DRIVEN DATA: The Tanzanian Water Crisis

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Overview

Tanzania, as a developing country, struggles with providing clean water to its population of over 57,000,000. There are many water points already established in the country, but some are in need of repair while others have failed altogether. As a result, many people are suffering. In this project, the objective is to dive into this crisis, focusing on the analysis of water well functionality accross the country in order to assess the level of the crisis and explore some possible solutions towards improving the situation for millions of people.

Business Problem:

Almost half the population of Tanzania is without basic access to safe water. Although there are many waterpoints already established in the country, a lot of them are in need of repair while others have failed altogether. It can assist the Tanzanian Ministry of Water on identifying pumps that are in need of repair and/or no longer functional.Understanding which pumps will fail and which will not may help improve maintenance operations and ensure that clean water is available to people residing in Tanzania. Note that this is a ternary classification problem by default, but can be engineered to be binary. Stakeholder: Ministry of Water and Irrigation,Goverment of Tanzania.

Dataset

The dataset provided on [https://www.drivendata.org/ (https://www.drivendata.org/)](https://www.drivendata.org/) by Taarifa and the Tanzanian Ministry of Water.

For this dataset, there are two subsections to the problem description:

Features

- List of features

Labels

- List of labels

The features in this dataset are:

- amount_tsh - Total static head (amount water available to waterpoint)
- date_recorded - The date the row was entered

- funder - Who funded the well
- gps_height - Altitude of the well
- installer - Organization that installed the well
- longitude - GPS coordinate
- latitude - GPS coordinate
- wpt_name - Name of the waterpoint if there is one
- num_private -
- basin - Geographic water basin
- subvillage - Geographic location
- region - Geographic location
- region_code - Geographic location (coded)
- district_code - Geographic location (coded)
- lga - Geographic location
- ward - Geographic location
- population - Population around the well
- public_meeting - True/False
- recorded_by - Group entering this row of data
- scheme_management - Who operates the waterpoint
- scheme_name - Who operates the waterpoint
- permit - If the waterpoint is permitted
- construction_year - Year the waterpoint was constructed
- extraction_type - The kind of extraction the waterpoint uses
- extraction_type_group - The kind of extraction the waterpoint uses
- extraction_type_class - The kind of extraction the waterpoint uses
- management - How the waterpoint is managed
- management_group - How the waterpoint is managed
- payment - What the water costs
- payment_type - What the water costs
- water_quality - The quality of the water
- quality_group - The quality of the water
- quantity - The quantity of water
- quantity_group - The quantity of water
- source - The source of the water
- source_type - The source of the water
- source_class - The source of the water
- waterpoint_type - The kind of waterpoint
- waterpoint_type_group - The kind of waterpoint

The labels in this dataset:

- Functional
- Non Functional
- Functional but needs repair.

Data Structure, Selection & Transformation:

The raw dataset contains 60,000 water pumps and 40 different features. Combining feature selection and engineering we reduced the dataset to 14 features. We are using Functional / Non-Functional/Functional but needs repair as our target. We made some additional small features changes to simplify the dataset detailed in the Main jupyter notebook.

Methods

Cleaning and Feature Engineering

This project uses data cleaning and feature engineering to also addressed the class imbalance between classes we have used SMOTE. We also cleaned up our data, as there were missing values in multiple columns. For example, if "construction year" of the waterpoint had a missing value, we filled that value with the mean construction year of all waterpoints within that given region. We also engineered one column "age" to equal the age of the waterpoint when the data was collected. Cleaning our data and building these features helped make our model more interpretable and significant.

Models Development

Classification was used in order to predict the status level of a pump. We trained four separate classifier models: K-Nearest Neighbor, Decision Trees,Random Forest, and XGBoost. Knn was our simplest model, and we tuned our models to get the best results.

Results

Our simplest model,XGBoost came back with a confusion matrix that produced a 82% accuracy score and a 86% precision score. For our purposes, we were looking to maximize precision as we want to reduce the amount of False positives (predicting the pump as non-functional when it is functional).

Importing the libraries.

In [1]:
```
#import libraries
import pandas as pd
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import matplotlib.ticker as mtick
import seaborn as sns
from scipy import stats
import numpy as np
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE
from sklearn.impute import KNNImputer
from sklearn.metrics import precision_score, recall_score, accuracy_sc
from sklearn.metrics import roc_curve, auc
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn import tree
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from sklearn import svm
from sklearn.metrics import f1_score, balanced_accuracy_score, plot_cc
```

Import the data

In [2]:
```
#obtain the data and read the file.
df = pd.read_csv('Tanzanian_WellDataset.csv', index_col= False)
df
```

Out[2]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latit
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825
...	...	...	...	...	...	...	...	
59395	60739	10.0	2013-05-03	Germany Republi	1210	CES	37.169807	-3.253
59396	27263	4700.0	2011-05-07	Cefa-njombe	1212	Cefa	35.249991	-9.070
59397	37057	0.0	2011-04-11	NaN	0	NaN	34.017087	-8.750
59398	31282	0.0	2011-03-08	Malec	0	Musa	35.861315	-6.378
59399	26348	0.0	2011-03-23	World Bank	191	World	38.104048	-6.747

59400 rows × 41 columns

In [3]:

```
#Selecting 20000,rows of the dataframe.
df = df.iloc[:20000,:]
df
```

Out[3]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847
...	...	...	...	...	...	...	...
19995	49338	100.0	2013-01-23	Concern	196	CONCERN	39.495034
19996	36601	0.0	2013-01-21	Fini Water	260	FINI WATER	38.954102
19997	13299	0.0	2013-02-24	Netherlands	0	DWE	33.591385
19998	57089	0.0	2012-10-17	Government Of Tanzania	0	Government	33.103730
19999	61035	0.0	2013-03-03	Danida	872	DANIDA	36.047885

20000 rows × 41 columns

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     20000 non-null  int64  
 1   amount_tsh             20000 non-null  float64
 2   date_recorded          20000 non-null  object 
 3   funder                 18778 non-null  object 
 4   gps_height             20000 non-null  int64  
 5   installer              18768 non-null  object 
 6   longitude              20000 non-null  float64
 7   latitude               20000 non-null  float64
 8   wpt_name               20000 non-null  object 
 9   num_private            20000 non-null  int64  
 10  basin                  20000 non-null  object 
 11  subvillage             19877 non-null  object 
 12  region                 20000 non-null  object 
 13  region_code            20000 non-null  int64  
 14  district_code          20000 non-null  int64  
 15  lga                    20000 non-null  object 
 16  ward                   20000 non-null  object 
 17  population             20000 non-null  int64  
 18  public_meeting         18861 non-null  object 
 19  recorded_by            20000 non-null  object 
 20  scheme_management      18668 non-null  object 
 21  scheme_name            10438 non-null  object 
 22  permit                 18969 non-null  object 
 23  construction_year      20000 non-null  int64  
 24  extraction_type        20000 non-null  object 
 25  extraction_type_group  20000 non-null  object 
 26  extraction_type_class  20000 non-null  object 
 27  management             20000 non-null  object 
 28  management_group       20000 non-null  object 
 29  payment                20000 non-null  object 
 30  payment_type           20000 non-null  object 
 31  water_quality          20000 non-null  object 
 32  quality_group          20000 non-null  object 
 33  quantity               20000 non-null  object 
 34  quantity_group         20000 non-null  object 
 35  source                 20000 non-null  object 
 36  source_type            20000 non-null  object 
 37  source_class           20000 non-null  object 
 38  waterpoint_type        20000 non-null  object 
 39  waterpoint_type_group  20000 non-null  object 
 40  status_group           20000 non-null  object 
dtypes: float64(3), int64(7), object(31)
memory usage: 6.3+ MB
```

In [5]:
```
#checking for null values:
df.isna().sum()
```

Out[5]:
```
id                          0
amount_tsh                  0
date_recorded               0
funder                   1222
gps_height                  0
installer                1232
longitude                   0
latitude                    0
wpt_name                    0
num_private                 0
basin                       0
subvillage                123
region                      0
region_code                 0
district_code               0
lga                         0
ward                        0
population                  0
public_meeting           1139
recorded_by                 0
scheme_management        1332
scheme_name              9562
permit                   1031
construction_year           0
extraction_type             0
extraction_type_group       0
extraction_type_class       0
management                  0
management_group            0
payment                     0
payment_type                0
water_quality               0
quality_group               0
quantity                    0
quantity_group              0
source                      0
source_type                 0
source_class                0
waterpoint_type             0
waterpoint_type_group       0
status_group                0
dtype: int64
```

Exploratory Data Analysis:

I will investigate the data, drop the columns that I will not be using and exploring the other features/columns of the dataset.

In [6]:
```
#dropping the columns with the missing values:
df = df.drop(columns=['installer','subvillage','public_meeting','schem
df
```

Out[6]:

	id	amount_tsh	date_recorded	funder	gps_height	longitude	latitude	wp
0	69572	6000.0	2011-03-14	Roman	1390	34.938093	-9.856322	
1	8776	0.0	2013-03-06	Grumeti	1399	34.698766	-2.147466	
2	34310	25.0	2013-02-25	Lottery Club	686	37.460664	-3.821329	
3	67743	0.0	2013-01-28	Unicef	263	38.486161	-11.155298	Na
4	19728	0.0	2011-07-13	Action In A	0	31.130847	-1.825359	
...	...	...	...	...	...	...	...	
19995	49338	100.0	2013-01-23	Concern	196	39.495034	-10.278200	Kil
19996	36601	0.0	2013-01-21	Fini Water	260	38.954102	-9.976577	
19997	13299	0.0	2013-02-24	Netherlands	0	33.591385	-3.149213	
19998	57089	0.0	2012-10-17	Government Of Tanzania	0	33.103730	-3.915889	M
19999	61035	0.0	2013-03-03	Danida	872	36.047885	-10.617697	M

20000 rows × 35 columns

In [7]:
```
#dropping the columns that I won't be using:
df = df.drop(columns=['water_quality','quantity_group','extraction_typ
df
```

Out[7]:

	id	amount_tsh	date_recorded	funder	gps_height	longitude	latitude	wp
0	69572	6000.0	2011-03-14	Roman	1390	34.938093	-9.856322	
1	8776	0.0	2013-03-06	Grumeti	1399	34.698766	-2.147466	
2	34310	25.0	2013-02-25	Lottery Club	686	37.460664	-3.821329	
3	67743	0.0	2013-01-28	Unicef	263	38.486161	-11.155298	Na
4	19728	0.0	2011-07-13	Action In A	0	31.130847	-1.825359	
...	...	...	...	...	...	...	...	
19995	49338	100.0	2013-01-23	Concern	196	39.495034	-10.278200	Kil
19996	36601	0.0	2013-01-21	Fini Water	260	38.954102	-9.976577	
19997	13299	0.0	2013-02-24	Netherlands	0	33.591385	-3.149213	
19998	57089	0.0	2012-10-17	Government Of Tanzania	0	33.103730	-3.915889	M
19999	61035	0.0	2013-03-03	Danida	872	36.047885	-10.617697	M

20000 rows × 26 columns

In [8]:
```
#Checking for null values.
df.isna().sum()
```

Out[8]:
```
id                          0
amount_tsh                  0
date_recorded               0
funder                   1222
gps_height                  0
longitude                   0
latitude                    0
wpt_name                    0
basin                       0
region                      0
region_code                 0
district_code               0
lga                         0
ward                        0
population                  0
recorded_by                 0
construction_year           0
extraction_type_class       0
management                  0
```

Exploring the columns:

Target variable:

Let's have a look at the target.

In [9]:
```
df['status_group'].value_counts()
```

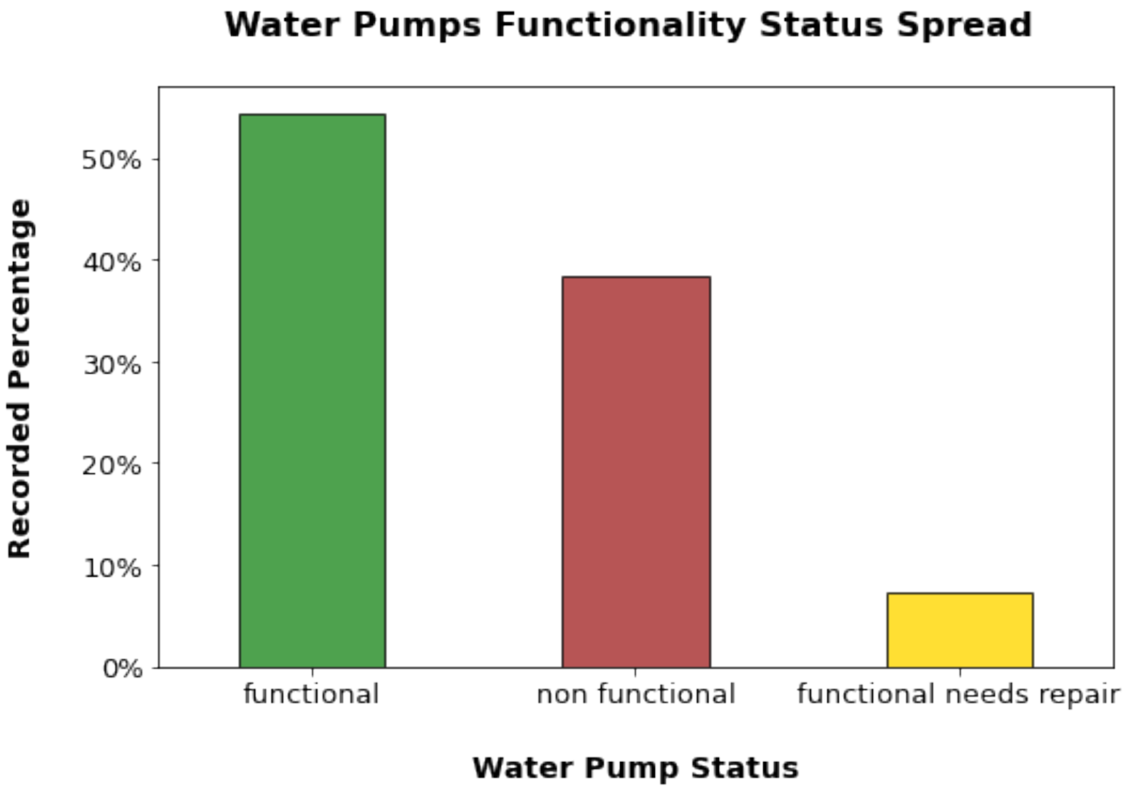
Out[9]:
```
functional                 10878
non functional              7680
functional needs repair     1442
Name: status_group, dtype: int64
```

In [10]:
```
df.status_group.value_counts(normalize=True)
```

Out[10]:
```
functional                 0.5439
non functional             0.3840
functional needs repair    0.0721
Name: status_group, dtype: float64
```

The master training set contains 59364 entries and 40 columns, with the target variable being status_group. This dataset has some class imbalances that would have to be addressed during modeling. Although this is a ternary dataset, one class "functional" takes up 54.3% of the whole training dataset, while "functional needs repair" is only 7.2%.

In [11]:
```
#Plot the status _group spread
ax = df.status_group.value_counts(normalize = True).plot(kind = 'bar',
                                                         color = ['for
                                                         edgecolor = '

#Format x- and y-axis
plt.xticks(fontsize = 13,  rotation = 0)
plt.xlabel('\nWater Pump Status', fontweight = 'bold', fontsize = 14 )
ax.yaxis.set_major_formatter(mtick.PercentFormatter(1.0))
plt.yticks(fontsize = 13)
plt.ylabel('Recorded Percentage\n', fontweight = 'bold', fontsize = 14

#Format plot
plt.title('Water Pumps Functionality Status Spread \n', fontsize = 16,
plt.savefig("status_spread.png")
```



In [12]:
```
df.describe()
```

Out[12]:

	id	amount_tsh	gps_height	longitude	latitude	region_code
count	20000.00000	20000.000000	20000.00000	20000.000000	2.000000e+04	20000.000000
mean	37007.70645	325.394430	666.81270	34.111313	-5.715622e+00	15.480050
std	21580.96974	3459.998068	693.17267	6.554726	2.948522e+00	17.892049
min	0.00000	0.000000	-63.00000	0.000000	-1.158630e+01	1.000000
25%	18314.75000	0.000000	0.00000	33.103252	-8.569859e+00	5.000000
50%	36892.50000	0.000000	364.00000	34.912733	-5.034241e+00	12.000000
75%	55895.50000	20.000000	1320.00000	37.210297	-3.325097e+00	17.000000
max	74246.00000	350000.000000	2770.00000	40.345193	-2.000000e-08	99.000000

Let's have a look at the amount of water in the well: amount_tsh

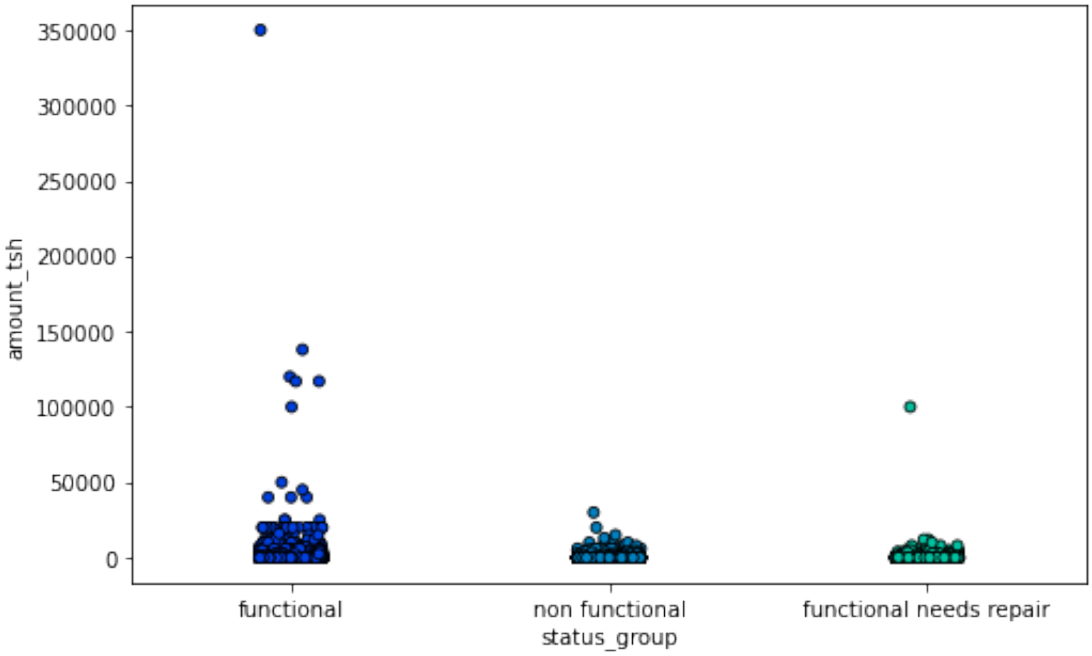
In [13]:
```
#looking at amount of water equal to zero.
df[df.amount_tsh == 0].status_group.value_counts(normalize=True)
```

Out[13]:
```
functional                 0.473756
non functional             0.453947
functional needs repair    0.072297
Name: status_group, dtype: float64
```

In [14]:
```
len(df[df.amount_tsh == 0])
```

Out[14]:
```
13984
```

In [15]:
```
#Plot to see the amount of water left.
fig, ax = plt.subplots(figsize = (8, 5))
sns.stripplot(x = 'status_group', y = 'amount_tsh', data = df, edgecol
              palette = "winter");
plt.savefig("status_group.png")
```



Lets look at construction year:

In [16]:
```
len(df[df.construction_year == 0])/len(df)
```

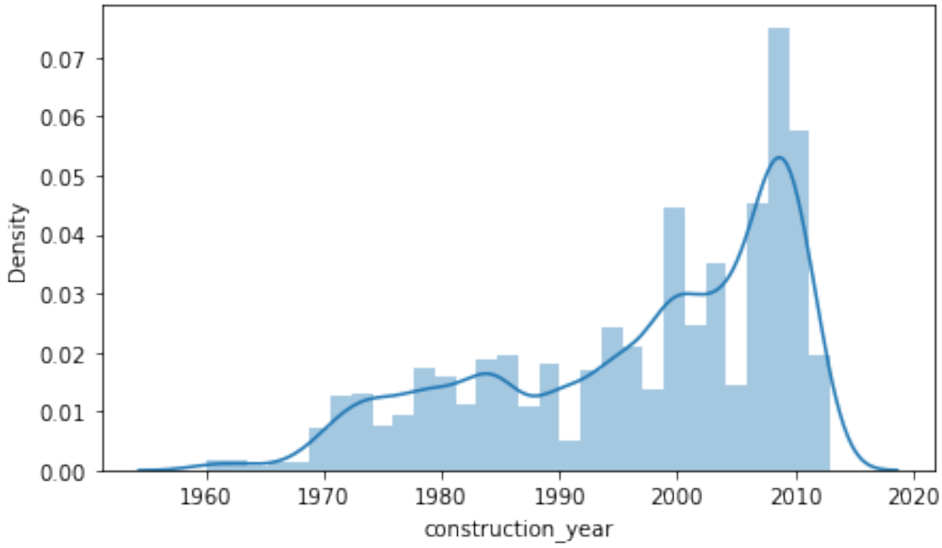
Out[16]:
```
0.3478
```

In [17]:
```
df[df.construction_year != 0].construction_year.describe()
```

Out[17]:
```
count    13044.000000
mean      1996.787182
std         12.583458
min       1960.000000
25%       1987.000000
50%       2000.000000
75%       2008.000000
max       2013.000000
Name: construction_year, dtype: float64
```

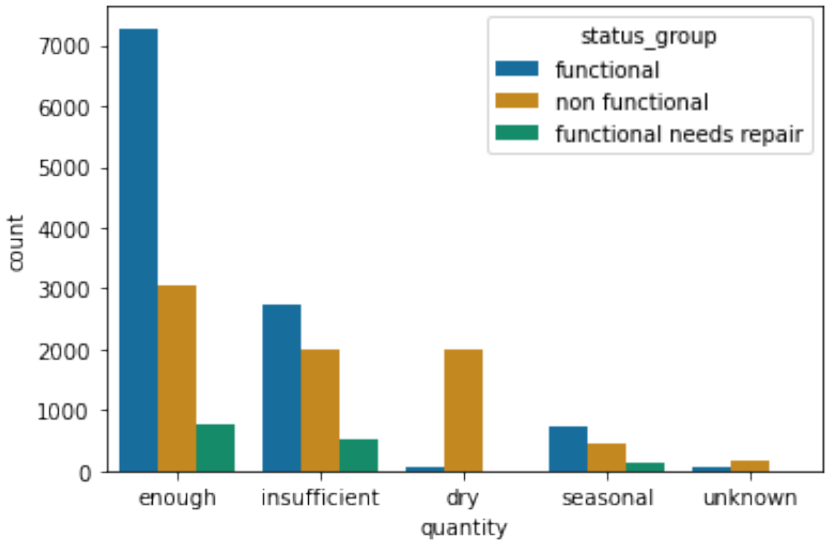
In [18]:
```
#Plot to see the construction yr of wells.
plt.figure(figsize=(7,4))
sns.distplot(df[df.construction_year != 0].construction_year);
```

```
/Users/Ravinder/opt/anaconda3/envs/learn-env/lib/python3.8/site-pack
ages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a d
eprecated function and will be removed in a future version. Please a
dapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histo
grams).
  warnings.warn(msg, FutureWarning)
```



Let's have a look at quanity of water in the wells:

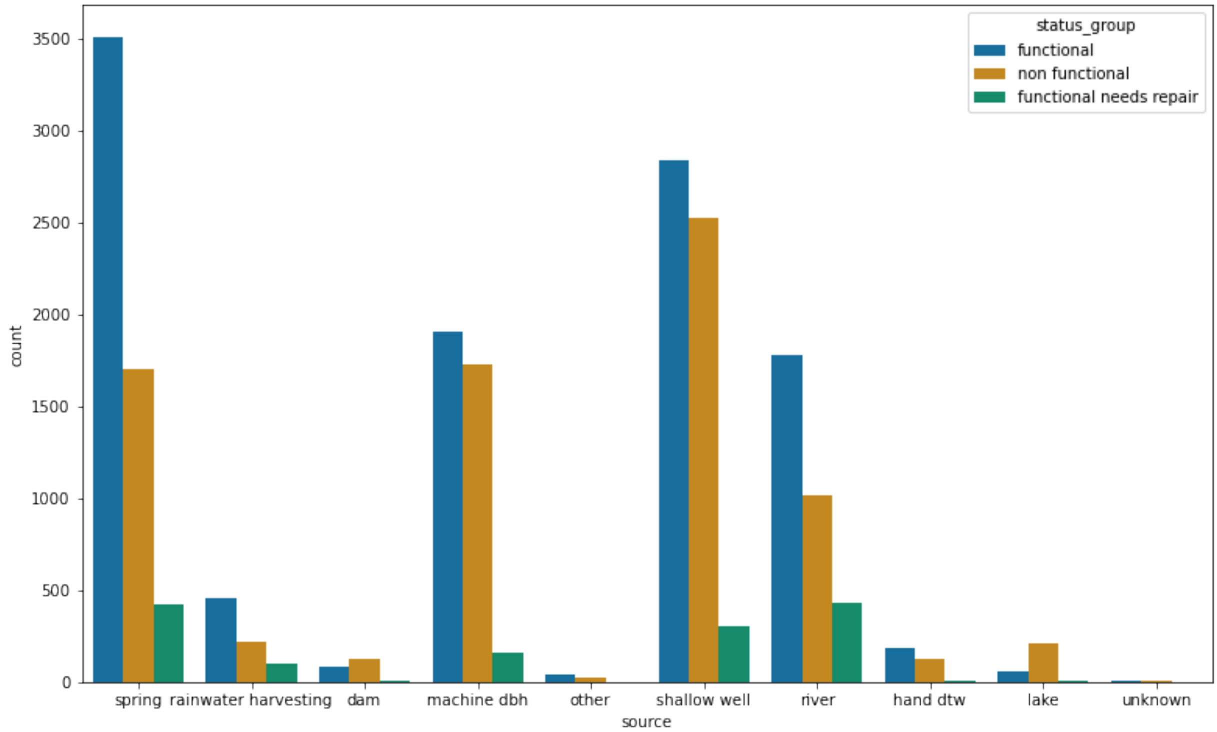
In [19]:
```
ax = sns.countplot(x='quantity', hue="status_group", data=df,palette =
plt.savefig('Quantity_left.png')
```



It can be observed that although there are enough water quantity in some wells, they are non-functional. When looking at this graph, dry quantity water points have a highly correlation with non-functionality. If the water point is dry or unknown, there is high chance thw water point is non functional. On the other hand, if the quantity is enough, there is a higher chance to find functional water points.

let's look at the source of the wells:

In [20]:
```
#Plotting to see source and their status
plt.figure(figsize=(13,8))
ax = sns.countplot(x='source', hue="status_group", data=df,palette = "
plt.savefig('Source.png')
```



Looking at funder of the wells:

In [21]:
```
#Counting the unque values.
df['funder'].value_counts().head(10)
```

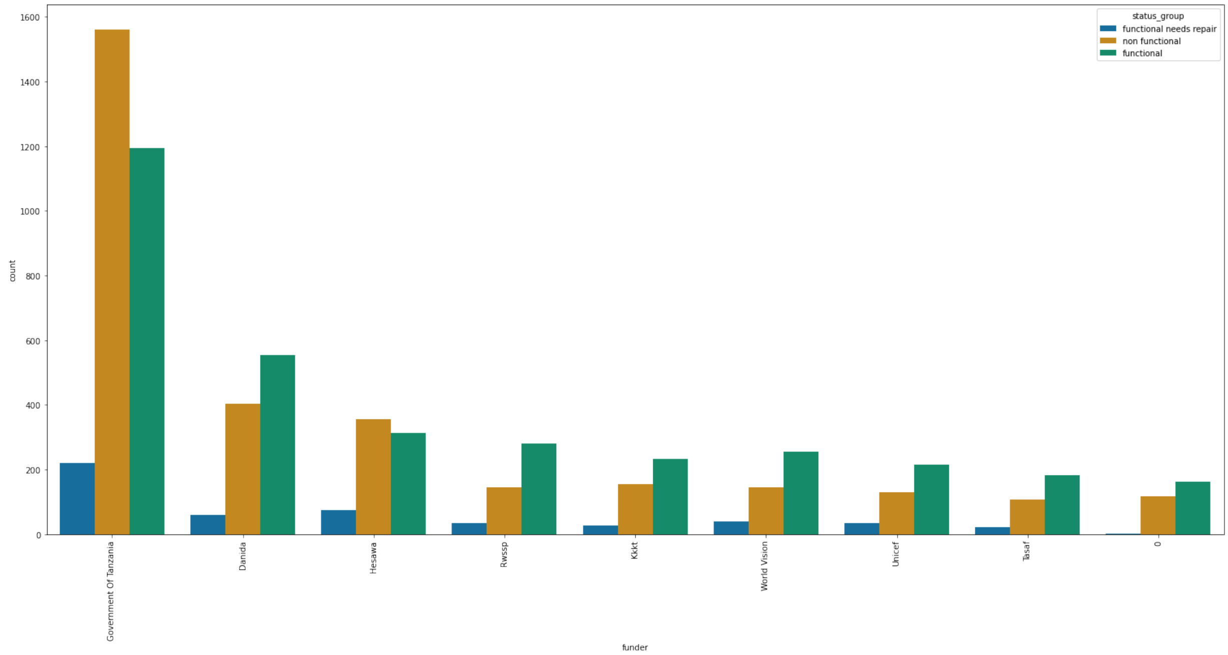
Out[21]:
```
Government Of Tanzania    2975
Danida                    1015
Hesawa                     742
Rwssp                      459
World Bank                 452
World Vision               438
Kkkt                       413
Unicef                     379
Tasaf                      310
0                          280
Name: funder, dtype: int64
```

This column is highly categorical column with thousands different values. So, we will take most common 10 values for future encoding.

In [22]:
```
df1 = df.loc[df['funder']== 'Government Of Tanzania']
df2 = df.loc[df['funder']== 'Danida']
df3 = df.loc[df['funder']== 'Hesawa']
df4 = df.loc[df['funder']== 'Rwssp']
df5 = df.loc[df['funder']== 'World']
df6 = df.loc[df['funder']== 'Kkkt']
df7 = df.loc[df['funder']== 'World Vision']
df8 = df.loc[df['funder']== 'Unicef']
df9 = df.loc[df['funder']== 'Tasaf']
df10 = df.loc[df['funder']== '0']
df_funder = pd.concat([df1,df2,df3,df4,df5,df6,df7,df8,df9,df10], ignc
```

In [23]:
```
#Plotting the funder of the wells.
plt.figure(figsize=(26,12))
ax = sns.countplot(x='funder', hue="status_group", data=df_funder,pale
ax.set_xticklabels(ax.get_xticklabels(),rotation=90)
```

Out[23]:
```
[Text(0, 0, 'Government Of Tanzania'),
 Text(1, 0, 'Danida'),
 Text(2, 0, 'Hesawa'),
 Text(3, 0, 'Rwssp'),
 Text(4, 0, 'Kkkt'),
 Text(5, 0, 'World Vision'),
 Text(6, 0, 'Unicef'),
 Text(7, 0, 'Tasaf'),
 Text(8, 0, '0')]
```



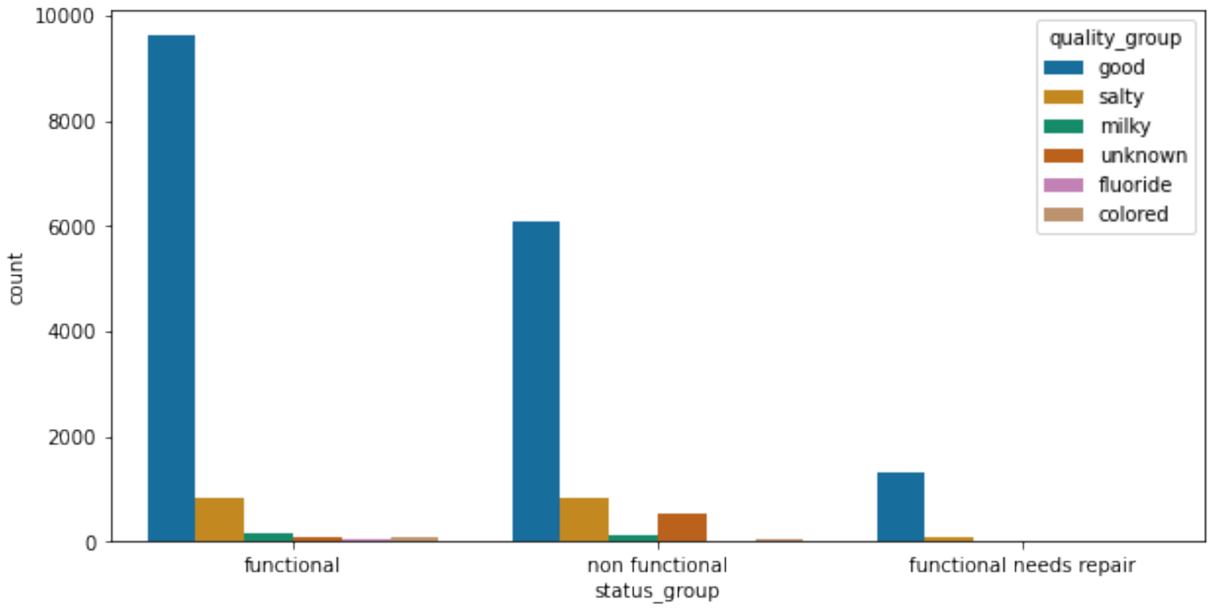
From the above plot, we realize that most of the water points which funded by government are non-functional.

Let's have a look at water quality in the wells:

In [24]:
```
df['quality_group'].value_counts()
```

Out[24]:
```
good        17040
salty        1775
unknown       650
milky         282
colored       176
fluoride       77
Name: quality_group, dtype: int64
```

In [25]:
```
plt.figure(figsize=(10,5))
ax = sns.countplot(x='status_group', hue="quality_group", data=df,pale
plt.savefig("Water_Quality.png")
```

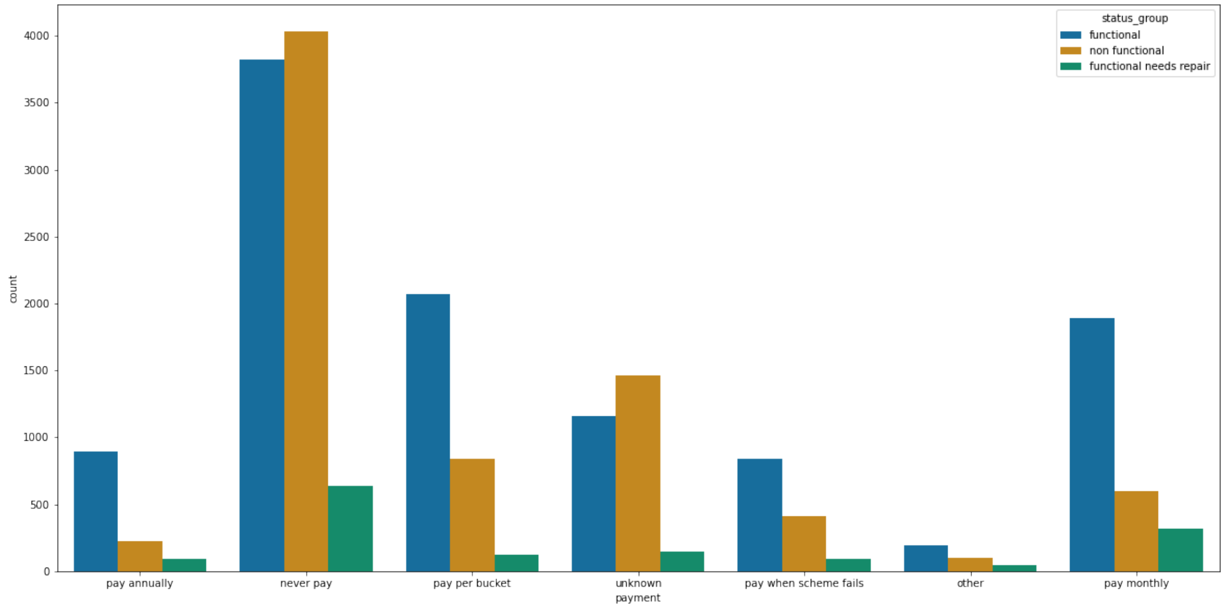


Lets's check which wells are well maintained which take payment.

In [26]:
```
df['payment'].value_counts()
```

Out[26]:
```
never pay               8492
pay per bucket          3035
pay monthly             2809
unknown                 2768
pay when scheme fails   1342
pay annually            1213
other                    341
Name: payment, dtype: int64
```

In [27]:
```
plt.figure(figsize=(20,10))
ax = sns.countplot(x='payment', hue="status_group", data=df,palette =
plt.savefig("Payemnt.png")
```



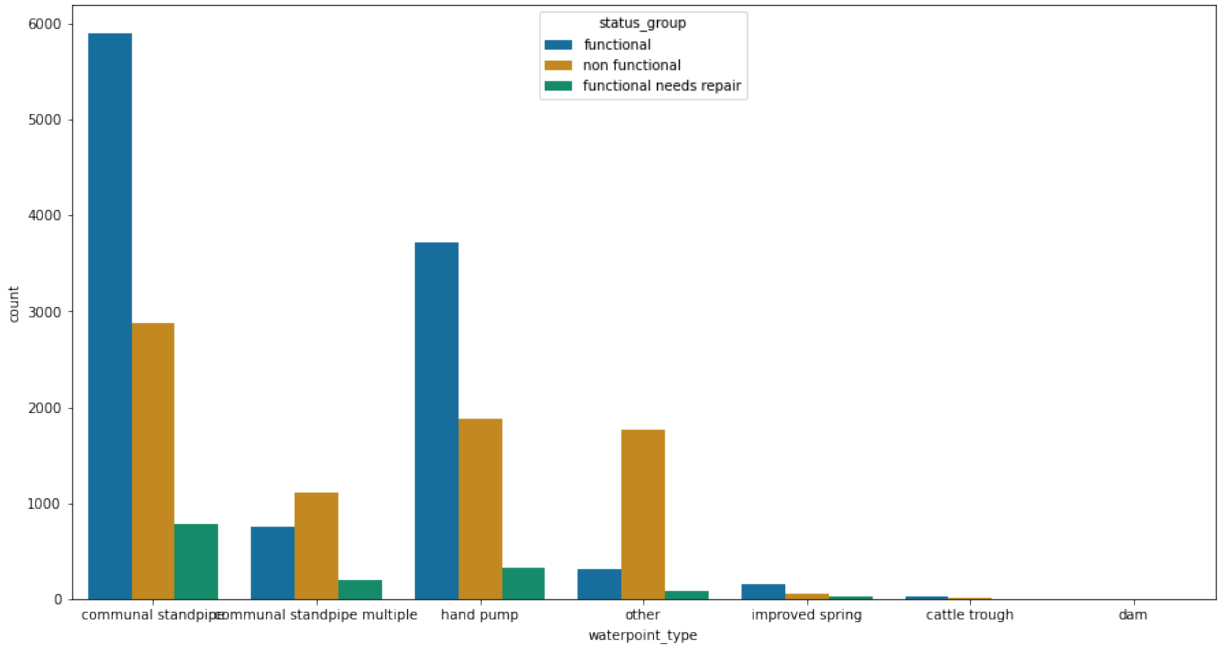
This feature shows us what the water cost. Mostly, there are lots of non-functional water points as nobody ever paid for them.

Which waterpoint_type's are the most functional:

In [28]:
```
df['waterpoint_type'].value_counts()
```

Out[28]:
```
communal standpipe             9559
hand pump                      5926
other                          2159
communal standpipe multiple    2069
improved spring                 246
cattle trough                    37
dam                               4
Name: waterpoint_type, dtype: int64
```

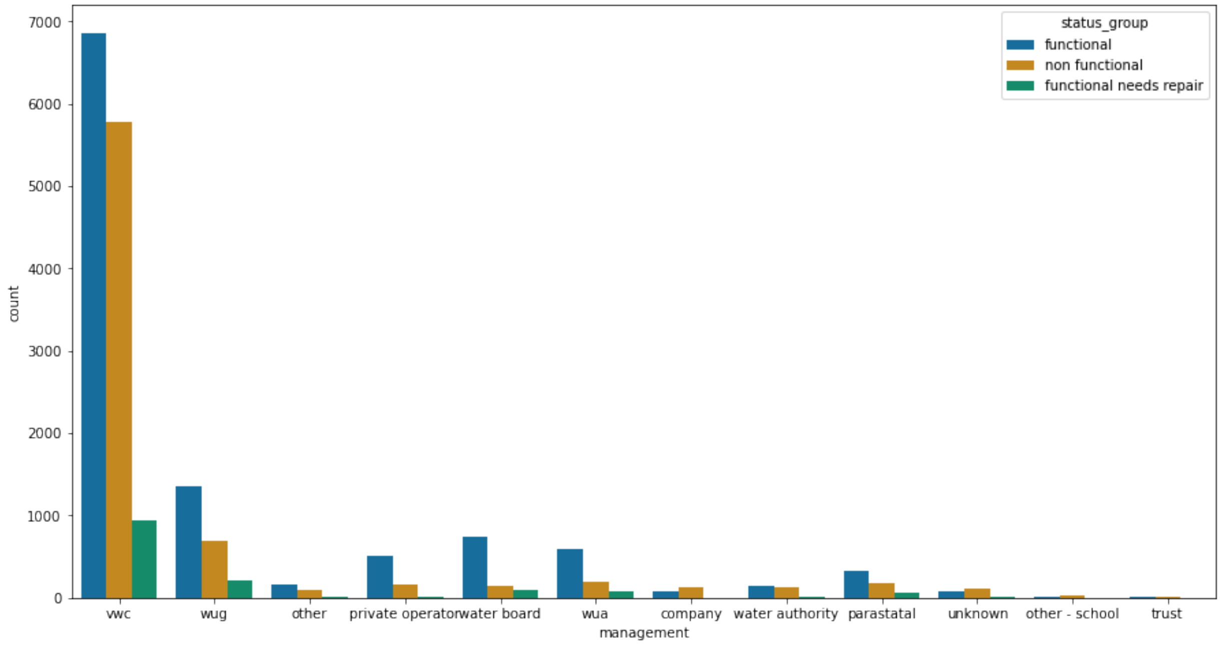
In [29]:
```
#plotting watertype with status_group
plt.figure(figsize=(15,8))
ax = sns.countplot(x='waterpoint_type', hue="status_group", data=df,pa
plt.savefig("Waterpoint_type.png")
```



It can be seen that waterpoint type has correlation with funtionality of water points. Such that, communal standpipe has higher possibility to have functional, although communal standpipe multiple and others have higher possibility for non-functionality.

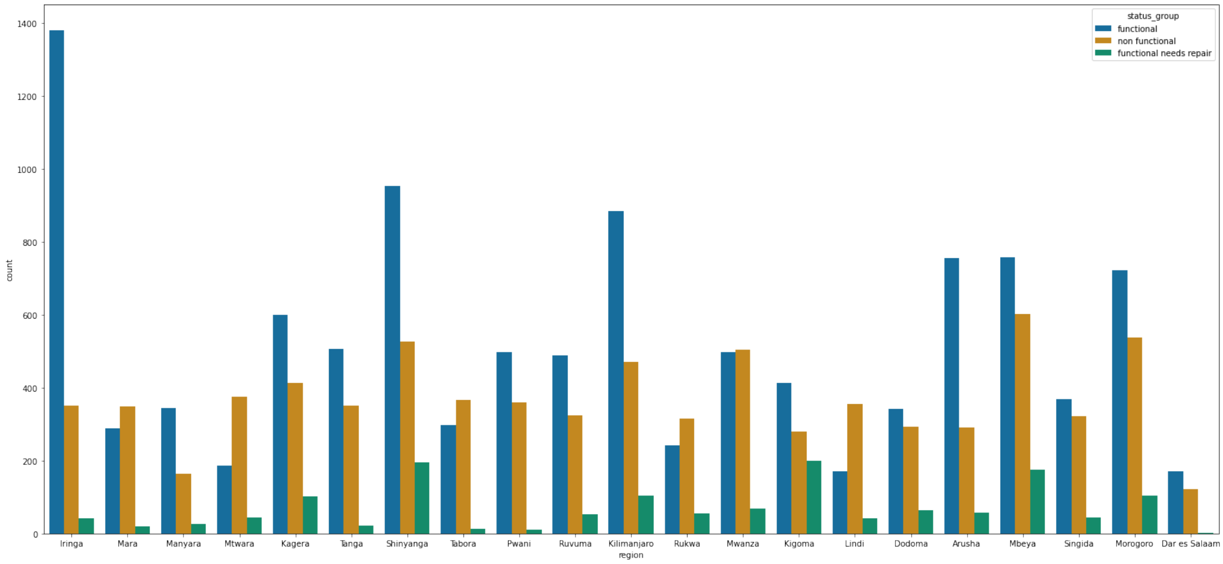
Which management company is maintaining most functional wells.

In [30]:
```
#plotting management.
plt.figure(figsize=(15,8))
ax = sns.countplot(x='management', hue="status_group", data=df,palette
plt.savefig("management.png")
```



Let's have a look at region column:

In [31]:
```
plt.figure(figsize=(26,12))
ax = sns.countplot(x='region', hue="status_group", data=df,palette = "
plt.savefig("Region.png")
```



Some regions has higher probability of functional water well. Klimanjaro and Arusha have Pangani basin which has higher water point between basins. It is also seen that they have higher portions for functional wells.

In [32]:
```
#taking a look at iringa it has the most functional wells.
df_iringa =df.loc[df['region']=='Iringa'] #to see the Iringa area
df_iringa
```

Out[32]:

	id	amount_tsh	date_recorded	funder	gps_height	longitude	latitude	wpt_na
0	69572	6000.0	2011-03-14	Roman	1390	34.938093	-9.856322	n
16	48451	500.0	2011-07-04	Unicef	1703	34.642439	-9.106185	Kwa J Mte
17	58155	0.0	2011-09-04	Unicef	1656	34.569266	-9.085515	Kwa R Cha
19	18274	500.0	2011-02-22	Danida	1763	34.508967	-9.894412	n
20	48375	200.0	2011-02-27	Twe	2216	34.473430	-9.594990	n
...	...	...	...	...	...	...	...	
19931	56712	2000.0	2011-02-25	Anglican Church	1862	35.931047	-8.267362	n
19943	55720	500.0	2011-04-16	Roman Catholic	1853	34.747690	-9.174723	K Sair Ki
19954	64171	2500.0	2011-03-15	Shipo	1608	34.760365	-8.922258	K Sin Mg
19960	65913	100.0	2011-02-18	Unice	2277	34.059099	-9.193125	n
19983	24666	2400.0	2011-03-17	Danida	1631	34.980971	-8.591899	n

1776 rows × 26 columns

Looking at population column:

In [33]:
```
df['population'].value_counts()
```

Out[33]:
```
0       7172
1       2403
200      659
150      633
250      580
        ...
1831       1
232        1
296        1
344        1
663        1
Name: population, Length: 719, dtype: int64
```

In [34]:
```
df.loc[df['population']==0].groupby('status_group').count()
```

Out[34]:

	id	amount_tsh	date_recorded	funder	gps_height	longitude	latitude	wpt_
status_group								
functional	3802	3802	3802	3406	3802	3802	3802	
functional needs repair	590	590	590	473	590	590	590	
non functional	2780	2780	2780	2592	2780	2780	2780	

3 rows × 25 columns

Some functional water points has zero population, it is weird so we will change zero population to mean

In [35]:
```
# to see without zero mean and median
df.loc[df['population']!=0].describe()
```

Out[35]:

	id	amount_tsh	gps_height	longitude	latitude	region_code
count	12828.000000	12828.000000	12828.000000	12828.000000	12828.000000	12828.000000
mean	36979.809635	460.885999	965.511927	36.119379	-6.163819	16.307686
std	21521.490357	4287.380875	615.241504	2.571485	2.736845	21.965966
min	1.000000	0.000000	-63.000000	29.612507	-11.586297	2.000000
25%	18398.250000	0.000000	341.000000	34.728677	-8.478582	4.000000
50%	36899.000000	0.000000	1126.000000	36.753321	-5.860612	10.000000
75%	55638.250000	100.000000	1468.000000	38.007032	-3.623242	16.000000
max	74246.000000	350000.000000	2770.000000	40.345193	-1.094797	99.000000

In [36]:
```
#replacing 0's with mean:
df['population'].replace(to_replace = 0 , value =278, inplace=True)
```

In [37]:
```
df.sort_values(by='population', ascending=False).head(100).groupby('st
```

Out[37]:

	id	amount_tsh	date_recorded	funder	gps_height	longitude	latitude	wpt_na
status_group								
functional	62	62	62	60	62	62	62	
functional needs repair	3	3	3	2	3	3	3	
non functional	35	35	35	34	35	35	35	

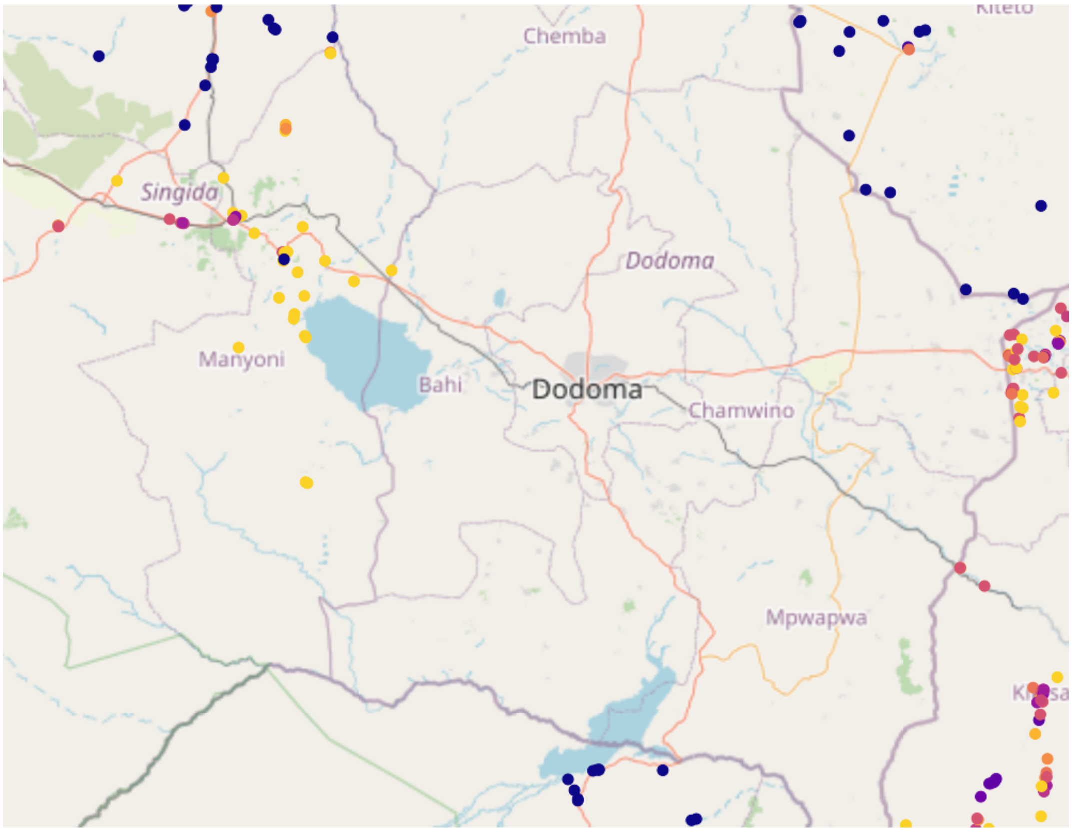
3 rows × 25 columns

In [38]:
```
df['population'].mean()
```

Out[38]: 278.5583

To see the most populated areas water point functionality , we did groupby. It shows that higher population areas have more functional water points

In [39]:
```
#creating a scatter plot to see where population around the well lies.
import plotly.express as px
fig = px.scatter_mapbox(df[df['population'] < 278],
                        lat='latitude',
                        lon='longitude',
                        color='population',
                        zoom=7)
fig.update_layout(mapbox_style='open-street-map')
plt.savefig('Population_around_well.pdf')
fig.show()
```



<Figure size 432x288 with 0 Axes>

In [40]:
```
#checking quality of water:
df_iringa.groupby(['quality_group','status_group']).count()
```

Out[40]:

quality_group	status_group	id	amount_tsh	date_recorded	funder	gps_height	longitude
good	functional	1376	1376	1376	1374	1376	1376
	functional needs repair	42	42	42	42	42	42
	non functional	333	333	333	333	333	333
salty	functional	5	5	5	5	5	5
	non functional	4	4	4	4	4	4
unknown	functional	1	1	1	1	1	1
	non functional	15	15	15	15	15	15

When we looked at the Iringa area which has higher water points. There are also 333 wells which has soft, good water but non-functional.

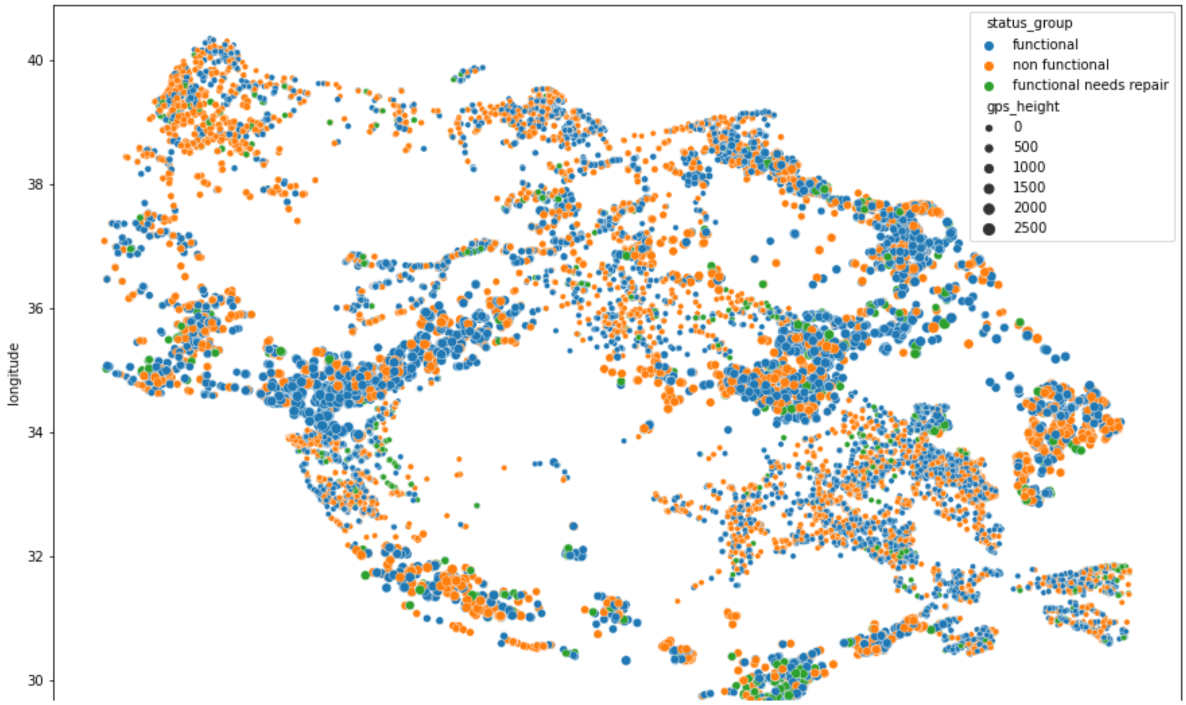
basin column:

In [41]:
```
df['basin'].value_counts()
```

Out[41]:
```
Lake Victoria              3449
Pangani                    3030
Rufiji                     2655
Internal                   2626
Lake Tanganyika            2152
Wami / Ruvu                2019
Lake Nyasa                 1657
Ruvuma / Southern Coast    1595
Lake Rukwa                  817
Name: basin, dtype: int64
```

Plotting gps_height with status_group:

In [42]:
```
fig, ax = plt.subplots(figsize=(15,10))
sns.scatterplot(data=df[df.longitude >= 25], x='latitude', y='longitud
                    size='gps_height', hue='status_group', ax=ax);
plt.savefig('HeightofWell')
```



We can see that waterpoints are more densely distributed in some regions that in others.

There seems to be a high amount of non functional wells in the Southeast and Northwest regions of Tanzania. Also, there are some large open spaces without any waterpoints being recorded. In addition, visually we can also see that more of the "larger" waterpoints (meaning they're higher in altitude gps_height) have been recorded as functional.

Let's have a look at categorical features:

Checking all the unique and missing values of each column:

We will create a function and check for the unique and missing values.

In [136]:
```
#Cretaing the function.
def checking_unique_missing(list):
    '''
    check the Feature Name, Number of Unique Values, Number of Missing V

    '''
    for i in list:
        print("Feature Name:", i)
        print("Number of Unique Values:", len(df[i].unique()))
        print("Unique Values:", df[i].unique())
        print("Missing Values:", df[i].isna().sum())
        print('\n')
```

In [44]:
```
checking_unique_missing(['extraction_type_class','payment','quality_gr
```

```
Feature Name: extraction_type_class
Number of Unique Values: 7
Unique Values: ['gravity' 'submersible' 'handpump' 'other' 'motorpum
p' 'wind-powered'
 'rope pump']
Missing Values: 0


Feature Name: payment
Number of Unique Values: 7
Unique Values: ['pay annually' 'never pay' 'pay per bucket' 'unknown
'
 'pay when scheme fails' 'other' 'pay monthly']
Missing Values: 0


Feature Name: quality_group
Number of Unique Values: 6
Unique Values: ['good' 'salty' 'milky' 'unknown' 'fluoride' 'colored
']
Missing Values: 0


Feature Name: quantity
Number of Unique Values: 5
Unique Values: ['enough' 'insufficient' 'dry' 'seasonal' 'unknown']
Missing Values: 0


Feature Name: source
Number of Unique Values: 10
Unique Values: ['spring' 'rainwater harvesting' 'dam' 'machine dbh'
'other'
 'shallow well' 'river' 'hand dtw' 'lake' 'unknown']
Missing Values: 0
```

```
Feature Name: source_class
Number of Unique Values: 3
Unique Values: ['groundwater' 'surface' 'unknown']
Missing Values: 0


Feature Name: waterpoint_type
Number of Unique Values: 7
Unique Values: ['communal standpipe' 'communal standpipe multiple' '
hand pump' 'other'
 'improved spring' 'cattle trough' 'dam']
Missing Values: 0


Feature Name: management
Number of Unique Values: 12
Unique Values: ['vwc' 'wug' 'other' 'private operator' 'water board'
'wua' 'company'
 'water authority' 'parastatal' 'unknown' 'other - school' 'trust']
Missing Values: 0


Feature Name: region
Number of Unique Values: 21
Unique Values: ['Iringa' 'Mara' 'Manyara' 'Mtwara' 'Kagera' 'Tanga'
'Shinyanga' 'Tabora'
 'Pwani' 'Ruvuma' 'Kilimanjaro' 'Rukwa' 'Mwanza' 'Kigoma' 'Lindi' 'D
odoma'
 'Arusha' 'Mbeya' 'Singida' 'Morogoro' 'Dar es Salaam']
Missing Values: 0


Feature Name: basin
Number of Unique Values: 9
Unique Values: ['Lake Nyasa' 'Lake Victoria' 'Pangani' 'Ruvuma / Sou
thern Coast'
 'Internal' 'Lake Tanganyika' 'Wami / Ruvu' 'Rufiji' 'Lake Rukwa']
Missing Values: 0


Feature Name: region_code
Number of Unique Values: 26
Unique Values: [11 20 21 90 18  4 17 14 60 10  3 15 19 16 80  1  6
2 12 13  5  7 99 24
  9  8]
Missing Values: 0


Feature Name: district_code
Number of Unique Values: 19
Unique Values: [ 5  2  4 63  1  8  3  6 43  7 23 33 53 62 60 30 13
0 80]
Missing Values: 0
```

In [45]:
```
df.describe()
```

Out[45]:

	id	amount_tsh	gps_height	longitude	latitude	region_code
count	20000.00000	20000.000000	20000.00000	20000.000000	2.000000e+04	20000.000000
mean	37007.70645	325.394430	666.81270	34.111313	-5.715622e+00	15.480050
std	21580.96974	3459.998068	693.17267	6.554726	2.948522e+00	17.892049
min	0.00000	0.000000	-63.00000	0.000000	-1.158630e+01	1.000000
25%	18314.75000	0.000000	0.00000	33.103252	-8.569859e+00	5.000000
50%	36892.50000	0.000000	364.00000	34.912733	-5.034241e+00	12.000000
75%	55895.50000	20.000000	1320.00000	37.210297	-3.325097e+00	17.000000
max	74246.00000	350000.000000	2770.00000	40.345193	-2.000000e-08	99.000000

Let's have a look at the continous features:

For the date_recorded column,I will split it into year,date and month.

The idea is to calculate the age of the well by: date_recorded - construction year

In [46]:
```
#Tidy up the date-yr-month into separate columns
df[["year", "month", "day"]] = df["date_recorded"].str.split("-", expa
df
```

Out[46]:

	id	amount_tsh	date_recorded	funder	gps_height	longitude	latitude	v
0	69572	6000.0	2011-03-14	Roman	1390	34.938093	-9.856322	
1	8776	0.0	2013-03-06	Grumeti	1399	34.698766	-2.147466	
2	34310	25.0	2013-02-25	Lottery Club	686	37.460664	-3.821329	
3	67743	0.0	2013-01-28	Unicef	263	38.486161	-11.155298	N
4	19728	0.0	2011-07-13	Action In A	0	31.130847	-1.825359	
...	...	...	...	...	...	...	...	

In [47]:
```
df['construction_year'].value_counts()
```

Out[47]:
```
0       6956
2010     917
2008     893
2009     838
2000     706
2007     538
2006     504
2003     449
2011     410
2012     390
2002     366
2004     362
1978     349
2005     335
1995     318
1999     318
1998     317
1990     317
1985     296
1980     285
1984     264
1996     259
1982     257
1972     243
1994     241
1974     238
1997     227
```

```
2001     199
1992     197
1993     191
1983     173
1975     171
1988     157
1986     152
1970     146
1976     141
1991     115
1989     104
1987      97
1981      81
1977      74
1973      61
2013      59
1979      53
1971      48
1960      38
1968      35
1967      31
1963      26
1969      21
1964      15
1962      13
1961       4
1965       3
1966       2
Name: construction_year, dtype: int64
```

In [48]:
```
df.describe()
```

Out[48]:

	id	amount_tsh	gps_height	longitude	latitude	region_code
count	20000.00000	20000.000000	20000.00000	20000.000000	2.000000e+04	20000.000000
mean	37007.70645	325.394430	666.81270	34.111313	-5.715622e+00	15.480050
std	21580.96974	3459.998068	693.17267	6.554726	2.948522e+00	17.892049
min	0.00000	0.000000	-63.00000	0.000000	-1.158630e+01	1.000000
25%	18314.75000	0.000000	0.00000	33.103252	-8.569859e+00	5.000000
50%	36892.50000	0.000000	364.00000	34.912733	-5.034241e+00	12.000000
75%	55895.50000	20.000000	1320.00000	37.210297	-3.325097e+00	17.000000
max	74246.00000	350000.000000	2770.00000	40.345193	-2.000000e-08	99.000000

Since, construction_year has lot of 0 values,to find the approx age of the wells,I am filling the 0 values with the median of the value: 1986, we will assume these wells are constructed after 1986.

In [49]:
```
df['construction_year']=df['construction_year'].replace(0,1986)
df
```

Out[49]:

	id	amount_tsh	date_recorded	funder	gps_height	longitude	latitude	wp
0	69572	6000.0	2011-03-14	Roman	1390	34.938093	-9.856322	
1	8776	0.0	2013-03-06	Grumeti	1399	34.698766	-2.147466	
2	34310	25.0	2013-02-25	Lottery Club	686	37.460664	-3.821329	
3	67743	0.0	2013-01-28	Unicef	263	38.486161	-11.155298	Na
4	19728	0.0	2011-07-13	Action In A	0	31.130847	-1.825359	
...	...	...	...	...	...	...	...	
19995	49338	100.0	2013-01-23	Concern	196	39.495034	-10.278200	Kil
19996	36601	0.0	2013-01-21	Fini Water	260	38.954102	-9.976577	
19997	13299	0.0	2013-02-24	Netherlands	0	33.591385	-3.149213	
19998	57089	0.0	2012-10-17	Government Of Tanzania	0	33.103730	-3.915889	M
19999	61035	0.0	2013-03-03	Danida	872	36.047885	-10.617697	M

20000 rows × 29 columns

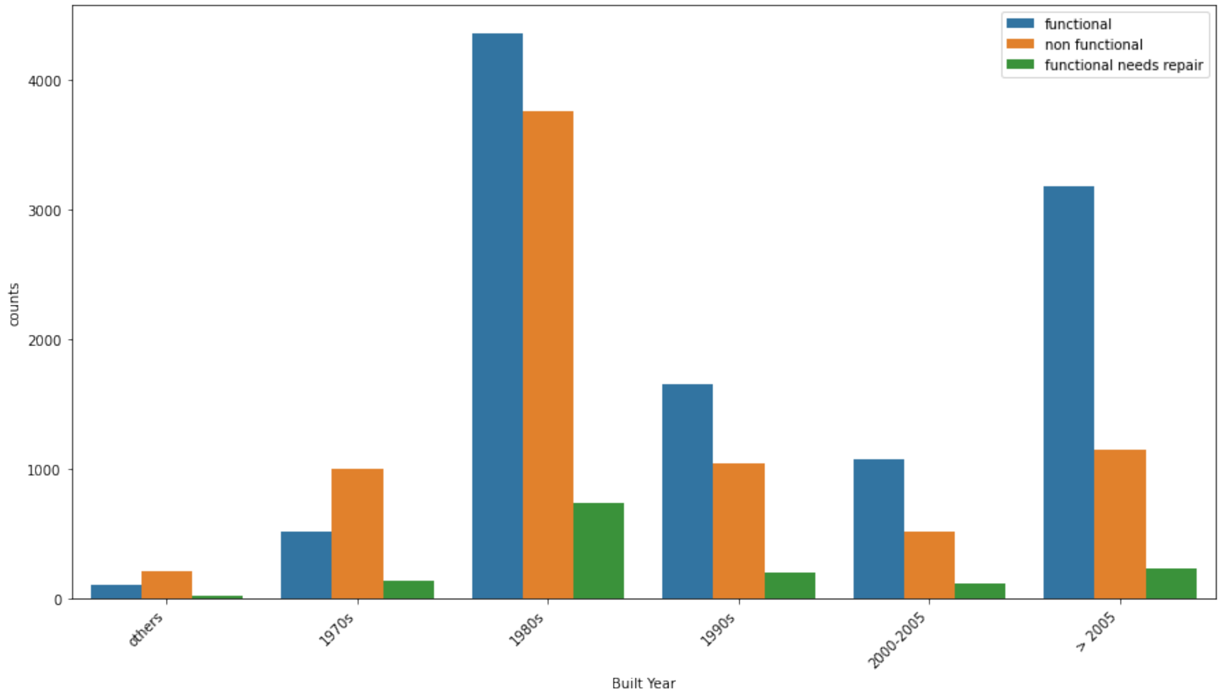
In [50]:
```
#Finding the age of well:
df["Age_of_Well"] = df.apply(lambda x: x['year'] - x['construction_yea
df
```

Out[50]:

	id	amount_tsh	date_recorded	funder	gps_height	longitude	latitude	v
0	69572	6000.0	2011-03-14	Roman	1390	34.938093	-9.856322	
1	8776	0.0	2013-03-06	Grumeti	1399	34.698766	-2.147466	
2	34310	25.0	2013-02-25	Lottery Club	686	37.460664	-3.821329	
3	67743	0.0	2013-01-28	Unicef	263	38.486161	-11.155298	N
4	19728	0.0	2011-07-13	Action In A	0	31.130847	-1.825359	
...	...	...	...	...	...	...	...	

In [51]:
```
#Viewing contruction_yr of wells and binning them:
view_age =[df.construction_year > 2005,
       df.construction_year > 2000,
       df.construction_year > 1990,
       df.construction_year > 1980,
       df.construction_year > 1970]
vals = ['after05', '00s', '90s', '80s', '70s']

df['year_built'] = np.select(view_age, vals, 'others')
```

In [52]:
```
#Plot to view the condition of wells according to their construction_y
fig = plt.figure(figsize = (15,8))

sns.countplot(x = 'year_built', hue = 'status_group', data = df,
              order = ['others', '70s', '80s', '90s', '00s', 'after05'

plt.xticks(rotation = 45, ha = 'right', ticks = range(0, 6),
           labels = ['others', '1970s', '1980s', '1990s', '2000-2005',
plt.xlabel('Built Year')
plt.ylabel('counts')
plt.legend(bbox_to_anchor = [1, 1])
fig.patch.set_visible(False)
plt.savefig("Built_year")

plt.show()
```



It seems condtion of wells built before 1980's is deteriorating and are mostly non-functional.

In [53]:
```
for col in df.columns:
    print(col, '\n', df[col].value_counts(normalize=True).head(), '\n\
```

```
id
 73284    0.00005
53999    0.00005
8929     0.00005
51079    0.00005
35556    0.00005
Name: id, dtype: float64


amount_tsh
 0.0       0.69920
500.0     0.05405
50.0      0.04320
20.0      0.02585
1000.0    0.02500
Name: amount_tsh, dtype: float64


date_recorded
```

Filler values found:

- population - 0 ,1
- construction_year - 0
- payment - unknown
- quality_group - unknown
- quantity - unknown
- extraction_type_class-other
- source_class -unknown
- waterpoint_type - other

Prepping the data:

I will separate continous features and categorical features in order to perform dummy encoding.

In [54]:
```
#choosing columns for our dataset.
df.columns
```

Out[54]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'longitude', 'latitude', 'wpt_name', 'basin', 'region', 'regi
on_code',
       'district_code', 'lga', 'ward', 'population', 'recorded_by',
       'construction_year', 'extraction_type_class', 'management', '
payment',
       'quality_group', 'quantity', 'source', 'source_class',
       'waterpoint_type', 'status_group', 'year', 'month', 'day',
       'Age_of_Well', 'year_built'],
      dtype='object')
```

Dropping the columns that have too many unique values,like region code,district code.

In [55]:
```
#Dropping the columns that don't need.
df_new = df.drop(['status_group','id','date_recorded','longitude','lat
df_new
```

Out[55]:

	amount_tsh	funder	gps_height	basin	region	population	recorded_by	co
0	6000.0	Roman	1390	Lake Nyasa	Iringa	109	GeoData Consultants Ltd	
1	0.0	Grumeti	1399	Lake Victoria	Mara	280	GeoData Consultants Ltd	
2	25.0	Lottery Club	686	Pangani	Manyara	250	GeoData Consultants Ltd	
3	0.0	Unicef	263	Ruvuma / Southern Coast	Mtwara	58	GeoData Consultants Ltd	
4	0.0	Action In A	0	Lake Victoria	Kagera	278	GeoData Consultants Ltd	
...	...	...	...	...	...	...	...	
19995	100.0	Concern	196	Ruvuma / Southern Coast	Lindi	1885	GeoData Consultants Ltd	
19996	0.0	Fini Water	260	Ruvuma / Southern Coast	Lindi	650	GeoData Consultants Ltd	
19997	0.0	Netherlands	0	Lake Victoria	Shinyanga	278	GeoData Consultants Ltd	
19998	0.0	Government Of Tanzania	0	Internal	Shinyanga	278	GeoData Consultants Ltd	
19999	0.0	Danida	872	Ruvuma / Southern Coast	Ruvuma	180	GeoData Consultants Ltd	

20000 rows × 19 columns

In [56]:
```
#Define target
target = df['status_group']
```

In [57]:
```
df_new.columns
```

Out[57]:
```
Index(['amount_tsh', 'funder', 'gps_height', 'basin', 'region', 'pop
ulation',
       'recorded_by', 'construction_year', 'extraction_type_class',
       'management', 'payment', 'quality_group', 'quantity', 'source
',
       'source_class', 'waterpoint_type', 'year', 'Age_of_Well', 'ye
ar_built'],
      dtype='object')
```

In [58]:
```
#Defining categorical and cntinuous features
continous_feats = ['amount_tsh', 'gps_height',
            'population', 'construction_year']
categorical_feats = list(df_new.drop(continous_feats, axis = 1).column
```

In [59]:
```
categorical_feats
```

Out[59]:
```
['funder',
 'basin',
 'region',
 'recorded_by',
 'extraction_type_class',
 'management',
 'payment',
 'quality_group',
 'quantity',
 'source',
 'source_class',
 'waterpoint_type',
 'year',
 'Age_of_Well',
 'year_built']
```

In [60]:
```
#Creating dummy variables:
dummy = pd.get_dummies(df[categorical_feats],drop_first =True)
dummy.shape
```

Out[60]:
```
(20000, 1224)
```

In [61]:
```
#Finalise df_new for modeling
df_new.drop(categorical_feats, axis = 1, inplace = True)
#df_new.drop(to_remove, axis = 1, inplace = True)

df_new = pd.concat ([df_new, dummy], axis = 1)
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Columns: 1228 entries, amount_tsh to year_built_others
dtypes: float64(1), int64(5), uint8(1222)
memory usage: 24.2 MB
```

In [62]:
```
#Let's view this new dataframe
df_new.head(5)
```

Out[62]:

	amount_tsh	gps_height	population	construction_year	year	Age_of_Well	funder_A/co Germany	fu
0	6000.0	1390	109	1999	2011	12	0	
1	0.0	1399	280	2010	2013	3	0	
2	25.0	686	250	2009	2013	4	0	
3	0.0	263	58	1986	2013	27	0	
4	0.0	0	278	1986	2011	25	0	

5 rows × 1228 columns

Modelling the data:

In [63]:
```
#Splitting the data into test,train:
X_train, X_test, y_train, y_test = train_test_split(df_new, target,tes
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[63]: ((15000, 1228), (5000, 1228), (15000,), (5000,))

In [64]:
```
#Instantial StandardScaler
scaler = StandardScaler()

#Transform the train and test sets
X_train = scaler.fit_transform(X_train)
X_test = scaler.fit_transform(X_test)

#Convert to DataFrae
X_train = pd.DataFrame(X_train, columns = df_new.columns)
X_train.head()
```

Out[64]:

	amount_tsh	gps_height	population	construction_year	year	Age_of_Well	funder_A/c German
0	-0.034967	0.843902	-0.626755	0.869737	1.119035	-0.784054	-0.02000
1	-0.085982	1.013189	0.047396	1.483314	1.119035	-1.404733	-0.02000
2	-0.085982	1.237458	-0.563624	1.220353	1.119035	-1.138728	-0.02000
3	0.296630	-0.315063	-0.626755	0.606775	1.119035	-0.518048	-0.02000
4	-0.034967	-0.326638	-0.178073	-0.708033	-0.953508	0.634642	-0.02000

5 rows × 1228 columns

Model Building:

For this project, I will be building several models using different classifiers and then compare the performance metrics to choose the best classifier.

The classifier's the data will be tested on:

- K-Nearest Neighbour
- Decision Tree Classifier
- Random Forest Classifier
- eXtreme Gradient Boosting (XGBoost)

Evaluation Metrics:

- Precision
- Recall
- Accuracy
- F1 Score
- We will also be looking at the confusion matrix.

Creating function to compare scores of all the models:

In [65]:
```
models_scores = pd.DataFrame(columns = ['Model', 'Precision', 'Recall'

# Creating the function
def calculate_scores(model, y_test, test_pred):
    '''
    parameters : (model:classifier model, y true value, y predicted valu

    Save precision, recall, accuracy, and f1 scores to a dataframe
    '''
    global scores_df

    # Calculating test scores
    precision = precision_score(y_test, test_pred, average='weighted')
    recall = recall_score(y_test, test_pred, average='weighted')
    accuracy = accuracy_score(y_test, test_pred)
    f1 = f1_score(y_test, test_pred, average='weighted')

    # Adding the scores into the dataframe
    models_scores.append({'Model':model, 'Precision':precision, 'Recall'
```

Check for Class Imbalance Issue:

In [66]:
```
print(y_train.value_counts(normalize=True))
```

```
functional                 0.5420
non functional             0.3848
functional needs repair    0.0732
Name: status_group, dtype: float64
```

The functional category makes up 54% and the non functional category makes up 38% of the training dataset. The problem lies with the functional needs repair category which make up only 7% of the dataset. Since it is important to address this imbalance we will try to fix this imbalance by using the SMOTE(Synthetic Minority Oversampling) tool.

Using SMOTE

In [67]:
```
#Instantiate and train
smote = SMOTE()

X_smote, y_smote = smote.fit_sample(X_train, y_train)
```

In [68]:
```
print(y_smote.value_counts(normalize=True))
```

```
functional                 0.333333
non functional             0.333333
functional needs repair    0.333333
Name: status_group, dtype: float64
```

Now,the all the categories have the same distribution of 33.33% each.

In [69]:
```
#new test,train,split with smote
X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote,
```

We are starting with KNN as our baseline model.

In [70]:
```
#Instantiate Classifier
KNN = KNeighborsClassifier()

#Fit model
KNN.fit(X_train, y_train)
```

Out[70]:
```
KNeighborsClassifier()
```

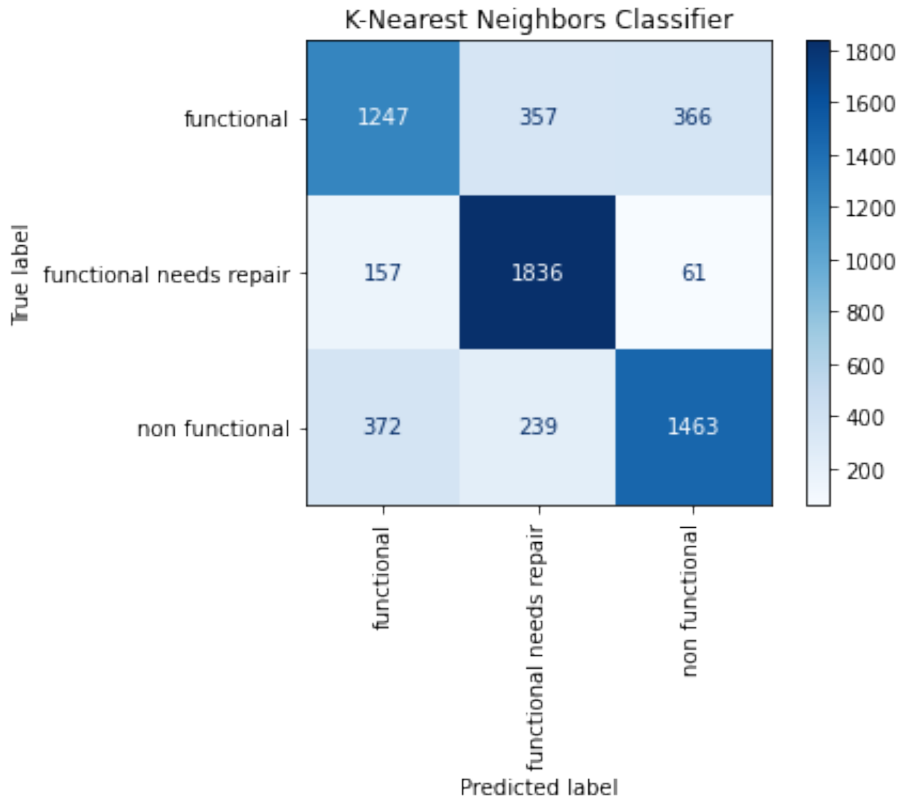
In [71]:
```
#Predict
train_pred = KNN.predict(X_train)
test_pred = KNN.predict(X_test)
```

In [135]:
```
import sklearn.metrics as metrics
from sklearn.metrics import accuracy_score

print(metrics.accuracy_score(y_test, test_pred))
#Print Classification Report
print('Training Data')
print(classification_report(y_train, train_pred))
print('\n')
print('Testing Data')
print(classification_report(y_test, test_pred))
# Update the scores dataframe
calculate_scores('KNN', y_test, test_pred)
```

```
0.8261725155788783
Training Data
                         precision    recall  f1-score   support

             functional       0.81      0.88      0.84      6160
functional needs repair       0.89      0.93      0.91      6076
         non functional       0.91      0.80      0.85      6056

               accuracy                           0.87     18292
              macro avg       0.87      0.87      0.87     18292
           weighted avg       0.87      0.87      0.87     18292



Testing Data
                         precision    recall  f1-score   support

             functional       0.76      0.83      0.79      1970
functional needs repair       0.86      0.91      0.88      2054
         non functional       0.87      0.74      0.80      2074

               accuracy                           0.83      6098
              macro avg       0.83      0.83      0.83      6098
           weighted avg       0.83      0.83      0.83      6098
```

In [73]:
```
#Plot a confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
#plot_confusion_matrix(KNN, X_test, y_test)

disp = plot_confusion_matrix(KNN, X_test, y_test,
                             cmap=plt.cm.Blues,
                             xticks_rotation='vertical')
disp.ax_.set_title('K-Nearest Neighbors Classifier')

print(disp.confusion_matrix)
```

```
[[1247  357  366]
 [ 157 1836   61]
 [ 372  239 1463]]
```



Comments: The K-Nearest Neighbors classifier doesn't seem to perform that well in all the three categories. The performance metrics for the test data is worse than it is for the training data, especially for the 'functional needs repair' category. This perhaps hints at overfitting. If the f-1 score for the 'functional needs repairs' category is low for all models, I would need to pay more attention to the recall score of this category which I believe is a little more imporant than the precision score is for our purpose.

After running the baseline model I will be hypertuning models using GridSearchCv to see how they perform.

Now we will run K-Nearest Neighbors using GridSearchCV.

In [74]:
```
from sklearn.model_selection import GridSearchCV
```

In [76]:
```
param_grid = {
    'n_neighbors' :[1,5,10], # default 5
    'weights': ['uniform','distance'], #default uniform
    'metric':['eculidean','manhattan']
}
knn = KNeighborsClassifier()
grid_search = GridSearchCV(knn, param_grid,verbose =1, cv = 3,scoring
grid_search.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 12 candidates, totalling 36 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent w
orkers.
[Parallel(n_jobs=-1)]: Done  36 out of  36 | elapsed: 11.4min finish
ed
```

Out[76]:
```
GridSearchCV(cv=3, estimator=KNeighborsClassifier(), n_jobs=-1,
             param_grid={'metric': ['eculidean', 'manhattan'],
                         'n_neighbors': [1, 5, 10],
                         'weights': ['uniform', 'distance']},
             scoring='accuracy', verbose=1)
```

In [ ]:
```
grid_search.best_params_
```

In [77]:
```
#tuned knn
knn_tuned = KNeighborsClassifier(n_neighbors = 10,weights ='distance',
knn_tuned.fit(X_train,y_train)
```

Out[77]:
```
KNeighborsClassifier(leaf_size=10, n_neighbors=10, weights='distance
')
```

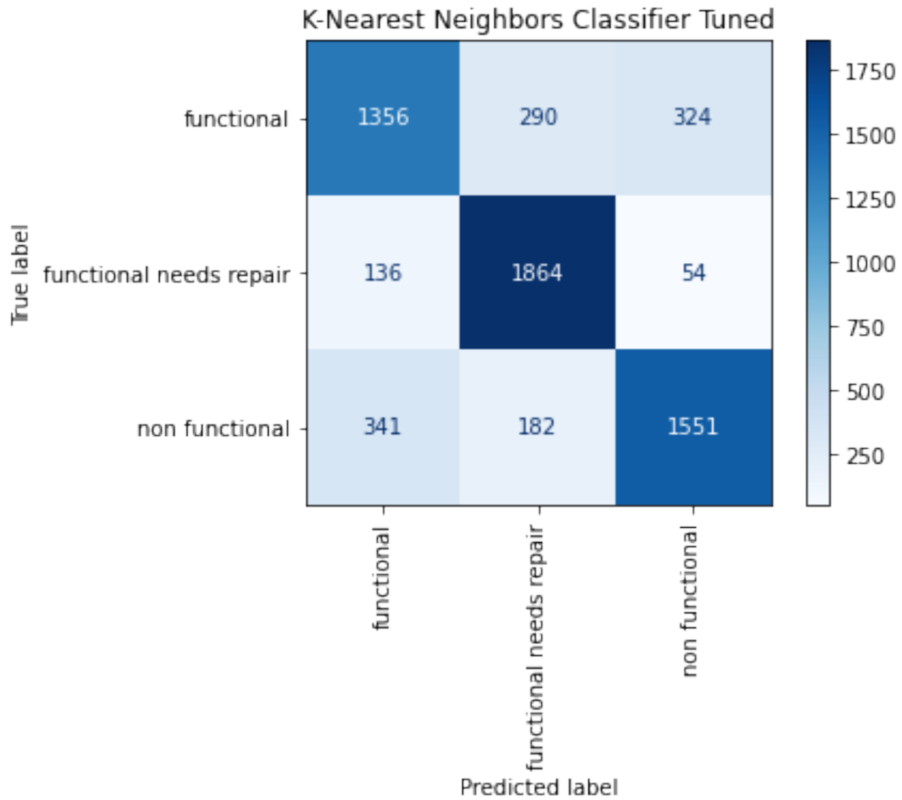
In [78]:
```
#predicting
test_pred = knn_tuned.predict(X_test)
train_pred = knn_tuned.predict(X_train)
```

In [133]:
```
import sklearn.metrics as metrics
from sklearn.metrics import accuracy_score
print(metrics.accuracy_score(y_test, test_pred))
#Print Classification Report
print('Training Data')
print(classification_report(y_train, train_pred))
print('\n')
print('Testing Data')
print(classification_report(y_test, test_pred))
# Update the scores dataframe
calculate_scores('K-Nearest Neighbor tuned', y_test, test_pred)
```

```
0.8261725155788783
Training Data
                         precision    recall  f1-score   support

             functional       0.81      0.88      0.84      6160
functional needs repair       0.89      0.93      0.91      6076
         non functional       0.91      0.80      0.85      6056

               accuracy                           0.87     18292
              macro avg       0.87      0.87      0.87     18292
           weighted avg       0.87      0.87      0.87     18292



Testing Data
                         precision    recall  f1-score   support

             functional       0.76      0.83      0.79      1970
functional needs repair       0.86      0.91      0.88      2054
         non functional       0.87      0.74      0.80      2074

               accuracy                           0.83      6098
              macro avg       0.83      0.83      0.83      6098
           weighted avg       0.83      0.83      0.83      6098


---------------------------------------------------------------------------
NameError                                 Traceback (most recent cal
l last)
<ipython-input-133-5a779c78b499> in <module>
     10 # Update the scores dataframe
     11 calculate_scores('K-Nearest Neighbor tuned', y_test,
test_pred)
---> 12 model_scores

NameError: name 'model_scores' is not defined
```

In [81]:
```
#Plot a confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
#plot_confusion_matrix(KNN, X_test, y_test)

disp = plot_confusion_matrix(knn_tuned, X_test, y_test,
                             cmap=plt.cm.Blues,
                             xticks_rotation='vertical')
disp.ax_.set_title('K-Nearest Neighbors Classifier Tuned')

print(disp.confusion_matrix)
```

```
[[1356  290  324]
 [ 136 1864   54]
 [ 341  182 1551]]
```



Comments: Knn tuned is performing better than the base one in terms to accuracy as well as precision.The no of false positives is less in knn_tuned, for functional needs repair and non functionals are less.

Decision Tree Classifier

The next model we will be taking a look is a single Decision Tree Classifier. I will be performing a grid search for criterion, max_depth, min_samples_split and also min_samples_leaf.

In [82]:
```
from sklearn.model_selection import train_test_split, GridSearchCV, cr
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifie
from sklearn.metrics import accuracy_score
```

In [83]:
```
X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote,
```

In [84]:
```
# Create the classifier, fit it on the training data and make predicti
decision_treeclf = DecisionTreeClassifier(criterion='entropy')

decision_treeclf.fit(X_train, y_train)
```

Out[84]:
```
DecisionTreeClassifier(criterion='entropy')
```

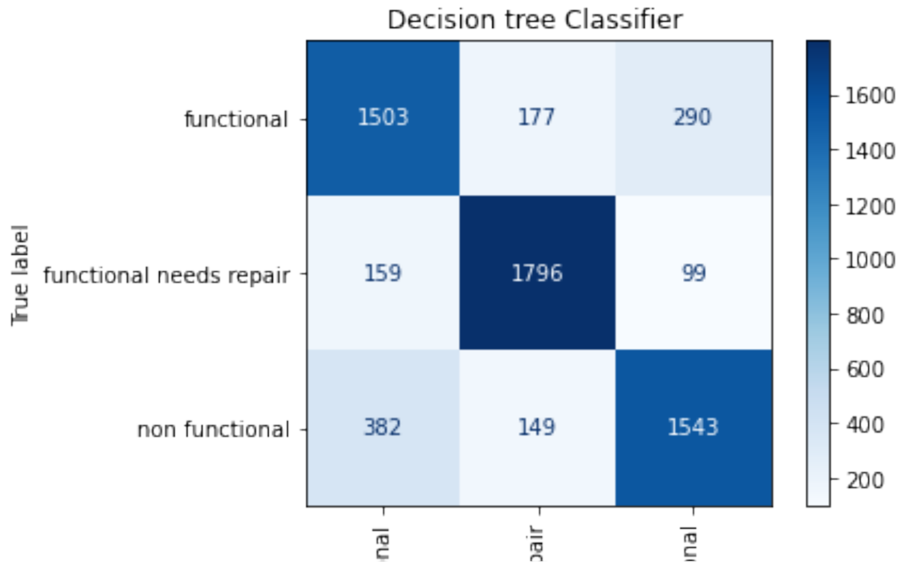
In [85]:
```
test_pred = decision_treeclf.predict(X_test)
train_pred = decision_treeclf.predict(X_train)
```

In [86]:
```
print(metrics.accuracy_score(y_test, test_pred))
#Print Classification Report
print('Training Data')
print(classification_report(y_train, train_pred))
print('\n')
print('Testing Data')
print(classification_report(y_test, test_pred))
# Update the scores dataframe
calculate_scores('Decision Tree', y_test, test_pred)
```

```
0.7940308297802559
Training Data
                         precision    recall  f1-score   support

             functional       0.95      0.97      0.96      6160
functional needs repair       0.96      0.98      0.97      6076
         non functional       0.99      0.95      0.97      6056

               accuracy                           0.97     18292
              macro avg       0.97      0.97      0.97     18292
           weighted avg       0.97      0.97      0.97     18292



Testing Data
                         precision    recall  f1-score   support

             functional       0.74      0.76      0.75      1970
functional needs repair       0.85      0.87      0.86      2054
         non functional       0.80      0.74      0.77      2074

               accuracy                           0.79      6098
              macro avg       0.79      0.79      0.79      6098
           weighted avg       0.79      0.79      0.79      6098
```

In [87]:
```
#Plot a confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
#plot_confusion_matrix(KNN, X_test, y_test)

disp = plot_confusion_matrix(decision_treeclf, X_test, y_test,
                             cmap=plt.cm.Blues,
                             xticks_rotation='vertical')
disp.ax_.set_title('Decision tree Classifier ')

print(disp.confusion_matrix)
```

```
[[1503  177  290]
 [ 159 1796   99]
 [ 382  149 1543]]
```



Decision Tree has performed better than Knn_Tuned in terms of accuracy but in terms of precision and no of false positives, there doesn't seems much improvement.So, we will be tuning it using GridsearchCV to see if those numbers change.

Hyperparameter Tuning of Decision Tree Classifier Using GridSearchCV:

In [89]:
```
#Hypertuning Decision_Tree
dt_clf = DecisionTreeClassifier()

dt_cv_score = cross_val_score(dt_clf, X_train, y_train, cv=3)
mean_dt_cv_score = np.mean(dt_cv_score)

print(f"Mean Cross Validation Score: {mean_dt_cv_score :.2%}")
```

```
Mean Cross Validation Score: 76.96%
```

In [90]:
```
dt_param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 2, 3, 4, 5, 6],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 3, 4, 5, 6]
}
# Instantiate GridSearchCV
dt_grid_search = GridSearchCV(dt_clf, dt_param_grid, cv=3, return_trai

# Fit to the data
dt_grid_search.fit(X_train, y_train)
```

Out[90]:
```
GridSearchCV(cv=3, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [None, 2, 3, 4, 5, 6],
                         'min_samples_leaf': [1, 2, 3, 4, 5, 6],
                         'min_samples_split': [2, 5, 10]},
             return_train_score=True)
```

In [91]:
```
# Mean training score
dt_gs_training_score = np.mean(dt_grid_search.cv_results_['mean_train_

# Mean test score
dt_gs_testing_score = dt_grid_search.score(X_test, y_test)

print(f"Mean Training Score: {dt_gs_training_score :.2%}")
print(f"Mean Test Score: {dt_gs_testing_score :.2%}")
print("Best Parameter Combination Found During Grid Search:")
dt_grid_search.best_params_
```

```
Mean Training Score: 60.86%
Mean Test Score: 79.27%
Best Parameter Combination Found During Grid Search:
```

Out[91]:
```
{'criterion': 'gini',
 'max_depth': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2}
```

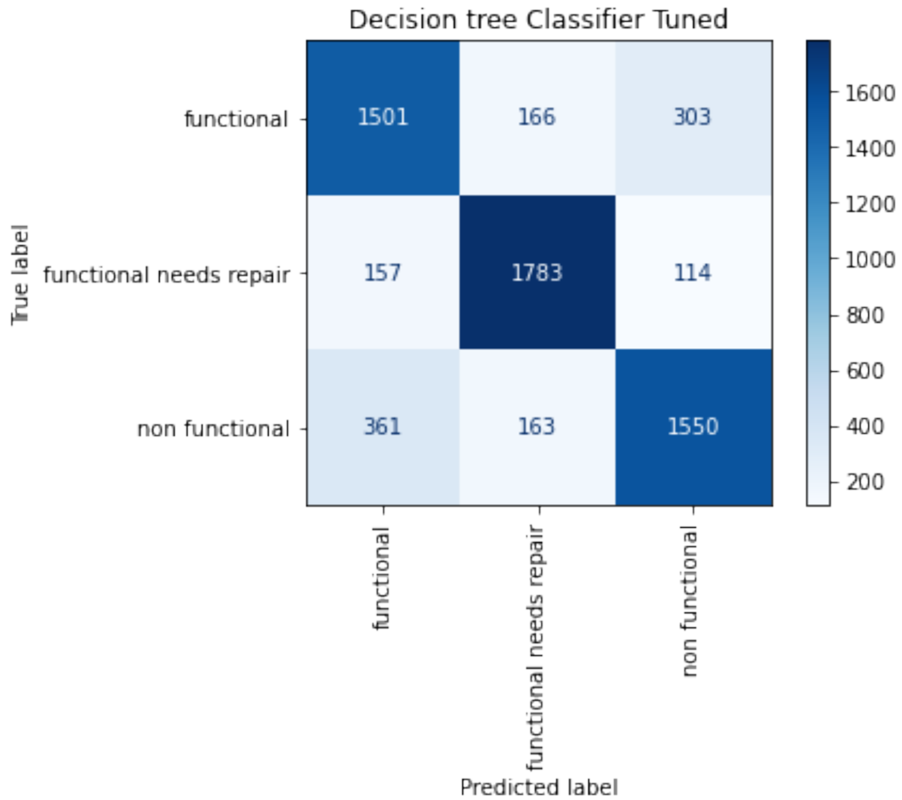
In [92]:
```
test_pred = dt_grid_search.predict(X_test)
train_pred = dt_grid_search.predict(X_train)
```

In [93]:
```
print(metrics.accuracy_score(y_test, test_pred))
#Print Classification Report
print('Training Data')
print(classification_report(y_train, train_pred))
print('\n')
print('Testing Data')
print(classification_report(y_test, test_pred))
# Update the scores dataframe
calculate_scores('Decision Tree tuned', y_test, test_pred)
```

```
0.7927189242374549
Training Data
                         precision    recall  f1-score   support

             functional       0.95      0.97      0.96      6160
functional needs repair       0.96      0.98      0.97      6076
         non functional       0.99      0.95      0.97      6056

               accuracy                           0.97     18292
              macro avg       0.97      0.97      0.97     18292
           weighted avg       0.97      0.97      0.97     18292



Testing Data
                         precision    recall  f1-score   support

             functional       0.74      0.76      0.75      1970
functional needs repair       0.84      0.87      0.86      2054
         non functional       0.79      0.75      0.77      2074

               accuracy                           0.79      6098
              macro avg       0.79      0.79      0.79      6098
           weighted avg       0.79      0.79      0.79      6098
```

In [95]:
```
#Plot a confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
#plot_confusion_matrix(KNN, X_test, y_test)

disp = plot_confusion_matrix(dt_grid_search, X_test, y_test,
                             cmap=plt.cm.Blues,
                             xticks_rotation='vertical')
disp.ax_.set_title('Decision tree Classifier Tuned')

print(disp.confusion_matrix)
```

```
[[1501  166  303]
 [ 157 1783  114]
 [ 361  163 1550]]
```



Decision Tree classifier_Tuned accuracy score is same as the base Decision Tree,doesn't show much improvement.

We will try another classifier.

Random Forest Classifier:

In [96]:
```
#Instantiate RandomForest Classifier
forest = RandomForestClassifier()
```

In [98]:
```
#Use GridSerchCV to determine best parameters
rf_param_grid = {'n_estimators': [100, 200, 500],
    'criterion': ['gini', 'entropy'],
    'max_depth': [3, 4, 5, 6],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [2, 5] }

#Instantiate GridSearchCV()
rf_grid_search = GridSearchCV(forest, rf_param_grid, cv = 3,n_jobs = -

#Fit to the data
rf_grid_search.fit(X_train, y_train)
```

Out[98]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [3, 4, 5, 6], 'min_samples_lea
f': [2, 5],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [100, 200, 500]})
```

In [342]:
```
rf_grid_search.best_params_
```

Out[342]:
```
{'criterion': 'gini',
 'max_depth': 6,
 'min_samples_leaf': 5,
 'min_samples_split': 2,
 'n_estimators': 200}
```

In [99]:
```
rf_tuned = RandomForestClassifier(n_estimators = 500,max_depth = 6,min
rf_tuned.fit(X_train,y_train)
```

Out[99]:
```
RandomForestClassifier(max_depth=6, min_samples_leaf=2, min_samples_
split=5,
                       n_estimators=500)
```

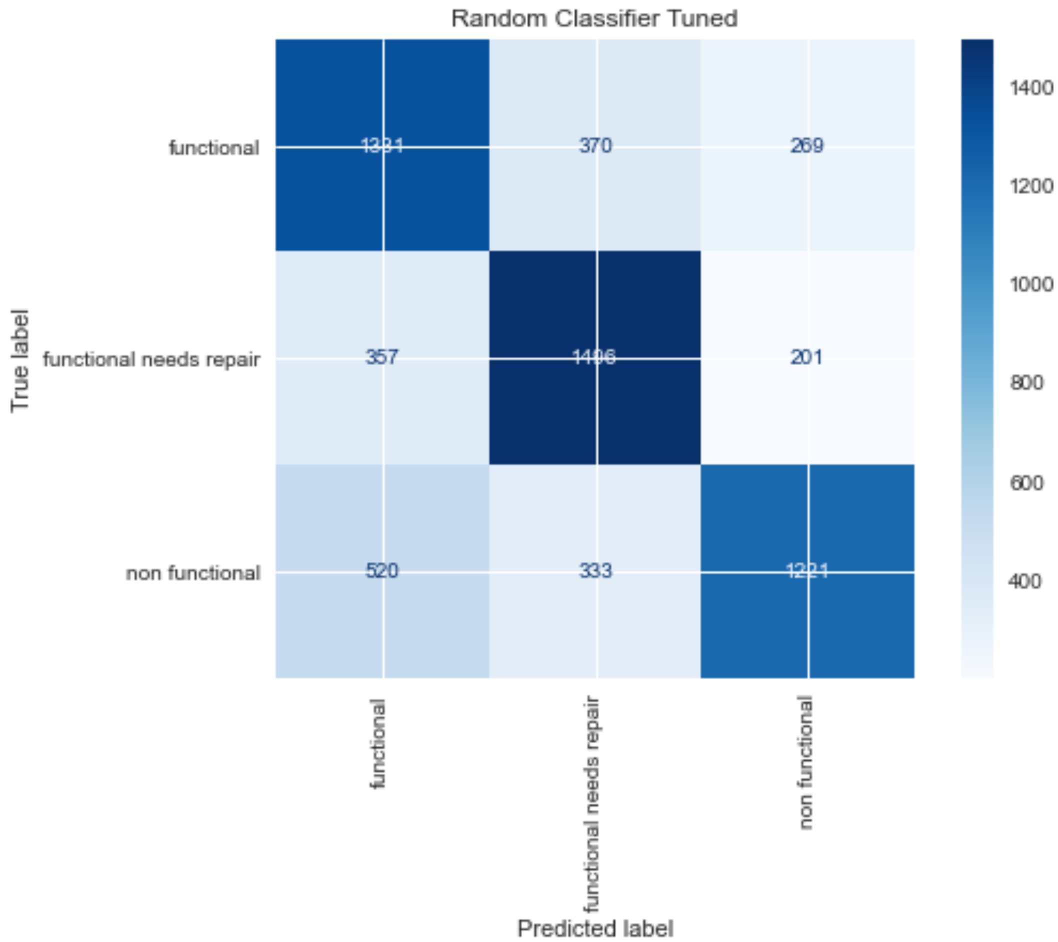
In [100]:
```
test_pred = rf_tuned.predict(X_test)
train_pred = rf_tuned.predict(X_train)
```

In [101]:
```
print(metrics.accuracy_score(y_test, test_pred))
#Print Classification Report
print('Training Data')
print(classification_report(y_train, train_pred))
print('\n')
print('Testing Data')
print(classification_report(y_test, test_pred))
# Update the scores dataframe
calculate_scores('Random forest Classifier', y_test, test_pred)
```

```
0.6564447359790095
Training Data
                         precision    recall  f1-score   support

            functional       0.67      0.67      0.67      6160
functional needs repair       0.65      0.79      0.71      6076
        non functional       0.70      0.55      0.61      6056

              accuracy                           0.67     18292
             macro avg       0.67      0.67      0.66     18292
          weighted avg       0.67      0.67      0.66     18292



Testing Data
                         precision    recall  f1-score   support

            functional       0.64      0.66      0.65      1970
functional needs repair       0.65      0.79      0.71      2054
        non functional       0.69      0.52      0.59      2074

              accuracy                           0.66      6098
             macro avg       0.66      0.66      0.65      6098
          weighted avg       0.66      0.66      0.65      6098
```

In [346]:
```
#Plot a confusion matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
#plot_confusion_matrix(KNN, X_test, y_test)

disp = plot_confusion_matrix(rf_tuned, X_test, y_test,
                             cmap=plt.cm.Blues,
                             xticks_rotation='vertical')
disp.ax_.set_title('Random Classifier Tuned')

print(disp.confusion_matrix)
```

```
[[1331  370  269]
 [ 357 1496  201]
 [ 520  333 1221]]
```



Random forest is not peforming well for accuracy nor for the precision.

We will try XG BOOST:

In [105]:
```
from xgboost import XGBClassifier
```

In [107]:
```
X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote,
```

In [114]:
```

›ile(r"\[|\]|<", re.IGNORECASE)

; = [regex.sub("_", col) if any(x in str(col) for x in set(('[', ']', '
```

In [115]:
```
baselinexgb = XGBClassifier()
baselinexgb.fit(X_train,y_train)
```

Out[115]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_i
d=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth
=6,
              min_child_weight=1, missing=nan, monotone_constraints=
'()',
              n_estimators=100, n_jobs=0, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=
0,
              reg_lambda=1, scale_pos_weight=None, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=
None)
```

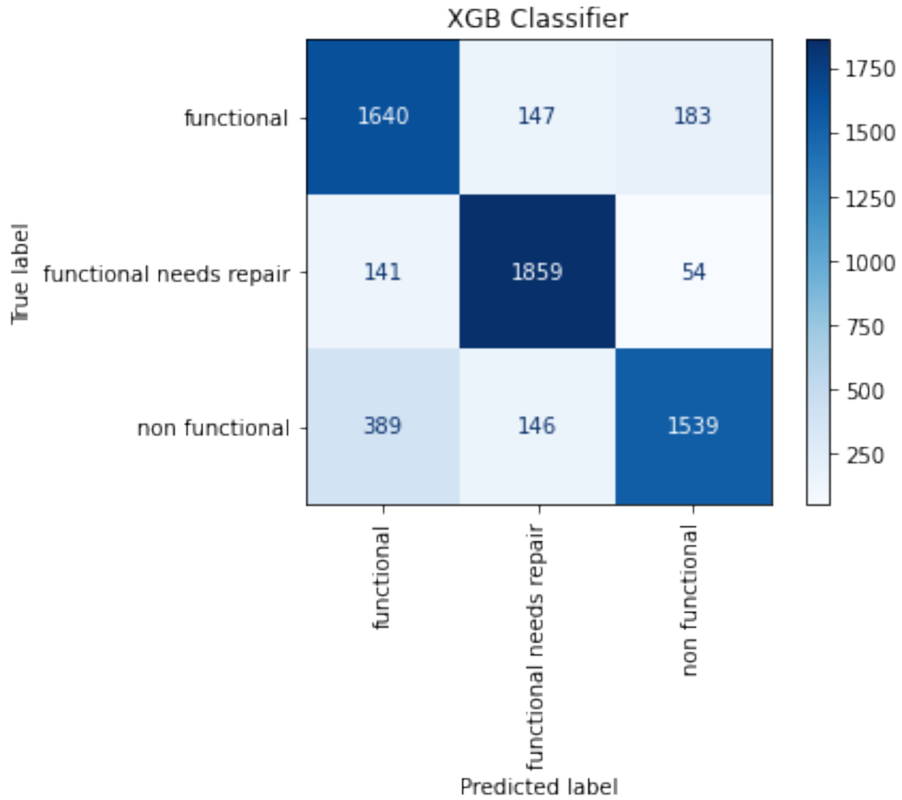
In [120]:
```
import re

regex = re.compile(r"\[|\]|<", re.IGNORECASE)

X_test.columns = [regex.sub("_", col) if any(x in str(col) for x in se


train_pred = baselinexgb.predict(X_train)
test_pred = baselinexgb.predict(X_test)
```

In [122]:
```
print(metrics.accuracy_score(y_test, test_pred))
#Print Classification Report
print('Training Data')
print(classification_report(y_train, train_pred))
print('\n')
print('Testing Data')
print(classification_report(y_test, test_pred))
# Update the scores dataframe
calculate_scores('XGBClassifier', y_test, test_pred)
```

```
0.8261725155788783
Training Data
                         precision    recall  f1-score   support

             functional       0.81      0.88      0.84      6160
functional needs repair       0.89      0.93      0.91      6076
         non functional       0.91      0.80      0.85      6056

               accuracy                           0.87     18292
              macro avg       0.87      0.87      0.87     18292
           weighted avg       0.87      0.87      0.87     18292



Testing Data
                         precision    recall  f1-score   support

             functional       0.76      0.83      0.79      1970
functional needs repair       0.86      0.91      0.88      2054
         non functional       0.87      0.74      0.80      2074

               accuracy                           0.83      6098
              macro avg       0.83      0.83      0.83      6098
           weighted avg       0.83      0.83      0.83      6098
```

In [125]:
```
disp = plot_confusion_matrix(baselinexgb, X_test, y_test,
                             cmap=plt.cm.Blues,
                             xticks_rotation='vertical')
disp.ax_.set_title('XGB Classifier')

print(disp.confusion_matrix)
```

```
[[1640  147  183]
 [ 141 1859   54]
 [ 389  146 1539]]
```



XGBoost is performing better than Random forest and decision Trees in terms of accuracy and precision.Since we are focussing more on lowering the no of false positives XGBoost performs better than KNN.

Comparing all the model scores:

XGBoost performed the best in terms of it's precision and accuracy.

Improvements

Since using GridSearchCV take up a lot of computational time, I couldn't put in more parameters like I wanted. Searching out more parameters might improve the model performance.

The model ability to predict non-functional needs repair is still lacking. I could try scrubbing the data in a diffrent way to make the model better.

Try out different types of filling missing values to see if it improves the model.

Instead of dropping the categorical variables like permit,and other duplicate columns we can find better ways to handle those data.

Next Steps:

We suggest adding using government oversight to make sure wells are installed at lower levels where possible.

Our recommendation is to setup a new fund / organisation to review and repair older wells in cooperation with non-governmental organisations assisting with wells construction.

Payment is a large issues especially when the average monthly salary in Tanzania is $50.

- Financial support systems from local government areas or districs in addition to payment arrangements in place is crucial to driving a reliable water system.
- Providing more continous data will be more helpful.

In [ ]:

```

```