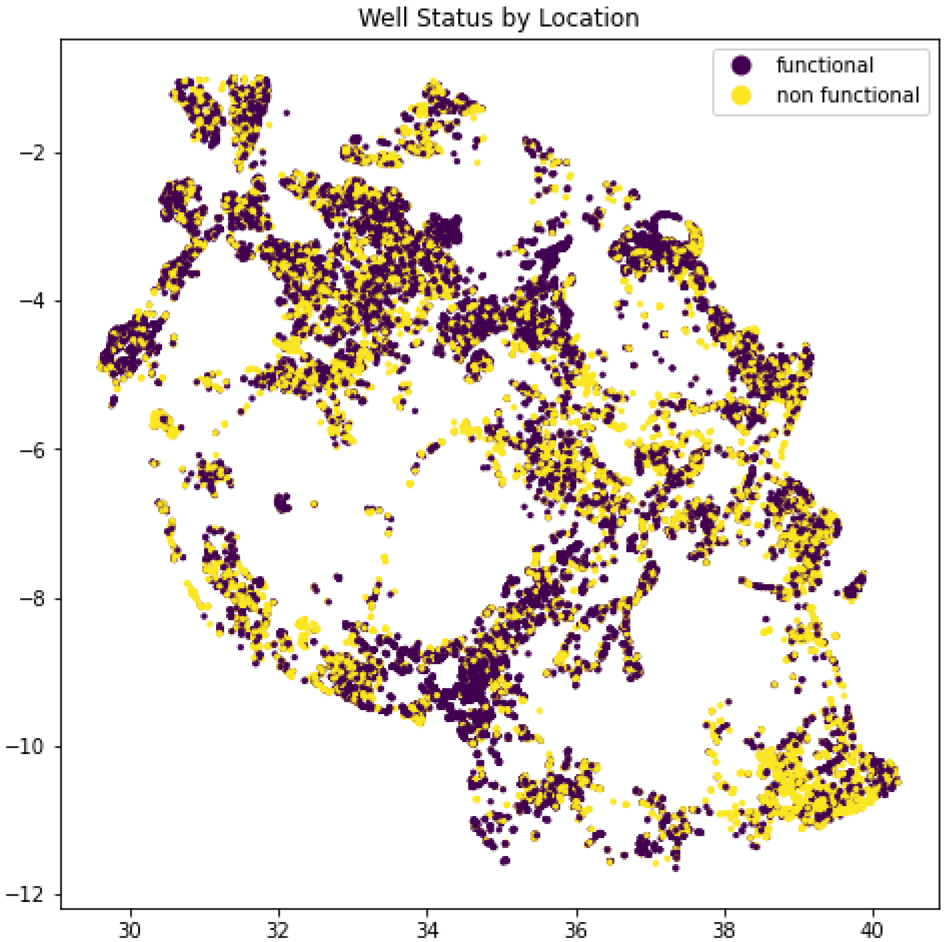
The majority of the wells are functional, with a distribution of approximately 3:2 between functional and non-functional wells.

In [356]:
```
# Checking the distribution of well status by  region
sns.countplot(data=train_df, x='region', hue='status_group', palette='viridis')
plt.xticks(rotation=90)
plt.title('Well Status by Region')
plt.show()
```



We can see that Iringa has the highest number of functioning wells followed by Kilimanjaro then Shinyanga. The highest number of non-functional wells are in Morogoro and Mbeya.

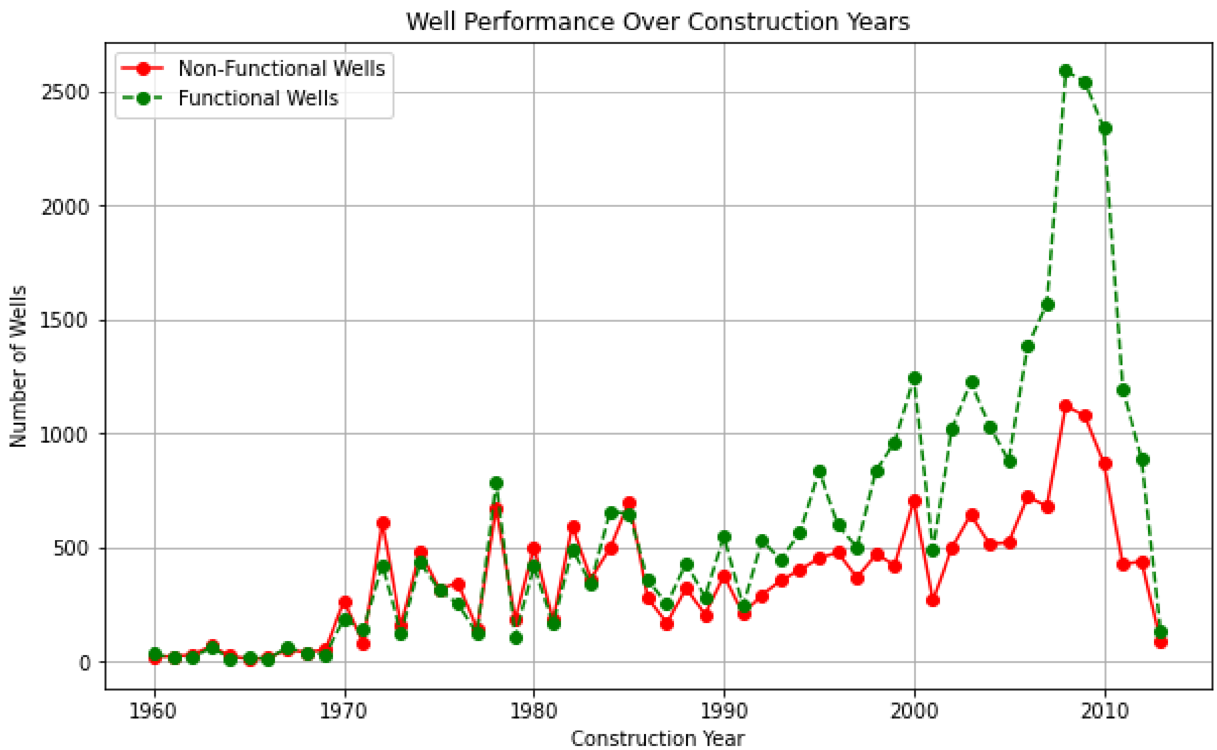
In [357]:
```
# Checking the map again and adding hue for status_group
gdf = gpd.GeoDataFrame(train_df, geometry=gpd.points_from_xy(train_df.longitude,
gdf.plot(figsize=(10,8), marker='o', column='status_group', cmap='viridis', leger
plt.title('Well Status by Location')
plt.show()
```



This shows the data in the shape of Tanzania! This gdf plot visualizes the geographic distribution of functional and non-functional wells. From it, we can observe:

- Non-functional wells are spread across the region but are more concentrated in the south eastern parts.
- Functional wells are more densely clustered in the central and western areas.
- Some areas show a mix of both, indicating varied well conditions within certain regions.
  The higher concentration of non-functional wells in the south east of Tanzania could indicate challenges such as poor maintenance, aged infrastructure, or unreliable sources of water feeding the wells.

In [358]:
```
# Checking the trend of well performance over time
# Filter by status group
non_functional_wells_per_year = train_df[train_df['status_group'] == 'non functio
functional_wells_per_year = train_df[train_df['status_group'] == 'functional'].gr

# Plotting a line graph
plt.figure(figsize=(10,6))
plt.plot(non_functional_wells_per_year.index, non_functional_wells_per_year.value
plt.plot(functional_wells_per_year.index, functional_wells_per_year.values, marke
plt.xlabel('Construction Year')
plt.ylabel('Number of Wells')
plt.title('Well Performance Over Construction Years')
plt.legend(loc='upper left')
plt.grid(True)
plt.show()
```



The plot shows an increasing trend in well construction, peaking around 2010, with functional wells consistently outnumbering non-functional ones. However, older wells tend to have a higher proportion of non-functional status, possibly due to aging infrastructure or lack of maintenance. More recent wells are more likely to be functional, suggesting improvements in construction quality, materials, and maintenance programs. However, the presence of non-functional wells in all time periods highlights that factors beyond age also play a role in well performance.

PRE-PROCESSING

For this section, we shall first split the data then apply the pre-processing on both the training and testing data sets

ENCODING AND TRANSFORMING

In [359]:
```
from sklearn.model_selection import train_test_split

# Defining features (X) and target (y)
X = train_df.drop(columns=['status_group'])
y = train_df['status_group']

# Split into training and test sets (80% train, 20% test). Stratify by y keeps th
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s
```

In [360]:
```
# Creating a copy of the data sets
X_train_encoded = X_train.copy()
X_test_encoded = X_test.copy()
```

In [361]:
```
# Creating a dataframe with the numeric cols and the categorical columns
number_columns = X_train_encoded.select_dtypes(include=np.number).columns.tolist(
categorical_cols = X_train_encoded.select_dtypes(exclude=np.number).columns.tolis

print("Categorical columns:", categorical_cols)
print("Number columns:", number_columns)
```

```
Categorical columns: ['funder', 'installer', 'basin', 'subvillage', 'region',
'lga', 'ward', 'public_meeting', 'scheme_management', 'scheme_name', 'permit',
'extraction_type', 'management_group', 'payment_type', 'water_quality', 'quanti
ty', 'source', 'waterpoint_type']
Number columns: ['amount_tsh', 'longitude', 'latitude', 'construction_year']
```

In [362]:
```
# Checking for unique values in each categorical column
for i in categorical_cols:
  print(f'The variable "{i}" has {X_train_encoded[i].nunique()} variables \n')
```

```
The variable "funder" has 1524 variables

The variable "installer" has 1672 variables

The variable "basin" has 9 variables

The variable "subvillage" has 15246 variables

The variable "region" has 21 variables

The variable "lga" has 119 variables

The variable "ward" has 1897 variables

The variable "public_meeting" has 2 variables

The variable "scheme_management" has 13 variables

The variable "scheme_name" has 2413 variables

The variable "permit" has 2 variables

The variable "extraction_type" has 18 variables

The variable "management_group" has 4 variables

The variable "payment_type" has 6 variables

The variable "water_quality" has 6 variables

The variable "quantity" has 5 variables

The variable "source" has 9 variables

The variable "waterpoint_type" has 7 variables
```

In [363]:
```
# Dropping columns due to high cardinality
X_train_encoded.drop(columns=['funder', 'installer', 'subvillage', 'lga', 'ward',
X_test_encoded.drop(columns=['funder', 'installer', 'subvillage', 'lga', 'ward',
```

In [364]:
```
# Re-defining categorical columns
categorical_cols = X_train_encoded.select_dtypes(exclude=np.number).columns.tolis
```

In [365]:
```
for i in categorical_cols:
  print(f'The variable "{i}" has {X_train_encoded[i].nunique()} variables: {X_tra
```

```
The variable "basin" has 9 variables: ['Internal' 'Rufiji' 'Ruvuma / Southern C
oast' 'Pangani' 'Lake Rukwa'
 'Wami / Ruvu' 'Lake Victoria' 'Lake Nyasa' 'Lake Tanganyika']

The variable "region" has 21 variables: ['Manyara' 'Iringa' 'Ruvuma' 'Tanga' 'R
ukwa' 'Morogoro' 'Kagera'
 'Kilimanjaro' 'Mara' 'Shinyanga' 'Lindi' 'Mbeya' 'Kigoma' 'Mtwara'
 'Pwani' 'Singida' 'Arusha' 'Dodoma' 'Tabora' 'Mwanza' 'Dar es Salaam']

The variable "public_meeting" has 2 variables: [True False]

The variable "scheme_management" has 13 variables: ['unknown' 'VWC' 'Water Boar
d' 'Parastatal' 'WUG' 'Water authority'
 'Company' 'Private operator' 'WUA' 'Other' 'SWC' 'Trust' 'None']

The variable "permit" has 2 variables: [True False]

The variable "extraction_type" has 18 variables: ['gravity' 'swn 80' 'india mar
k ii' 'ksb' 'unknown' 'walimi' 'nira/tanira'
 'submersible' 'mono' 'windmill' 'climax' 'afridev' 'india mark iii'
 'other - rope pump' 'other - swn 81' 'cemo' 'other - play pump'
 'other - mkulima/shinyanga']

The variable "management_group" has 4 variables: ['unknown' 'user-group' 'paras
tatal' 'commercial']

The variable "payment_type" has 6 variables: ['never pay' 'monthly' 'per bucke
t' 'on failure' 'unknown' 'annually']

The variable "water_quality" has 6 variables: ['soft' 'salty' 'fluoride' 'unkno
wn' 'milky' 'coloured']

The variable "quantity" has 5 variables: ['enough' 'insufficient' 'unknown' 'dr
y' 'seasonal']

The variable "source" has 9 variables: ['spring' 'shallow well' 'machine dbh'
'river' 'rainwater harvesting'
 'unknown' 'dam' 'lake' 'hand dtw']

The variable "waterpoint_type" has 7 variables: ['improved spring' 'communal st
andpipe' 'hand pump' 'unknown'
 'communal standpipe multiple' 'cattle trough' 'dam']
```

Encoding the categorical variables using one-hot, ordinal and label encoding.

In [366]:
```
# Using One Hot Encoding for low cardinality nominal data
from sklearn.preprocessing import OneHotEncoder

ohe_cols = ['public_meeting', 'permit', 'payment_type', 'quantity', 'source', 'wa

# Initialize OneHotEncoder
ohe = OneHotEncoder(drop='first', sparse=False)

# Fit on training data and transform both train & test
encoded_ohe_train = ohe.fit_transform(X_train_encoded[ohe_cols])
encoded_ohe_test = ohe.transform(X_test_encoded[ohe_cols])

# Convert to DataFrame and set correct column names
encoded_ohe_train_df = pd.DataFrame(encoded_ohe_train, columns=ohe.get_feature_na
encoded_ohe_test_df = pd.DataFrame(encoded_ohe_test, columns=ohe.get_feature_name

# Drop original categorical columns
X_train_encoded.drop(columns=ohe_cols, inplace=True)
X_test_encoded.drop(columns=ohe_cols, inplace=True)

# Concatenation the new encoded columns
X_train_encoded = pd.concat([X_train_encoded, encoded_ohe_train_df], axis=1)
X_test_encoded = pd.concat([X_test_encoded, encoded_ohe_test_df], axis=1)
```

In [367]:
```
# Using Ordinal Encoding for ordered categories
from sklearn.preprocessing import OrdinalEncoder

ordinal_cols = ['water_quality']
quality_order = [['soft', 'milky', 'salty', 'coloured', 'fluoride', 'unknown']]

# Initializing the encoder
ordinal_enc = OrdinalEncoder(categories=quality_order)

# Transform both train and test data
X_train_encoded[ordinal_cols] = ordinal_enc.fit_transform(X_train_encoded[ordinal
X_test_encoded[ordinal_cols] = ordinal_enc.transform(X_test_encoded[ordinal_cols]

# Ensure dtype is preserved (as OrdinalEncoder returns float by default)
X_train_encoded[ordinal_cols] = X_train_encoded[ordinal_cols].astype(int)
X_test_encoded[ordinal_cols] = X_test_encoded[ordinal_cols].astype(int)
```

In [368]:
```
# Using Label Encoding for high cardinality nominal data
from sklearn.preprocessing import LabelEncoder

label_cols = ['region', 'scheme_management', 'extraction_type', 'basin']
le = LabelEncoder()

for col in label_cols:
    X_train_encoded[col] = le.fit_transform(X_train_encoded[col])
    X_test_encoded[col] = le.transform(X_test_encoded[col])
```

In [369]:
```
# Reindex the test set to match the train set
X_test_encoded = X_test_encoded.reindex(columns=X_train_encoded.columns, fill_val
```

In [370]:
```
# Using ordinal encoding for the target variable
# Defining the order of categories
status_order = [['non functional', 'functional']]

# Initializing OrdinalEncoder
ordinal_enc_target = OrdinalEncoder(categories=status_order)

# Fitting and transforming the train and test target variable using numpy to resh
y_train_transformed = ordinal_enc_target.fit_transform(y_train.to_numpy().reshape
y_test_transformed = ordinal_enc_target.transform(y_test.to_numpy().reshape(-1, 1

# Convert back to a 1D array
y_train_transformed = y_train_transformed.ravel()
y_test_transformed = y_test_transformed.ravel()
```

SCALING

In [371]:
```
# Creating a copy of the data
X_train_transformed = X_train_encoded.copy()
X_test_transformed = X_test_encoded.copy()
```

In [372]:
```
X_train_encoded[number_columns]
```

Out[372]:

	amount_tsh	longitude	latitude	construction_year
40554	500.0	35.371668	-4.263098	2002
25171	500.0	34.912992	-8.954426	2006
28622	200.0	36.084544	-10.921422	2000
35113	30.0	38.286935	-5.778625	1970
23503	500.0	32.107949	-8.912064	1984
...	...	...	...	...
29444	33.0	37.450929	-3.495127	2008
46519	500.0	36.778837	-2.556306	2012
55239	500.0	34.700531	-9.107210	1974
7511	500.0	34.433609	-9.299510	1967
41966	500.0	35.367572	-4.148880	1991

41147 rows × 4 columns

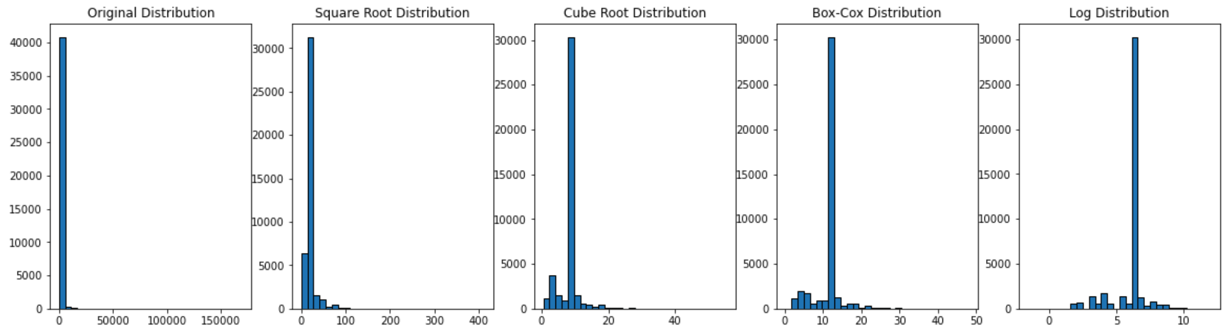
In [373]:
```
# Checking for skewness in the numerical columns
for i, col in enumerate(number_columns):
    print(f"Column: {col}, Skewness: {X_train_transformed[col].skew():.2f}")
```

```
Column: amount_tsh, Skewness: 38.58
Column: longitude, Skewness: -0.18
Column: latitude, Skewness: -0.26
Column: construction_year, Skewness: -0.70
```

For the amount_tsh column, we shall compare various scalers to see which one best corrects this heavily right skewed column.

In [374]:
```
import scipy.stats as stats

# Assuming 'amount_tsh' is in df
df = X_train_transformed.copy()

# Function to calculate skewness
def check_skewness(col):
    return stats.skew(df[col])

# Original skewness
original_skew = check_skewness('amount_tsh')

# Square root transformation
df['amount_tsh_sqrt'] = np.sqrt(df['amount_tsh'])
sqrt_skew = check_skewness('amount_tsh_sqrt')

# Cube root transformation
df['amount_tsh_cbrt'] = np.cbrt(df['amount_tsh'])
cbrt_skew = check_skewness('amount_tsh_cbrt')

# Box-Cox transformation
df['amount_tsh_boxcox'], lambda_boxcox = stats.boxcox(df['amount_tsh'] + 1)
boxcox_skew = check_skewness('amount_tsh_boxcox')

# Log transformation
df['amount_tsh_log'] = np.log(df['amount_tsh'])
log_skew = check_skewness('amount_tsh_log')

# Print skewness values
print(f'Original Skewness: {original_skew}')
print(f'Square Root Skewness: {sqrt_skew}')
print(f'Cube Root Skewness: {cbrt_skew}')
print(f'Box-Cox Skewness: {boxcox_skew} (Lambda: {lambda_boxcox})')
print(f'Log Skewness: {log_skew}')

# Plot histograms to visualize
fig, axes = plt.subplots(1, 5, figsize=(20, 5))

for ax, col, title in zip(
    axes,
    ['amount_tsh', 'amount_tsh_sqrt', 'amount_tsh_cbrt', 'amount_tsh_boxcox', 'ar
    ['Original', 'Square Root', 'Cube Root', 'Box-Cox', 'Log']
):
    ax.hist(df[col], bins=30, edgecolor='black')
    ax.set_title(f'{title} Distribution')

plt.show()
```

```
Original Skewness: 38.58122532115044
Square Root Skewness: 6.7560753882906575
Cube Root Skewness: 2.406337295410395
Box-Cox Skewness: 0.3271753766434505 (Lambda: 0.19402421454632152)
Log Skewness: -1.4375502939355969
```



From the above, we can see that box-cox corrects the data the best. Therefore we shall proceed with this.

In [375]:
```
# Apply Box-Cox transformation on training set and capture the lambda value
X_train_transformed['amount_tsh_boxcox'], lambda_boxcox = stats.boxcox(X_train_tr
boxcox_skew = check_skewness('amount_tsh_boxcox')

# Drop the original 'amount_tsh' column
X_train_transformed.drop('amount_tsh', axis=1, inplace=True)

print(f'Box-Cox Skewness: {boxcox_skew} (Lambda: {lambda_boxcox})')
```

```
Box-Cox Skewness: 0.3271753766434505 (Lambda: 0.19402421454632152)
```

In [376]:
```
# Apply the same lambda to the test set
X_test_transformed['amount_tsh_boxcox'] = stats.boxcox(X_test_transformed['amount
boxcox_skew = check_skewness('amount_tsh_boxcox')

# Drop the original 'amount_tsh' column
X_test_transformed.drop('amount_tsh', axis=1, inplace=True)

print(f'Box-Cox Skewness: {boxcox_skew} (Lambda: {lambda_boxcox})')
```

```
Box-Cox Skewness: 0.3271753766434505 (Lambda: 0.19402421454632152)
```

In [377]:
```
# Transforming construction_year using apply min-max scaling
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train_transformed[['construction_year']] = scaler.fit_transform(X_train_transfo
X_test_transformed[['construction_year']] = scaler.transform(X_test_transformed[[
```

From the above, we can see that all our numerical columns are within -1 to 1 range. This indicates that the data is approximately symmetric to moderately skewed.

In [378]:
```python
# Checking that we have consistency in columns in the train and test sets
X_train_transformed.columns == X_test_transformed.columns
```

Out[378]:
```
array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True])
```

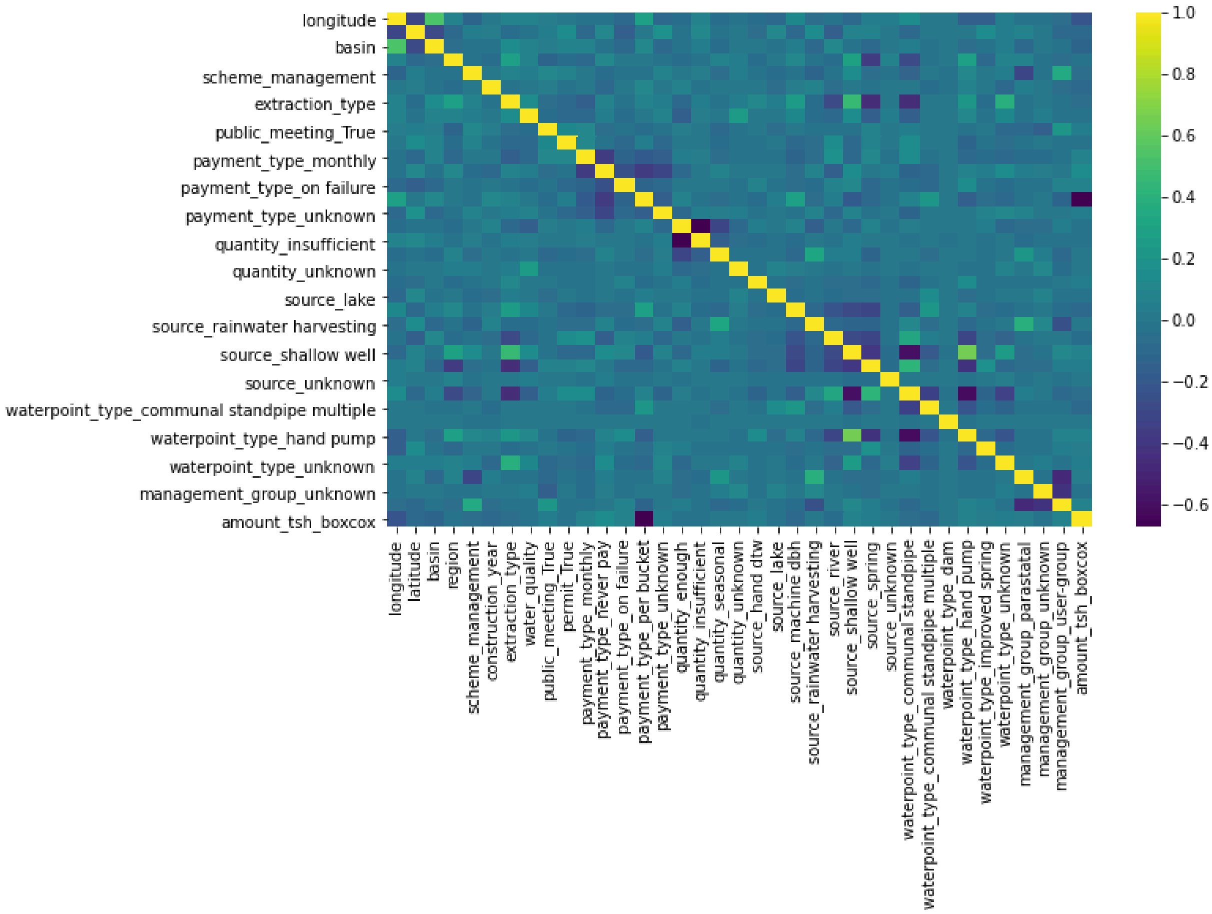
In [379]:
```python
X_train_transformed
```

Out[379]:

	longitude	latitude	basin	region	scheme_management	construction_year	extraction_typ
40554	35.371668	-4.263098	0	8	12	0.792453	
25171	34.912992	-8.954426	6	3	7	0.867925	
28622	36.084544	-10.921422	7	16	7	0.754717	1
35113	38.286935	-5.778625	5	20	7	0.188679	
23503	32.107949	-8.912064	2	15	7	0.452830	
...	...	...	...	...	...	...	.
29444	37.450929	-3.495127	5	6	10	0.905660	1
46519	36.778837	-2.556306	0	0	3	0.981132	
55239	34.700531	-9.107210	6	3	8	0.264151	
7511	34.433609	-9.299510	1	3	7	0.132075	
41966	35.367572	-4.148880	0	8	7	0.584906	1

41147 rows × 37 columns

In [380]:
```python
# Checking if we have any highly correlated features
corr = X_train_transformed.corr()
plt.figure(figsize=(10,6))
sns.heatmap(corr, annot=False, cmap="viridis")
plt.show()
```



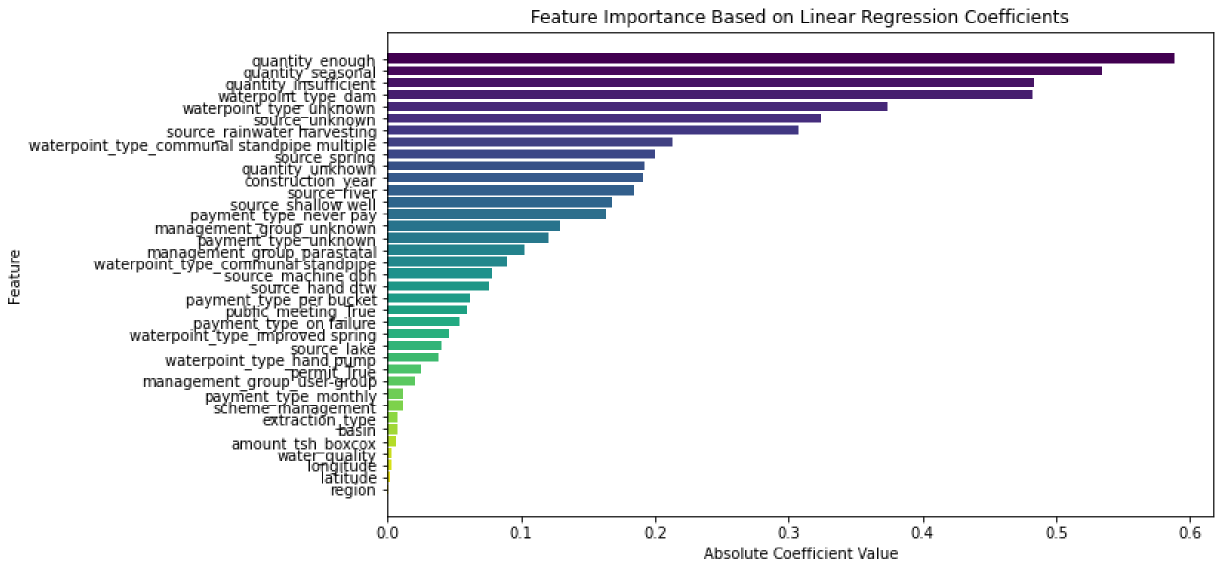
We can see that we do not have any highly correlated columns.

Using linear regression on the transformed data and feature importance to determine which features highly influence functionality of the wells.

In [381]:
```python
from sklearn.linear_model import LinearRegression

X = X_train_transformed
y = y_train_transformed

# Train the linear regression model
model = LinearRegression()
model.fit(X, y)

# Get feature importance (absolute coefficient values)
feature_importance = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': np.abs(model.coef_)  # Take absolute value
}).sort_values(by='Coefficient', ascending=False)

# Display the most important features
print(feature_importance)
```

```
                                    Feature  Coefficient
15                          quantity_enough     0.588034
17                        quantity_seasonal     0.534650
16                    quantity_insufficient     0.482819
29                      waterpoint_type_dam     0.481742
32                  waterpoint_type_unknown     0.373921
26                           source_unknown     0.324068
22               source_rainwater harvesting     0.306886
28  waterpoint_type_communal standpipe multiple     0.212891
25                            source_spring     0.199559
18                         quantity_unknown     0.192540
5                         construction_year     0.191738
23                             source_river     0.184711
24                      source_shallow well     0.168243
11                     payment_type_never pay     0.163129
34                 management_group_unknown     0.129540
14                     payment_type_unknown     0.120802
33               management_group_parastatal     0.103024
27          waterpoint_type_communal standpipe     0.089572
21                      source_machine dbh     0.077972
19                          source_hand dtw     0.076043
13                   payment_type_per bucket     0.062139
8                         public_meeting_True     0.059959
12                   payment_type_on failure     0.054533
31             waterpoint_type_improved spring     0.046379
20                              source_lake     0.040698
30                  waterpoint_type_hand pump     0.038697
9                               permit_True     0.025068
35               management_group_user-group     0.021032
10                     payment_type_monthly     0.011601
4                         scheme_management     0.011560
6                           extraction_type     0.007628
2                                     basin     0.006985
36                          amount_tsh_boxcox     0.006488
7                             water_quality     0.003014
0                                 longitude     0.002854
1                                  latitude     0.001479
3                                    region     0.001160
```

In [382]:
```
# Visualising these results
# Create color mapping using viridis
colors = plt.cm.viridis(np.linspace(0, 1, len(feature_importance)))

# Plot feature importance
plt.figure(figsize=(10, 6))
plt.barh(feature_importance['Feature'], feature_importance['Coefficient'], color=
plt.xlabel('Absolute Coefficient Value')
plt.ylabel('Feature')
plt.title('Feature Importance Based on Linear Regression Coefficients')
plt.gca().invert_yaxis()  # Invert y-axis to show the most important feature at t
plt.show()
```



From the above, we can see that 'quantity', 'waterpoint_type', 'source', 'construction_year', 'payment_type' and 'management_group' are the leading indicators of the functionality of a well.

CLASSIFICATION MODELING

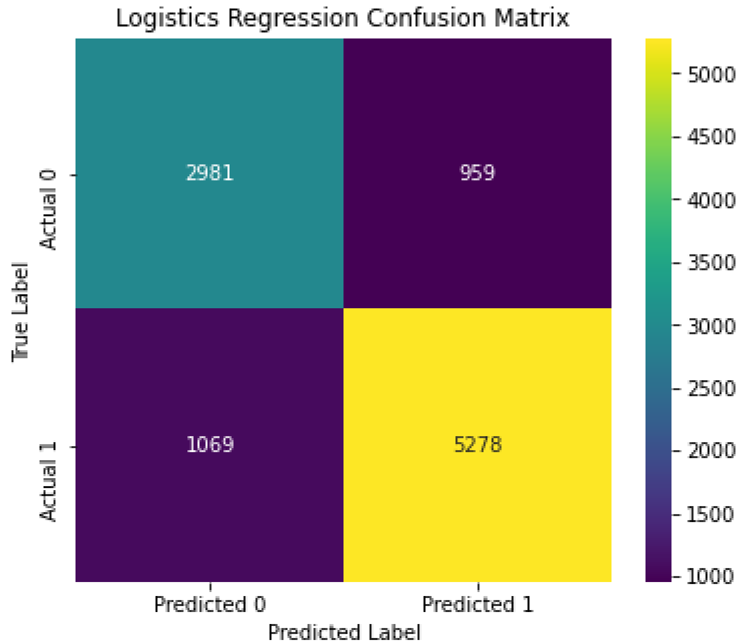
We shall model using Logistic Regression, Random Forest, K-NN and Decision Trees. We shall then apply tuning to see whether we can improve the models further. For each model we shall use accuracy, recall, precision and F-beta score as evaluation metrics and we shall round each off to 4 decimal places for uniformity. Comparison of the models and evaluation shall be done at the Evaluation step.

LOGISTIC REGRESSION

We shall use Logistic regression as our base model.

In [383]:
```
# Importing logistic regression and metrics
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_sco

# Initializing and training the logistic regression model
logreg_model = LogisticRegression(class_weight='balanced', random_state=42)
logreg_model.fit(X_train_transformed, y_train_transformed)

# Making predictions on the test set
y_pred_logreg = logreg_model.predict(X_test_transformed)

# Evaluating the model
accuracy_logreg = accuracy_score(y_test_transformed, y_pred_logreg)
recall_logreg = recall_score(y_test_transformed, y_pred_logreg)
precision_logreg = precision_score(y_test_transformed, y_pred_logreg)
f1_logreg = f1_score(y_test_transformed, y_pred_logreg)

print('Model 1 - LogReg:')
print(f"Accuracy: {accuracy_logreg:.4f}")
print(f"Recall: {recall_logreg:.4f}")
print(f"Precision: {precision_logreg:.4f}")
print(f"F1-score: {f1_logreg:.4f}")

# Classification report
print(classification_report(y_test_transformed, y_pred_logreg))

# Computing confusion matrix
cm = confusion_matrix(y_test_transformed, y_pred_logreg)
plt.figure(figsize=(6,5))
sns.heatmap(cm_dt, annot=True, fmt='d', cmap='viridis',
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Logistics Regression Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

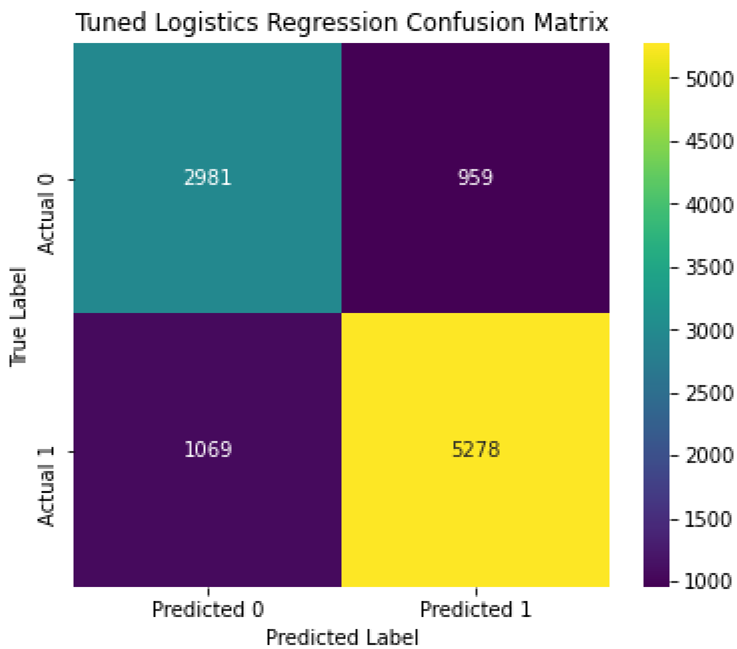
```
Model 1 - LogReg:
Accuracy: 0.7554
Recall: 0.8133
Precision: 0.7950
F1-score: 0.8040
              precision    recall  f1-score   support

         0.0       0.69      0.66      0.67      3940
         1.0       0.80      0.81      0.80      6347

    accuracy                           0.76     10287
   macro avg       0.74      0.74      0.74     10287
weighted avg       0.75      0.76      0.75     10287
```



Let us explore using RFE here because it helps eliminate irrelevant features, reducing noise and improving model performance by selecting only the most important predictors. This will highlight the top 10 features in the models, which is helpful information for this analysis.

In [384]:
```
# Import necessary libraries
from sklearn.feature_selection import RFE

# Initialize Logistic Regression
logreg = LogisticRegression(class_weight='balanced', random_state=42, max_iter=50

# Apply Recursive Feature Elimination (RFE)
rfe = RFE(estimator=logreg, n_features_to_select=10)
X_train_selected = rfe.fit_transform(X_train_transformed, y_train_transformed)
X_test_selected = rfe.transform(X_test_transformed)

# Train Logistic Regression on selected features
logreg.fit(X_train_selected, y_train_transformed)

# Predictions
y_pred = logreg.predict(X_test_selected)

# Evaluation Metrics
accuracy_logreg_optm = accuracy_score(y_test_transformed, y_pred)
recall_logreg_optm = recall_score(y_test_transformed, y_pred)
precision_logreg_optm = precision_score(y_test_transformed, y_pred)
f1_logreg_optm = f1_score(y_test_transformed, y_pred)

print('Model 2 - LogReg with RFE:')
print(f"Accuracy: {accuracy_logreg_optm:.4f}")
print(f"Recall: {recall_logreg_optm:.4f}")
print(f"Precision: {precision_logreg_optm:.4f}")
print(f"F1-score: {f1_logreg_optm:.4f}")
print("\nClassification Report:\n", classification_report(y_test_transformed, y_p

# Confusion Matrix
cm = confusion_matrix(y_test_transformed, y_pred)
plt.figure(figsize=(6,5))
sns.heatmap(cm_dt, annot=True, fmt='d', cmap='viridis',
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Tuned Logistics Regression Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()

# Show selected features
selected_features = X_train_transformed.columns[rfe.support_]
print("\nSelected Features after RFE:\n", selected_features)
```

```
Model 2 - LogReg with RFE:
Accuracy: 0.7579
Recall: 0.8714
Precision: 0.7677
F1-score: 0.8163

Classification Report:
              precision    recall  f1-score   support

         0.0       0.74      0.58      0.65      3940
         1.0       0.77      0.87      0.82      6347

    accuracy                           0.76     10287
   macro avg       0.75      0.72      0.73     10287
weighted avg       0.76      0.76      0.75     10287
```




```
Selected Features after RFE:
 Index(['construction_year', 'quantity_enough', 'quantity_insufficient',
       'quantity_seasonal', 'quantity_unknown', 'source_lake',
       'source_rainwater harvesting',
       'waterpoint_type_communal standpipe multiple', 'waterpoint_type_dam',
       'waterpoint_type_unknown'],
      dtype='object')
```

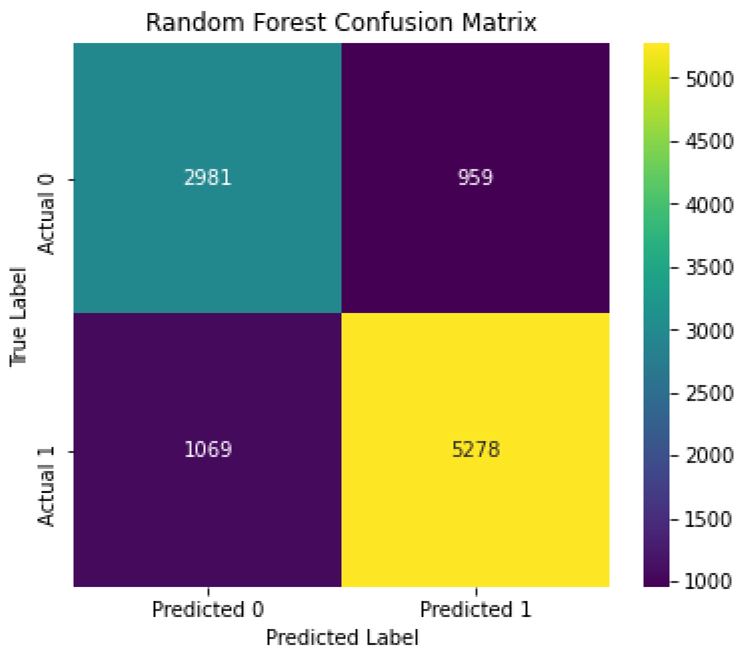
From the above, we can see that model 2 shows an improvement in recall (from 0.8133 to 0.8714) and F1-score (from 0.8040 to 0.8163), indicating better identification of the positive class. However, this comes at the cost of slightly lower precision (from 0.7950 to 0.7677), meaning more false positives. The accuracy of both models remains similar, with model 2 showing a minor improvement (from 0.7554 to 0.7579). Since RFE helps refine feature selection and improve model performance, it is worth exploring more robust models like Random Forest, which can inherently handle feature importance and offer better generalization.

We can also note that the RFI selected 'construction_year', 'quantity','source', and 'waterpoint_type' as the most important features. This is similar to what we attained using linear regression.

RANDOM FOREST

In [385]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_sco

# Initialize the Random Forest model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)

# Train the model
rf_model.fit(X_train_transformed, y_train_transformed)

# Make predictions
y_pred_rf = rf_model.predict(X_test_transformed)

# Evaluate the model
accuracy_rf = accuracy_score(y_test_transformed, y_pred_rf)
recall_rf = recall_score(y_test_transformed, y_pred_rf)
precision_rf = precision_score(y_test_transformed, y_pred_rf)
f1_rf = f1_score(y_test_transformed, y_pred_rf)

# Print results
print('Model 3 - RF:')
print(f'Accuracy: {accuracy_rf:.4f}')
print(f'Recall: {recall_rf:.4f}')
print(f'Precision: {precision_rf:.4f}')
print(f'F1-score: {f1_rf:.4f}')
print('\nClassification Report:\n', classification_report(y_test_transformed, y_p

# Confusion Matrix
cm_rf = confusion_matrix(y_test_transformed, y_pred_rf)
plt.figure(figsize=(6,5))
sns.heatmap(cm_dt, annot=True, fmt='d', cmap='viridis',
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Random Forest Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

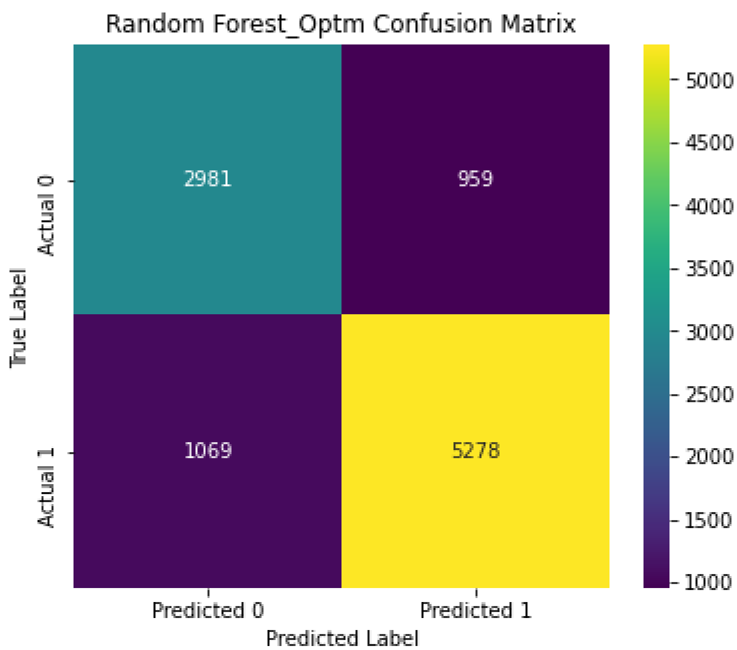
```
Model 3 - RF:
Accuracy: 0.8465
Recall: 0.8955
Precision: 0.8612
F1-score: 0.8780

Classification Report:
              precision    recall  f1-score   support

         0.0       0.82      0.77      0.79      3940
         1.0       0.86      0.90      0.88      6347

    accuracy                           0.85     10287
   macro avg       0.84      0.83      0.84     10287
weighted avg       0.85      0.85      0.85     10287
```



We shall try improve this model using hyperparameter tuning.

In [386]:
```
# Tuning the random forest model using GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Define parameter grid using typical ranges
param_grid = {
#     (More trees reduce variance)
    'n_estimators': [100, 200, 300],
#     (Shallower trees prevent overfitting)
    'max_depth': [10, 20, 30],
#     (Higher values prevent overfitting)
    'min_samples_split': [2, 5, 10],
#     (Higher values make trees less complex)
    'min_samples_leaf': [1, 2, 4]
}

# Initialize Random Forest model
rf = RandomForestClassifier(random_state=42, n_jobs=-1)

# Perform Grid Search with 5-fold cross-validation
grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='accuracy', verbose=2, r
grid_search.fit(X_train_transformed, y_train_transformed)

# Print best parameters
print('Best Parameters:', grid_search.best_params_)

# Train the best model
best_rf = grid_search.best_estimator_
y_pred_optimized = best_rf.predict(X_test_transformed)

# Evaluate the optimized model
accuracy_rf_optm = accuracy_score(y_test_transformed, y_pred_optimized)
recall_rf_optm = recall_score(y_test_transformed, y_pred_optimized)
precision_rf_optm = precision_score(y_test_transformed, y_pred_optimized)
f1_rf_optm = f1_score(y_test_transformed, y_pred_optimized)

print('Model 4 - RF Optm:')
print(f'Accuracy: {accuracy_rf_optm:.4f}')
print(f'Recall: {recall_rf_optm:.4f}')
print(f'Precision: {precision_rf_optm:.4f}')
print(f'F1-score: {f1_rf_optm:.4f}')
print(classification_report(y_test_transformed, y_pred_optimized))

# Confusion Matrix
cm_rf = confusion_matrix(y_test_transformed, y_pred_optimized)
plt.figure(figsize=(6,5))
sns.heatmap(cm_dt, annot=True, fmt='d', cmap='viridis',
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Random Forest_Optm Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Fitting 5 folds for each of 81 candidates, totalling 405 fits
Best Parameters: {'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 
5, 'n_estimators': 300}
Model 4 - RF Optm:
Accuracy: 0.8538
Recall: 0.9239
Precision: 0.8517
F1-score: 0.8863
              precision    recall  f1-score   support

         0.0       0.86      0.74      0.80      3940
         1.0       0.85      0.92      0.89      6347

    accuracy                           0.85     10287
   macro avg       0.85      0.83      0.84     10287
weighted avg       0.85      0.85      0.85     10287
```

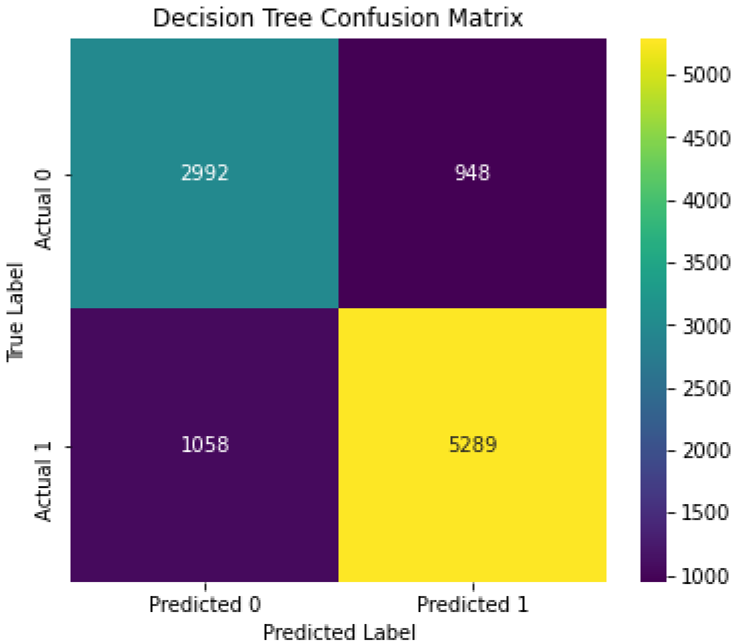


Model 3 performed well, achieving an accuracy of 84.65%, recall of 89.55%, and an F1-score of 87.80%. After hyperparameter tuning using GridSearchCV, the optimized Random Forest model improved performance further, increasing accuracy to 85.38%, recall to 92.39%, and the F1-score to 88.63%. The tuning process identified optimal parameters such as `max_depth: 20`, `min_samples_leaf: 1`, `min_samples_split: 5`, and `n_estimators: 300`, which contributed to this enhancement. With Random Forest showing strong results, it would be insightful to compare its performance to a Decision Tree model to analyze how a single tree fares against an ensemble approach.

DECISION TREES

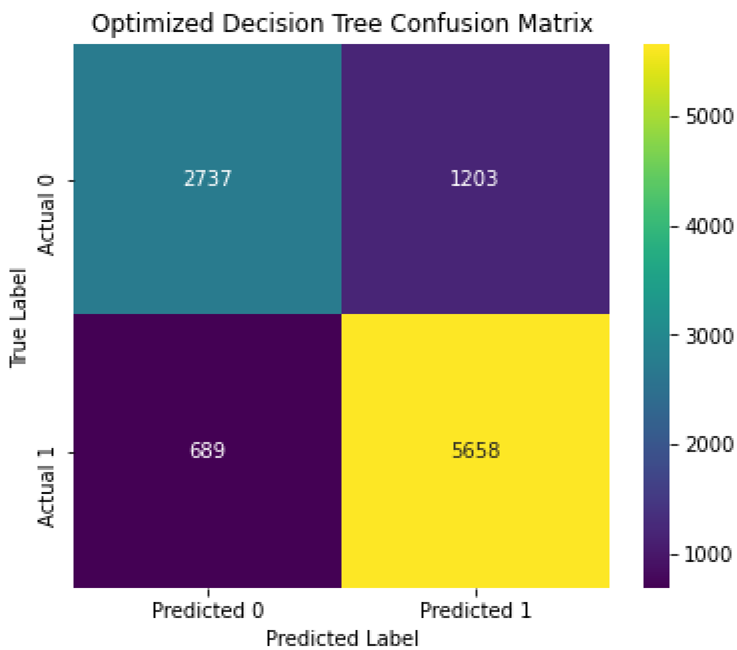
In [387]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_sc

# Initialize Decision Tree model
dt_model = DecisionTreeClassifier(random_state=42)

# Train the model
dt_model.fit(X_train_transformed, y_train_transformed)

# Make predictions
y_pred_dt = dt_model.predict(X_test_transformed)

# Evaluate the model
accuracy_dt = accuracy_score(y_test_transformed, y_pred_dt)
recall_dt = recall_score(y_test_transformed, y_pred_dt)
precision_dt = precision_score(y_test_transformed, y_pred_dt)
f1_dt = f1_score(y_test_transformed, y_pred_dt)

print('Model 5 - DT:')
print(f'Accuracy: {accuracy_dt:.4f}')
print(f'Recall: {recall_dt:.4f}')
print(f'Precision: {precision_dt:.4f}')
print(f'F1-score: {f1_dt:.4f}')
print(classification_report(y_test_transformed, y_pred_dt))

# Plot confusion matrix
cm_dt = confusion_matrix(y_test_transformed, y_pred_dt)
plt.figure(figsize=(6,5))
sns.heatmap(cm_dt, annot=True, fmt='d', cmap='viridis',
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Decision Tree Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Model 5 - DT:
Accuracy: 0.8050
Recall: 0.8333
Precision: 0.8480
F1-score: 0.8406
              precision    recall  f1-score   support

         0.0       0.74      0.76      0.75      3940
         1.0       0.85      0.83      0.84      6347

    accuracy                           0.80     10287
   macro avg       0.79      0.80      0.79     10287
weighted avg       0.81      0.80      0.81     10287
```


Decision Tree Confusion Matrix
True Label
Actual 0
Actual 1
2992
948
1058
5289
Predicted 0
Predicted 1
Predicted Label
5000
4500
4000
3500
3000
2500
2000
1500
1000

In [388]:
```
# Hyperparameter tuning using GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_sco

# Define the model
dt = DecisionTreeClassifier(random_state=42)

# Define the hyperparameter grid
param_grid = {
#     (None allows the model to find the best depth on its own)
    'max_depth': [5, 10, 15, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'criterion': ['gini', 'entropy']
}

# Perform Grid Search with cross-validation
grid_search = GridSearchCV(dt, param_grid, cv=5, scoring='f1', n_jobs=-1)
grid_search.fit(X_train_transformed, y_train_transformed)

# Get the best parameters
best_params = grid_search.best_params_
print(f'Best Hyperparameters: {best_params}')

# Train the model with the best hyperparameters
# (Using 2 asterisks to unpack the best params disctionary)
best_dt = DecisionTreeClassifier(**best_params, random_state=42)
best_dt.fit(X_train_transformed, y_train_transformed)

# Make predictions
y_pred_best_dt = best_dt.predict(X_test_transformed)

# Evaluate the optimized model
accuracy_dt_optm = accuracy_score(y_test_transformed, y_pred_best_dt)
recall_dt_optm = recall_score(y_test_transformed, y_pred_best_dt)
precision_dt_optm = precision_score(y_test_transformed, y_pred_best_dt)
f1_dt_optm = f1_score(y_test_transformed, y_pred_best_dt)

print('Model 6 - DT Optm:')
print(f'Accuracy: {accuracy_dt_optm:.4f}')
print(f'Recall: {recall_dt_optm:.4f}')
print(f'Precision: {precision_dt_optm:.4f}')
print(f'F1-score: {f1_dt_optm:.4f}')
print(classification_report(y_test_transformed, y_pred_best_dt))

# Plot confusion matrix
cm_best_dt = confusion_matrix(y_test_transformed, y_pred_best_dt)
plt.figure(figsize=(6,5))
sns.heatmap(cm_best_dt, annot=True, fmt='d', cmap='viridis',
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Optimized Decision Tree Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Best Hyperparameters: {'criterion': 'gini', 'max_depth': 15, 'min_samples_lea
f': 1, 'min_samples_split': 2}
Model 6 - DT Optm:
Accuracy: 0.8161
Recall: 0.8914
Precision: 0.8247
F1-score: 0.8568
              precision    recall  f1-score   support

         0.0       0.80      0.69      0.74      3940
         1.0       0.82      0.89      0.86      6347

    accuracy                           0.82     10287
   macro avg       0.81      0.79      0.80     10287
weighted avg       0.81      0.82      0.81     10287
```

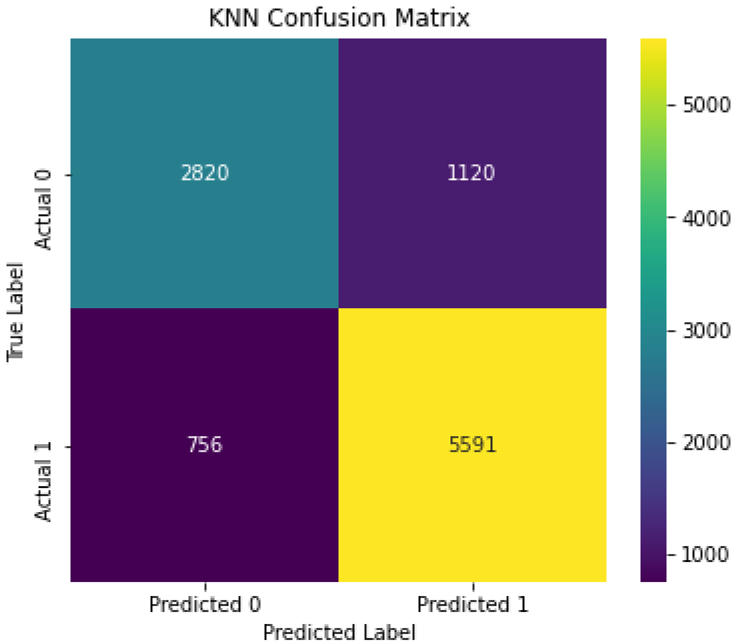


Model 6 shows improved recall (0.8914 vs. 0.8333) and a slightly better F1-score (0.8568 vs. 0.8406) compared to model 5. However, the precision is slightly lower (0.8247 vs. 0.8480), likely due to the model favoring recall over precision. The hyperparameter tuning resulted in a minor boost in accuracy (0.8161 vs. 0.8050), indicating a better balance in classification performance. While decision trees offer interpretability, they may still be prone to overfitting, prompting the need to explore K-Nearest Neighbors (KNN), which takes a different approach by classifying data points based on their proximity to neighbors, making it more flexible but potentially sensitive to noisy data.

K-NN

In [389]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_sco

# Initialize KNN model with a default value of k
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train_transformed, y_train_transformed)

# Make predictions
y_pred_knn = knn.predict(X_test_transformed)

# Evaluate the model
accuracy_knn = accuracy_score(y_test_transformed, y_pred_knn)
recall_knn = recall_score(y_test_transformed, y_pred_knn)
precision_knn = precision_score(y_test_transformed, y_pred_knn)
f1_knn = f1_score(y_test_transformed, y_pred_knn)

print('Model 7 - K-NN:')
print(f'Accuracy: {accuracy_knn:.4f}')
print(f'Recall: {recall_knn:.4f}')
print(f'Precision: {precision_knn:.4f}')
print(f'F1-score: {f1_knn:.4f}')
print(classification_report(y_test_transformed, y_pred_knn))

# Plot confusion matrix
cm_knn = confusion_matrix(y_test_transformed, y_pred_knn)
plt.figure(figsize=(6,5))
sns.heatmap(cm_knn, annot=True, fmt='d', cmap='viridis',
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('KNN Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

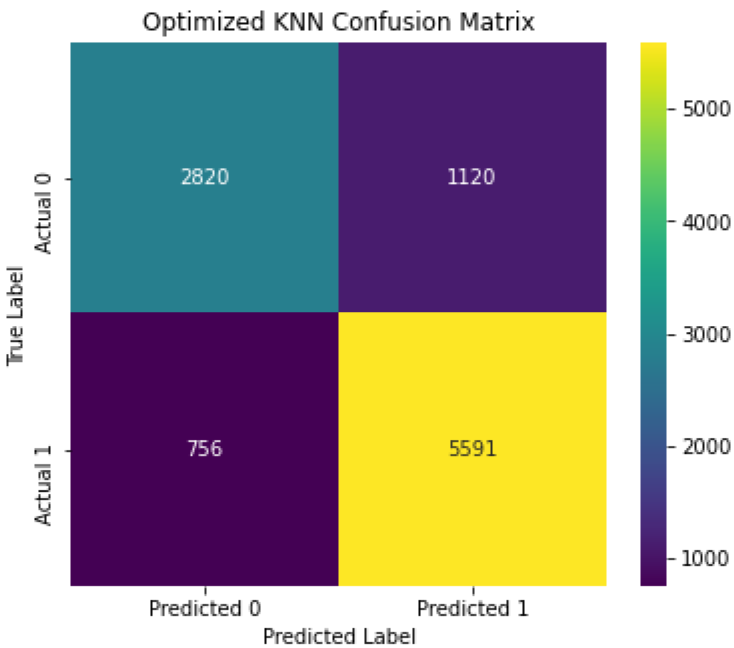
```
Model 7 - K-NN:
Accuracy: 0.8176
Recall: 0.8809
Precision: 0.8331
F1-score: 0.8563
              precision    recall  f1-score   support

         0.0       0.79      0.72      0.75      3940
         1.0       0.83      0.88      0.86      6347

    accuracy                           0.82     10287
   macro avg       0.81      0.80      0.80     10287
weighted avg       0.82      0.82      0.82     10287
```



Improving the model by hyperparameter tuning.

In [390]:
```
from sklearn.model_selection import GridSearchCV

# Define the hyperparameter grid (testing odd values of k to avoid ties)
param_grid = {'n_neighbors': [3, 5, 7, 9, 11, 13, 15]}

# Perform Grid Search
grid_search_knn = GridSearchCV(KNeighborsClassifier(), param_grid, cv=5, scoring=
grid_search_knn.fit(X_train_transformed, y_train_transformed)

# Get the best k value
best_k = grid_search_knn.best_params_['n_neighbors']
print(f'Best k value: {best_k}')

# Train KNN with the best k
best_knn = KNeighborsClassifier(n_neighbors=best_k)
best_knn.fit(X_train_transformed, y_train_transformed)

# Make predictions
y_pred_best_knn = best_knn.predict(X_test_transformed)

# Evaluate the optimized model
accuracy_knn_optm = accuracy_score(y_test_transformed, y_pred_best_knn)
recall_knn_optm = recall_score(y_test_transformed, y_pred_best_knn)
precision_knn_optm = precision_score(y_test_transformed, y_pred_best_knn)
f1_knn_optm = f1_score(y_test_transformed, y_pred_best_knn)

print('Model 8 - K-NN Optm:')
print(f'Accuracy: {accuracy_knn_optm:.4f}')
print(f'Recall: {recall_knn_optm:.4f}')
print(f'Precision: {precision_knn_optm:.4f}')
print(f'F1-score: {f1_knn_optm:.4f}')
print(classification_report(y_test_transformed, y_pred_best_knn))

# Plot confusion matrix
cm_best_knn = confusion_matrix(y_test_transformed, y_pred_best_knn)
plt.figure(figsize=(6,5))
sns.heatmap(cm_best_knn, annot=True, fmt='d', cmap='viridis',
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title('Optimized KNN Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Best k value: 5
Model 8 - K-NN Optm:
Accuracy: 0.8176
Recall: 0.8809
Precision: 0.8331
F1-score: 0.8563
              precision    recall  f1-score   support

         0.0       0.79      0.72      0.75      3940
         1.0       0.83      0.88      0.86      6347

    accuracy                           0.82     10287
   macro avg       0.81      0.80      0.80     10287
weighted avg       0.82      0.82      0.82     10287
```



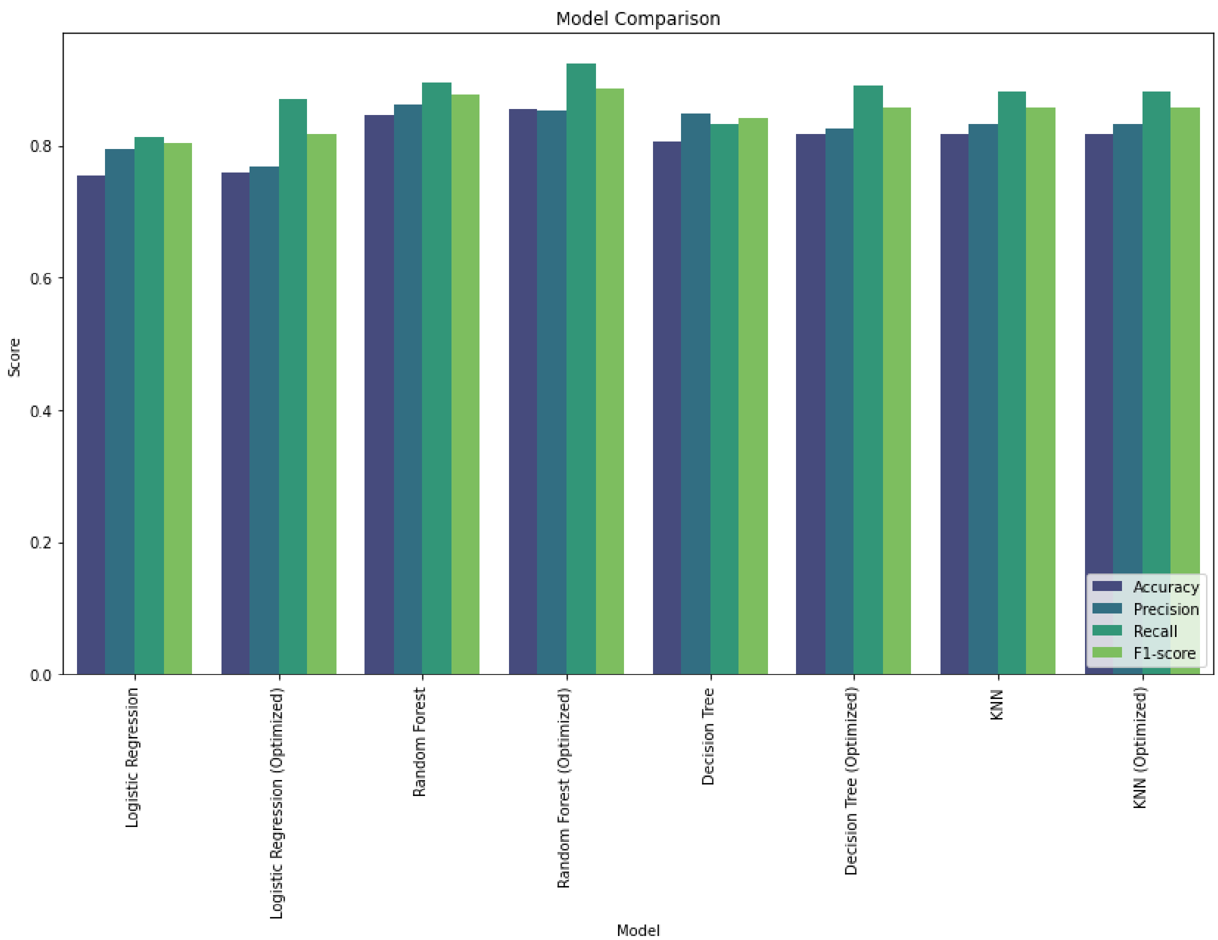
Both K-NN models performed similarly indicating that optimizing k had minimal impact on performance.

EVALUATION

In [391]:
```
# Store model performance
model_results = pd.DataFrame({
    'Model': ['Logistic Regression','Logistic Regression (Optimized)','Random For
    'Accuracy': [accuracy_logreg, accuracy_logreg_optm, accuracy_rf,  accuracy_rf
    'Precision': [precision_logreg, precision_logreg_optm, precision_rf,  precisi
    'Recall': [recall_logreg, recall_logreg_optm, recall_rf,  recall_rf_optm, rec
    'F1-score': [f1_logreg, f1_logreg_optm, f1_rf,  f1_rf_optm, f1_dt, f1_dt_optm
})

# Display comparison table
print(model_results)
```

```
                             Model  Accuracy  Precision    Recall  F1-score
0              Logistic Regression  0.755419   0.795010  0.813298  0.804050
1  Logistic Regression (Optimized)  0.757947   0.767661  0.871435  0.816263
2                    Random Forest  0.846505   0.861212  0.895541  0.878041
3        Random Forest (Optimized)  0.853796   0.851707  0.923901  0.886336
4                    Decision Tree  0.804997   0.848004  0.833307  0.840591
5        Decision Tree (Optimized)  0.816079   0.824661  0.891445  0.856753
6                              KNN  0.817634   0.833110  0.880889  0.856333
7                  KNN (Optimized)  0.817634   0.833110  0.880889  0.856333
```

In [392]:
```
# Bar plot for accuracy, precision, recall and F1 score
# Set figure size
plt.figure(figsize=(14, 8))

# Melt data for easier plotting
model_results_melted = model_results.melt(id_vars='Model', var_name='Metric', val

# Plot
sns.barplot(x='Model', y='Score', hue='Metric', data=model_results_melted, palett
plt.xticks(rotation=90)
plt.title('Model Comparison')
plt.ylabel('Score')
plt.legend(loc='lower right')
plt.show()
```



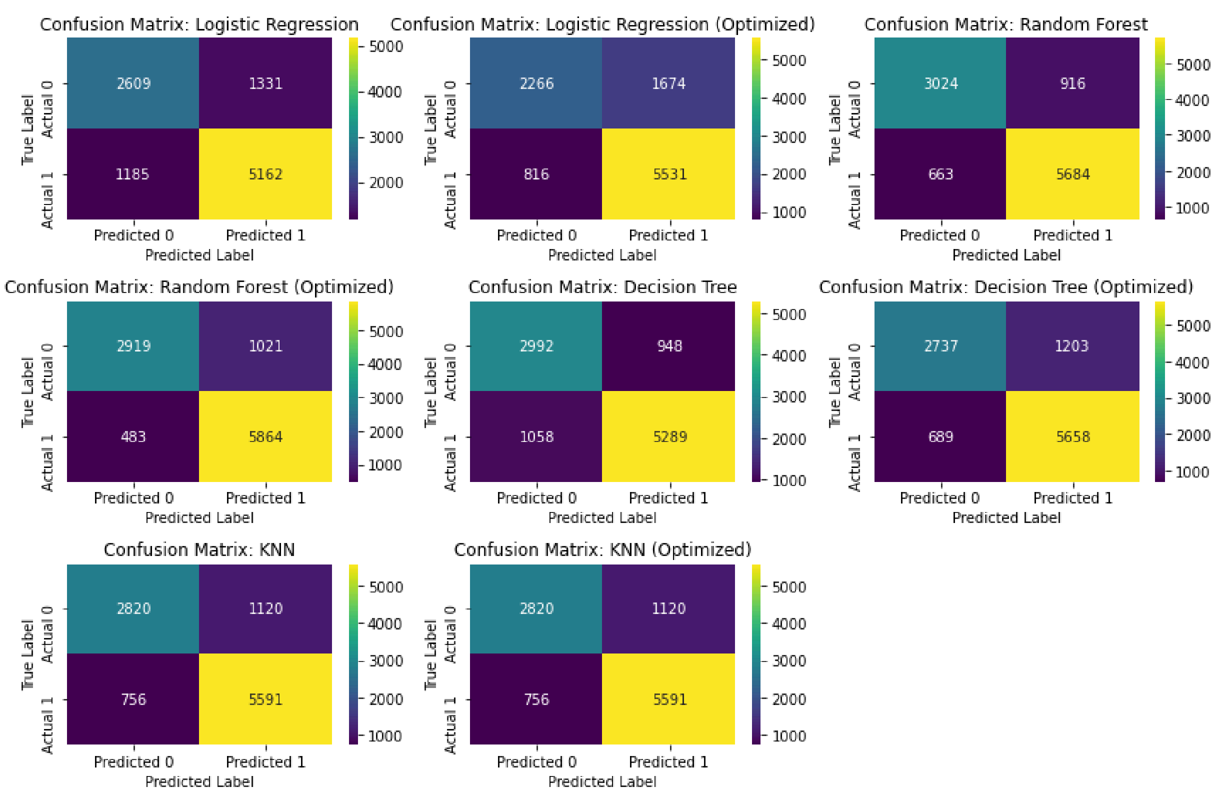
Each of the above models has been evaluated on how well it predicts whether or not a well is functional. From the bar chart above, we can make the following deductions:

1. Optimized models generally outperform their baseline counterparts. This suggests that tuning helped refine decision boundaries and improve model performance.
2. Random Forest (Optimized) performs best overall. It has the highest Recall, which indicates that it effectively identifies wells that are functional or non-functional. High Precision and F1-score also suggest a good balance between correctly identifying functional wells and minimizing false positives.

3. Decision Tree and KNN perform similarly, but not as well as Random Forest.Both models have comparable Accuracy and F1-score but slightly lower Recall than Random Forest. This suggests that while they are effective classifiers, they may misclassify some wells.
4. Logistic Regression has the lowest performance. Logistic Regression, both baseline and optimized, has the lowest scores, especially in Recall. This indicates that it struggles with capturing complex patterns in the dataset, likely due to its linear nature.

Well functionality is likely a complex classification problem requiring non-linear decision boundaries, as Random Forest and Decision Tree models outperform Logistic Regression. Recall is crucial in this context missing out on non-functional wells could mean leaving defective or broken wells in use, leading to water supply issues.
Random Forest is the best choice if the goal is to maximize predictive performance and correctly classify as many wells as possible. This model will help identify which wells are non - functional for

In [393]:
```
# Comparison of the confusion matrices for the various models.
from sklearn.metrics import confusion_matrix

models = ['Logistic Regression','Logistic Regression (Optimized)','Random Forest'
y_preds = [y_pred_logreg, y_pred, y_pred_rf, y_pred_optimized, y_pred_dt, y_pred_

plt.figure(figsize=(12, 10))

for i, (model, y_pred) in enumerate(zip(models, y_preds)):
    cm = confusion_matrix(y_test_transformed, y_pred)

    plt.subplot(4, 3, i + 1)
    sns.heatmap(cm, annot=True, fmt='d', cmap='viridis',
                xticklabels=['Predicted 0', 'Predicted 1'],
                yticklabels=['Actual 0', 'Actual 1'])
    plt.title(f'Confusion Matrix: {model}')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')

plt.tight_layout()
plt.show()
```



Before analysing, let us first take note of the following:

1. Misclassifying a non-functional well as functional could result in communities relying on a faulty water source.
2. If a functional well is misclassified as non-functional, it may lead to unnecessary repairs or neglect.

Random Forest (Optimized) is the most reliable model, making it the best choice for minimizing misclassifications.

It has the lowest false negatives (483) and false positives (1021) compared to other models. It correctly classifies most functional wells (5864 True Positives) and non-functional wells (2919 True Negatives). This suggests that it is the most reliable model for predicting well functionality.

Decision Tree and KNN models perform well also but have higher false negatives. Logistic Regression struggles with classification

CONCLUSIONS

From our analysis, we have concluded the following in line with our objectives:

1. What factors contribute most to well failures? From linear regression and recursive feature elimination, 'quantity', 'waterpoint_type', 'source', 'construction_year', 'payment_type' and 'management_group' stand out as the leading predictors to the functionality of a well.

2. Which regions have the highest concentration of non-functional wells? The geopandas plot has clearly identified a high cluster of non-functional wells in the south east of Tanzania. The government should consider allocating resources towards repair and maintenance in this area, to ensure the residents get good water supply.

3. How does the construction year affect well failure rates? From the line plot, it is clear that more recent wells are more likely to be functional, suggesting improvements in construction quality, materials, and maintenance programs. However, the presence of non-functional wells in all time periods highlights that factors beyond age also play a role in well performance.

MODELING EVALUATION SUMMARY

After modeling a logistic regression, random forest, decision tree, K-NN and their relative optimised models, **The Optimised Random Forest model** stands out as the best performing model with an accuracy-85.38%, recall-92.39%, precision-85.17% and F1-score-88.63%. The best parameters after tuning are max_depth: 20, min_samples_leaf: 1, min_samples_split: 5, and n_estimators: 300.

RECOMMENDATIONS

Further Recommendations for Improvement include:

1. Deeper Analysis of Key Features - Once the most influential factors affecting well functionality are identified, analyze their impact—do they contribute positively or negatively? Understanding these relationships will help the government of Tanzania make informed investment decisions to enhance well longevity.
2. Feature Engineering for Better Insights - Instead of using construction year as a standalone feature, create a new variable, *"well age"*, to better capture the patterns related to functionality. This could improve the model's ability to detect trends over time.

3. Utilization of Test Dataset - Since the Test Dataset; loaded earlier in the data understanding stage; was originally part of the dataset, explore ways to incorporate it during deployment or further analysis. Given that it lacks the target variable, consider leveraging it for validation, unsupervised learning, or as input for semi-supervised techniques.
4. The model could be further analysed as a ternary classification problem to include the 'functional but needs repair' as a category on its own. This will help the client be able to plan