Tanzanian Water Wells

Problem Description

Water Aid is an NGO based in the United Kingdom that works on access to clean water around the world. They consider access to clean water, decent toilets and good hygiene as basic human rights. For over 30 years, they have been working in partnership to improve access to these three essentials through a combination of programmatic and policy work.

Water Aid works in several countries around the globe, including Tanzania. According to the World Sector Report (2019) around 60% of Tanzanians have access to improved water, but the degree of water access, and the water quality and quantity, varies. Drought, landscape change, and the amplifying effects of climate change are straining existing surface water supplies.

Water Aid is launching a program to repair non-functioning wells in the cross country shared water basins of Eastern Africa. The status of the wells is not clearly recorded in countries surrounding Tanzania. Identifying non-functioning wells, securing funding, and traveling to these rural locations to repair wells is both time and resource intensive. They need a predictive model that accurately identifies which wells are not functioning to reduce cost and ensure they are using their resources wisely. They also need to identify a specific water basin to begin their work.

Goals

There are three data science goals to address Water Aid's need for accurately identifying non-functioning wells:

1. Using an iterative process, build a predictive machine learning model based on existing water well data to accurately classify non-functioning wells.
2. Deliver two recommendations to Water Aid: a specific transboundary water basin to begin their operations, and one feature characteristic of the wells in this basin that will

lead to higher chance of identifying non-functioning wells.

Load Packages and Data

In [426]:

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns

%matplotlib inline

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder, F
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoost
from sklearn.metrics import plot_confusion_matrix, recall_score,\
    accuracy_score, precision_score, f1_score

from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImPipeline
```

In [427]:

```
# Load the predictor data

wells = pd.read_csv('training_set_values.csv')
wells.head()
```

Out[427]:

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

5 rows × 40 columns

In [428]:
```
# Load the target data

target = pd.read_csv('training_set_labels.csv')

target.head()
```

Out[428]:

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

1. Exploratory Data Analysis

Get a sense of the big picture for the dataset. Prepare the data for further analysis. Gain an understanding of the variables, or predictors in this case. Study the relationship between variables. Make plan for initial model.

In [429]:
```
# Identify size of dataset

print("Records for wells:", wells.shape)
print()
print("Records for target:", target.shape)
```

```
Records for wells: (59400, 40)

Records for target: (59400, 2)
```

In [430]:

```
# Identify datatypes and record amount for each predictor

wells.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 [431]:

```
# Examine numerical predictors mean, min, max

wells.describe()
```

Out[431]:

	id	amount_tsh	gps_height	longitude	latitude	num_private
count	59400.000000	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.000000
mean	37115.131768	317.650385	668.297239	34.077427	-5.706033e+00	0.474141
std	21453.128371	2997.574558	693.116350	6.567432	2.946019e+00	12.236230
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
75%	55656.500000	20.000000	1319.250000	37.178387	-3.326156e+00	0.000000
max	74247.000000	350000.000000	2770.000000	40.345193	-2.000000e-08	1776.000000

In [432]:

```
# Missing data total
wells.isna().sum().sum()
```

Out[432]: 46094

In [433]:
```
# Missing data by predictor

wells.isna().sum()
```

Out[433]:
```
id                           0
amount_tsh                   0
date_recorded                0
funder                    3635
gps_height                   0
installer                 3655
longitude                    0
latitude                     0
wpt_name                     0
num_private                  0
basin                        0
subvillage                 371
region                       0
region_code                  0
district_code                0
lga                          0
ward                         0
population                   0
public_meeting            3334
recorded_by                  0
scheme_management         3877
scheme_name              28166
permit                    3056
construction_year            0
extraction_type              0
extraction_type_group        0
extraction_type_class        0
management                   0
management_group             0
payment                      0
payment_type                 0
water_quality                0
quality_group                0
quantity                     0
quantity_group               0
source                       0
source_type                  0
source_class                 0
waterpoint_type              0
waterpoint_type_group        0
dtype: int64
```

In [434]:
```
# Data missing for target
target.isna().sum()
```

Out[434]:
```
id              0
status_group    0
dtype: int64
```

In [435]:

```
# Examine value counts for the target, consider imbalance in targe
target['status_group'].value_counts()
```

Out[435]:

```
functional                 32259
non functional             22824
functional needs repair     4317
Name: status_group, dtype: int64
```

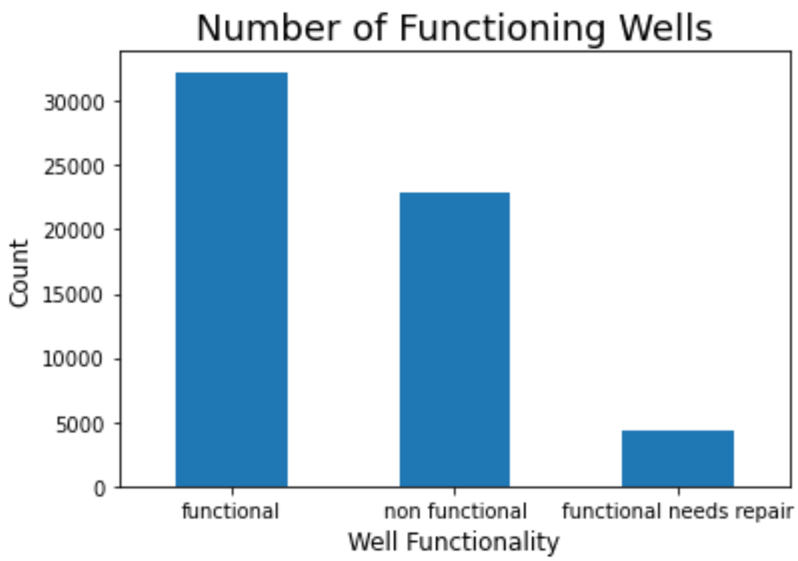
In [436]:

```
# Percentage makeup of target values
print("Functional percentage:", round(32259/59400*100, 2))
print("Non functional percentage:", round(22824/59400*100, 2))
print("Functional needs repair percentage:", round(4317/59400*100,
```

```
Functional percentage: 54.31
Non functional percentage: 38.42
Functional needs repair percentage: 7.27
```

In [437]:

```
# Visually plot target variable counts

target.status_group.value_counts().plot(kind="bar")
plt.title("Number of Functioning Wells",fontsize= 18)
plt.xlabel("Well Functionality", fontsize = 12)
plt.xticks(rotation=0)
plt.ylabel("Count", fontsize = 12)
plt.show();

plt.savefig('Number of Functioning Wells')
```




```
<Figure size 432x288 with 0 Axes>
```

In [438]:

```
# Identify unique values per column
print(wells.nunique())
```

```
id                       59400
amount_tsh                  98
date_recorded              356
funder                    1897
gps_height                2428
installer                 2145
longitude                57516
latitude                 57517
wpt_name                 37400
num_private                 65
basin                        9
subvillage               19287
region                      21
region_code                 27
district_code               20
lga                        125
ward                      2092
population                1049
public_meeting               2
recorded_by                  1
scheme_management           12
scheme_name               2696
permit                       2
construction_year           55
extraction_type             18
extraction_type_group       13
extraction_type_class        7
management                  12
management_group             5
payment                      7
payment_type                 7
water_quality                8
quality_group                6
quantity                     5
quantity_group               5
source                      10
source_type                  7
source_class                 3
waterpoint_type              7
waterpoint_type_group        6
dtype: int64
```

In [439]:
```
# Concatenate preds and target for heatmap

df = pd.concat([wells, target], axis =1)

df = df.loc[:,~df.columns.duplicated()].copy()

df.head()
```

Out[439]:

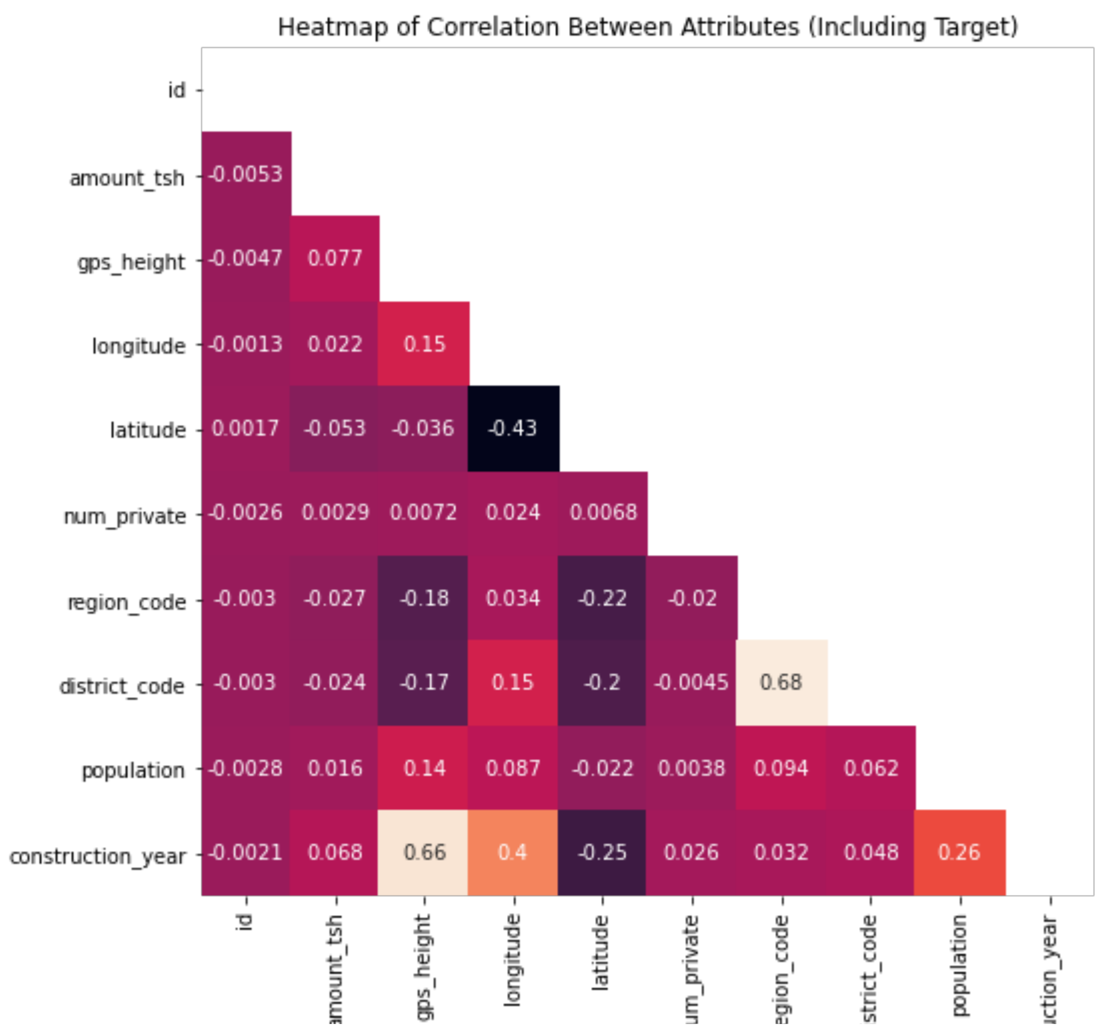
	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	w
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	
3	67743	0.0	2013-01-28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

5 rows × 41 columns

Correlation of numeric data

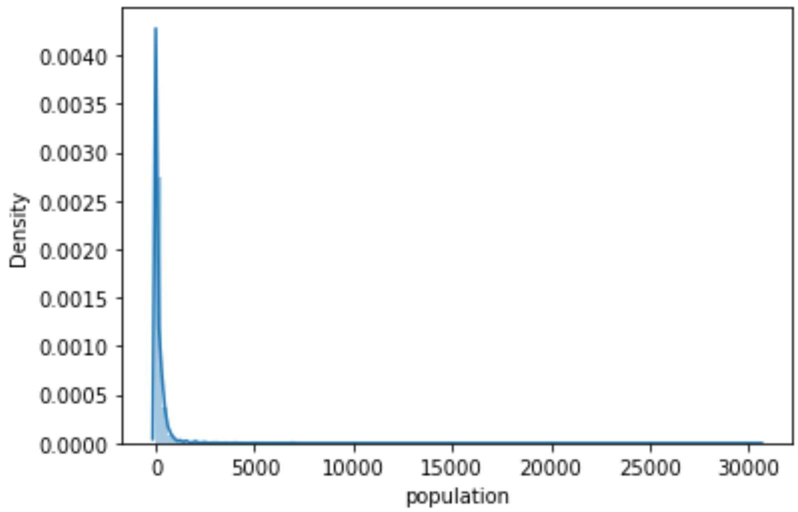
In [440]:

```python
# Create a heatmap to examine the correlational coefficents


corr = df.corr()

# Set up figure and axes
fig, ax = plt.subplots(figsize=(8, 12))

# Plot a heatmap of the correlations

sns.heatmap(

    data=corr,

    mask=np.triu(np.ones_like(corr, dtype=bool)),

    ax=ax,

    annot=True,
    # Customizes colorbar appearance
    cbar_kws={"label": "Correlation", "orientation": "horizontal",
)

# Customize the plot appearance
ax.set_title("Heatmap of Correlation Between Attributes (Including
```



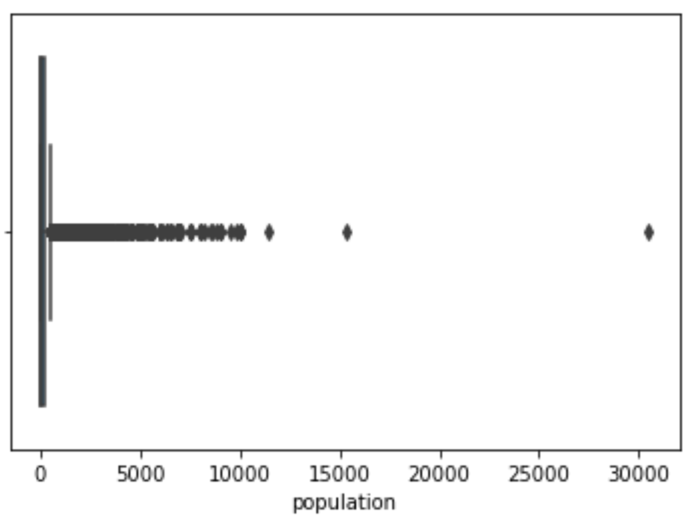
In [441]:
```
# Check distribution for numeric data
import warnings
warnings.filterwarnings('ignore')

print(sns.distplot(wells.population, bins = 100))


```

AxesSubplot(0.125,0.125;0.775x0.755)



In [442]:
```
# Identify range of population and any outliers

sns.boxplot(wells.population)

```

Out[442]: <AxesSubplot:xlabel='population'>



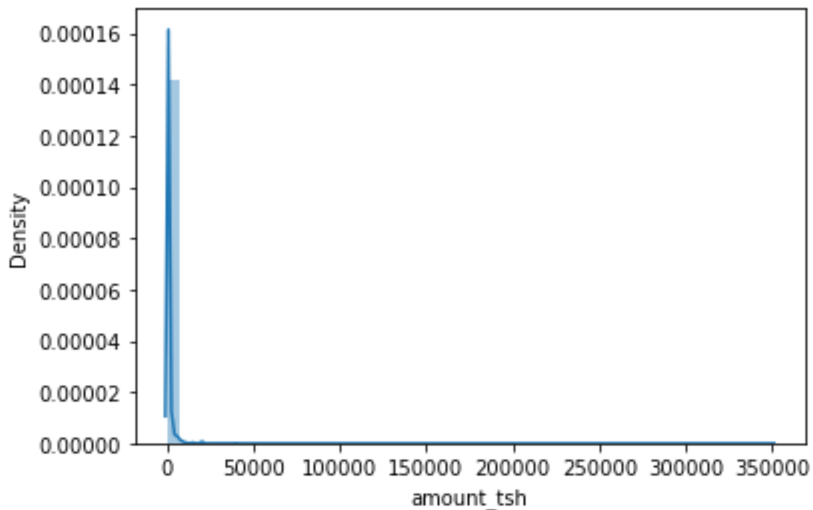
In [443]:
```
# Identify population counts
print(wells.population.value_counts())
print(wells.population.nunique())
```

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

Total Static Head data

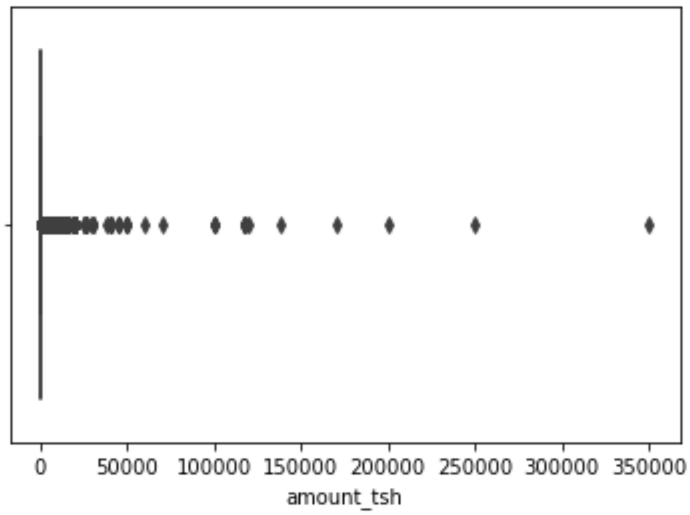
In [444]:
```
# Plot and descrive total static head

sns.distplot(wells.amount_tsh)

print(wells.amount_tsh.describe())

```

```
count     59400.000000
mean        317.650385
std        2997.574558
min           0.000000
25%           0.000000
50%           0.000000
75%          20.000000
max      350000.000000
Name: amount_tsh, dtype: float64
```



In [445]:
```
# Identify range and outliers of total static head

sns.boxplot(wells.amount_tsh)
```

Out[445]: <AxesSubplot:xlabel='amount_tsh'>



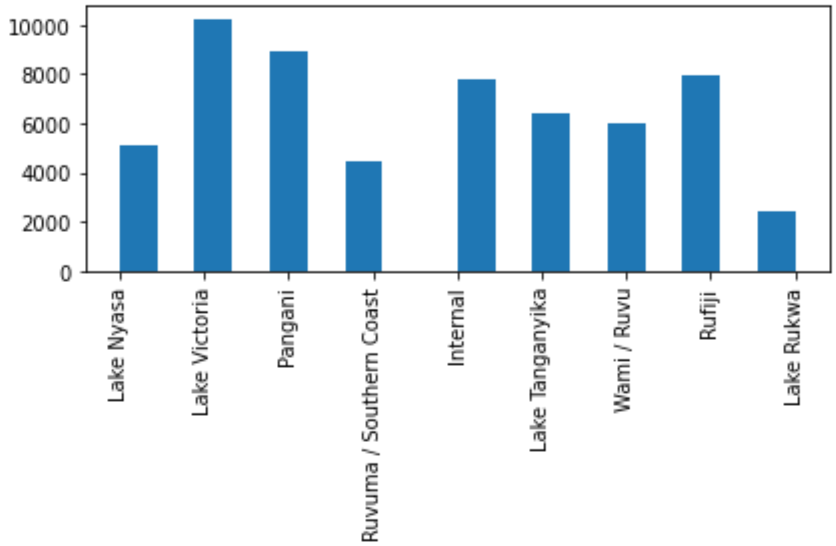
In [446]:
```
# Identify how many wells do not have static head

print(wells.amount_tsh.value_counts())
```

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

Geographic Data

In [447]:

```
# plot basins
fig, axs = plt.subplots(1, 1,
                        figsize =(6, 4),
                        tight_layout = True)

axs.hist(wells.basin, bins = 18)
plt.xticks(rotation = 90)

plt.show()
```



In [448]:

```
# How many wells are in each basin

wells.basin.value_counts()
```

Out[448]:

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

In [449]:
```

wells.region.value_counts()
```

Out[449]:
```
Iringa           5294
Shinyanga        4982
Mbeya            4639
Kilimanjaro      4379
Morogoro         4006
Arusha           3350
Kagera           3316
Mwanza           3102
Kigoma           2816
Ruvuma           2640
Pwani            2635
Tanga            2547
Dodoma           2201
Singida          2093
Mara             1969
Tabora           1959
Rukwa            1808
Mtwara           1730
Manyara          1583
Lindi            1546
Dar es Salaam     805
Name: region, dtype: int64
```

In [450]:
```
wells.district_code.value_counts()
```

Out[450]:
```
1     12203
2     11173
3      9998
4      8999
5      4356
6      4074
7      3343
8      1043
30      995
33      874
53      745
43      505
13      391
23      293
63      195
62      109
60       63
0        23
80       12
67        6
Name: district_code, dtype: int64
```

In [451]:
```
wells.region_code.value_counts()
```

Out[451]:
```
11    5300
17    5011
12    4639
3     4379
5     4040
18    3324
19    3047
2     3024
16    2816
10    2640
4     2513
1     2201
13    2093
14    1979
20    1969
15    1808
6     1609
21    1583
80    1238
60    1025
90     917
7      805
99     423
9      390
24     326
8      300
40       1
Name: region_code, dtype: int64
```

Water attributes

In [452]:
```
wells.water_quality.value_counts()
```

Out[452]:
```
soft                  50818
salty                  4856
unknown                1876
milky                   804
coloured                490
salty abandoned         339
fluoride                200
fluoride abandoned       17
Name: water_quality, dtype: int64
```

In [453]:
```
1 wells.quality_group.value_counts()
```

Out[453]:
```
good        50818
salty        5195
unknown      1876
milky         804
colored       490
fluoride      217
Name: quality_group, dtype: int64
```

In [454]:
```
1 wells.quantity.value_counts()
```

Out[454]:
```
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: quantity, dtype: int64
```

In [455]:
```
1 wells.quantity_group.value_counts()
```

Out[455]:
```
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: quantity_group, dtype: int64
```

In [456]:
```
1 wells.scheme_name.value_counts()
```

Out[456]:
```
K                                682
None                             644
Borehole                         546
Chalinze wate                    405
M                                400
                                ...
Mws                                1
Mpal                               1
Malemeo gravity water supply       1
Bulenya water supply               1
UNICRF                             1
Name: scheme_name, Length: 2696, dtype: int64
```

In [457]:
```
1 wells.scheme_management.value_counts()
```

Out[457]:
```
VWC                 36793
WUG                  5206
Water authority      3153
WUA                  2883
Water Board          2748
Parastatal           1680
Private operator     1063
Company              1061
Other                 766
SWC                    97
Trust                  72
None                    1
Name: scheme_management, dtype: int64
```

In [458]:
```
1 wells.extraction_type.value_counts()
```

Out[458]:
```
gravity                      26780
nira/tanira                   8154
other                         6430
submersible                   4764
swn 80                        3670
mono                          2865
india mark ii                 2400
afridev                       1770
ksb                           1415
other - rope pump              451
other - swn 81                 229
windmill                       117
india mark iii                  98
cemo                            90
other - play pump               85
walimi                          48
climax                          32
other - mkulima/shinyanga        2
Name: extraction_type, dtype: int64
```

In [459]:
```
1 wells.extraction_type_group.value_counts()
```

Out[459]:
```
gravity            26780
nira/tanira         8154
other               6430
submersible         6179
swn 80              3670
mono                2865
india mark ii       2400
afridev             1770
rope pump            451
other handpump       364
other motorpump      122
wind-powered         117
india mark iii        98
Name: extraction_type_group, dtype: int64
```

In [460]:
```
1 wells.extraction_type_class.value_counts()
```

Out[460]:
```
gravity          26780
handpump         16456
other             6430
submersible       6179
motorpump         2987
rope pump          451
wind-powered       117
Name: extraction_type_class, dtype: int64
```

In [461]:
```
1 wells.source.value_counts()
```

Out[461]:
```
spring                  17021
shallow well            16824
machine dbh             11075
river                    9612
rainwater harvesting     2295
hand dtw                  874
lake                      765
dam                       656
other                     212
unknown                    66
Name: source, dtype: int64
```

In [462]:
```
1 wells.source_type.value_counts()
```

Out[462]:
```
spring                  17021
shallow well            16824
borehole                11949
river/lake              10377
rainwater harvesting     2295
dam                       656
other                     278
Name: source_type, dtype: int64
```

In [463]:
```
1 wells.waterpoint_type_group.value_counts()
```

Out[463]:
```
communal standpipe    34625
hand pump             17488
other                  6380
improved spring         784
cattle trough           116
dam                       7
Name: waterpoint_type_group, dtype: int64
```

In [464]:
```
1 wells.source_class.value_counts()
```

Out[464]:
```
groundwater    45794
surface        13328
unknown          278
Name: source_class, dtype: int64
```

In [465]:
```
1 wells.waterpoint_type.value_counts()
```

Out[465]:
```
communal standpipe             28522
hand pump                      17488
other                           6380
communal standpipe multiple     6103
improved spring                  784
cattle trough                    116
dam                                7
Name: waterpoint_type, dtype: int64
```

Organizational attributes

In [466]:
```
1 wells.funder.value_counts()
```

Out[466]:
```
Government Of Tanzania          9084
Danida                          3114
Hesawa                          2202
Rwssp                           1374
World Bank                      1349
                                ...
Fida                               1
Kigoma Municipal Council           1
Abc-ihushi Development Cent        1
Tag Church Ub                      1
Nyamingu Subvillage                1
Name: funder, Length: 1897, dtype: int64
```

In [467]:
```
1 wells.num_private.value_counts()
```

Out[467]:
```
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 [468]:
```
1 wells.permit.value_counts()
```

Out[468]:
```
True     38852
False    17492
Name: permit, dtype: int64
```

In [469]:
```
wells.management.value_counts()
```

Out[469]:
```
vwc                 40507
wug                  6515
water board          2933
wua                  2535
private operator     1971
parastatal           1768
water authority       904
other                 844
company               685
unknown               561
other - school         99
trust                  78
Name: management, dtype: int64
```

In [470]:
```
wells.management_group.value_counts()
```

Out[470]:
```
user-group    52490
commercial     3638
parastatal     1768
other           943
unknown         561
Name: management_group, dtype: int64
```

In [471]:
```
wells.payment.value_counts()
```

Out[471]:
```
never pay                25348
pay per bucket            8985
pay monthly               8300
unknown                   8157
pay when scheme fails     3914
pay annually              3642
other                     1054
Name: payment, dtype: int64
```

In [472]:
```
wells.payment_type.value_counts()
```

Out[472]:
```
never pay     25348
per bucket     8985
monthly        8300
unknown        8157
on failure     3914
annually       3642
other          1054
Name: payment_type, dtype: int64
```

In [473]:
```
with pd.option_context('display.max_rows', 5, 'display.max_columns
    display(wells[1000:1020])
```

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	lati
1000	47384	250.0	2013-02-14	Oxfam	1409	OXFAM	30.105401	-4.367
1001	11570	0.0	2012-10-12	Resolute Mining	0	Consulting Engineer	33.210098	-4.049
...	...	...	...	...	...	...	...	
1018	41433	0.0	2011-03-05	Government Of Tanzania	1307	DWE	38.325050	-4.464
1019	21810	0.0	2013-01-17	Bulyahunlu Gold Mine	0	Bulyahunlu Gold Mine	32.370100	-3.281

20 rows × 40 columns

2. Preprocess data, Initial Model

Redundant data columns where the data is included in other columns that contain more expansive information should be dropped: water attributes, geographic attributes, include water include regional columns, water extraction and source types.

Drop columns that do not contribute to the model. These include water id, names of the waterpoint, names of subvillages.

Make plan for missing categorical and numeric data.

In [474]:
```
# Drop redundant data columns and columns that do not contribute t
wells.drop(columns = ['id', 'wpt_name', 'region', 'recorded_by', '
           'scheme_management', 'extraction_type_group', 'payment_
           'quality_group', 'quantity_group', 'source_type', 'wate

```

In [475]:
```
wells.columns
```

Out[475]:
```
Index(['amount_tsh', 'date_recorded', 'funder', 'gps_height', 'instal
ler',
       'longitude', 'latitude', 'num_private', 'basin', 'region_code
',
       'district_code', 'lga', 'ward', 'population', 'public_meeting
',
       'permit', 'construction_year', 'extraction_type',
       'extraction_type_class', 'management', 'management_group', 'pa
yment',
       'water_quality', 'quantity', 'source', 'source_class',
       'waterpoint_type_group'],
      dtype='object')
```

In [476]:
```
# Check missing data
wells.isna().sum()
```

Out[476]:
```
amount_tsh                  0
date_recorded               0
funder                   3635
gps_height                  0
installer                3655
longitude                   0
latitude                    0
num_private                 0
basin                       0
region_code                 0
district_code               0
lga                         0
ward                        0
population                  0
public_meeting           3334
permit                   3056
construction_year           0
extraction_type             0
extraction_type_class       0
management                  0
management_group            0
payment                     0
water_quality               0
quantity                    0
source                      0
source_class                0
waterpoint_type_group       0
dtype: int64
```

In [477]:
```
# Replace Nan in public_meeting and permit as False

wells['public_meeting'] = wells['public_meeting'].fillna('False').
wells.public_meeting.head()
```

Out[477]:
```
0    True
1    True
2    True
3    True
4    True
Name: public_meeting, dtype: bool
```

In [478]:
```
# replace missing permit data as False
wells['permit'] = wells['permit'].fillna('False').astype('bool')
wells.permit.head()
```

Out[478]:
```
0    False
1     True
2     True
3     True
4     True
Name: permit, dtype: bool
```

In [479]:
```
# Convert "date_recorded" to month_recorded

import datetime

wells['date_recorded'] = pd.to_datetime(wells['date_recorded'])
wells['month_recorded'] = wells['date_recorded'].dt.month
wells['month_recorded']
```

Out[479]:
```
0        3
1        3
2        2
3        1
4        7
        ..
59395    5
59396    5
59397    4
59398    3
59399    3
Name: month_recorded, Length: 59400, dtype: int64
```

In [480]:
```
wells.drop('date_recorded', axis = 1, inplace = True)
```

Initial Model - Logistic Regression

Use a Logistic Regression model in a pipeline for initial model results.

In [481]:
```
# Assign the predictors and target
X = wells
y = target['status_group']
```

In [482]:
```
# Perform a train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_siz
```

In [483]:
```
X_train.columns
```

Out[483]:
```
Index(['amount_tsh', 'funder', 'gps_height', 'installer', 'longitude
',
       'latitude', 'num_private', 'basin', 'region_code', 'district_c
ode',
       'lga', 'ward', 'population', 'public_meeting', 'permit',
       'construction_year', 'extraction_type', 'extraction_type_class
',
       'management', 'management_group', 'payment', 'water_quality',
       'quantity', 'source', 'source_class', 'waterpoint_type_group',
       'month_recorded'],
      dtype='object')
```

In [484]:

```
# Examine data types and record counts
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 44550 entries, 24947 to 56422
Data columns (total 27 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   amount_tsh             44550 non-null  float64
 1   funder                 41859 non-null  object 
 2   gps_height             44550 non-null  int64  
 3   installer              41850 non-null  object 
 4   longitude              44550 non-null  float64
 5   latitude               44550 non-null  float64
 6   num_private            44550 non-null  int64  
 7   basin                  44550 non-null  object 
 8   region_code            44550 non-null  int64  
 9   district_code          44550 non-null  int64  
 10  lga                    44550 non-null  object 
 11  ward                   44550 non-null  object 
 12  population             44550 non-null  int64  
 13  public_meeting         44550 non-null  bool   
 14  permit                 44550 non-null  bool   
 15  construction_year      44550 non-null  int64  
 16  extraction_type        44550 non-null  object 
 17  extraction_type_class  44550 non-null  object 
 18  management             44550 non-null  object 
 19  management_group       44550 non-null  object 
 20  payment                44550 non-null  object 
 21  water_quality          44550 non-null  object 
 22  quantity               44550 non-null  object 
 23  source                 44550 non-null  object 
 24  source_class           44550 non-null  object 
 25  waterpoint_type_group  44550 non-null  object 
 26  month_recorded         44550 non-null  int64  
dtypes: bool(2), float64(3), int64(7), object(15)
memory usage: 8.9+ MB
```

In [539]:
```


# create subpipe for numeric data

subpipe_num = Pipeline(steps=[('num_impute', SimpleImputer()),
                            ('ss', StandardScaler())])

# create subpipe for categorical data, use SimpleImputer for 'miss

subpipe_cat = Pipeline(steps=[('cat_impute', SimpleImputer(strateg
                              ('ohe', OneHotEncoder(sparse=False, h

# combine subpipes into ColumnTransformer

CT = ColumnTransformer(transformers=[('subpipe_num', subpipe_num,
                                    ('subpipe_cat', subpipe_cat, [



                            remainder='passthrough')


```

In [540]:
```
#Perform Logistic Regression for initial model

log_reg_pipe = Pipeline(steps = [('ct', CT),
                            ('log_reg', LogisticRegression(random_s
```

In [541]:
```
# Fit the logistic regression model
log_reg_pipe.fit(X_train, y_train)
```

Out[541]:
```
Pipeline(steps=[('ct',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('subpipe_num',
                                                  Pipeline(steps=[('n
um_impute',
                                                                   Si
mpleImputer()),
                                                                  ('s
s',
                                                                   St
andardScaler())]),
                                                  [0, 2, 4, 5, 12]),
                                                 ('subpipe_cat',
                                                  Pipeline(steps=[('c
at_impute',
                                                                   Si
mpleImputer(fill_value='missing',

strategy='constant')),
                                                                  ('o
he',
                                                                   On
eHotEncoder(handle_unknown='ignore',

sparse=False))]),
                                                  [1, 3, 6, 7, 8, 9,
10, 11, 13,
                                                   14, 15, 16, 17, 1
8, 19, 20,
                                                   21, 22, 23, 24, 2
5, 26])])),
                ('log_reg', LogisticRegression(random_state=42))])
```

Evaluate initial model

In [542]:
```
# Score the log reg model
log_reg_pipe.score(X_train, y_train)
```

Out[542]:
```
0.8025813692480359
```

In [543]:
```
# create predicted target variable
y_hat = log_reg_pipe.predict(X_test)
```

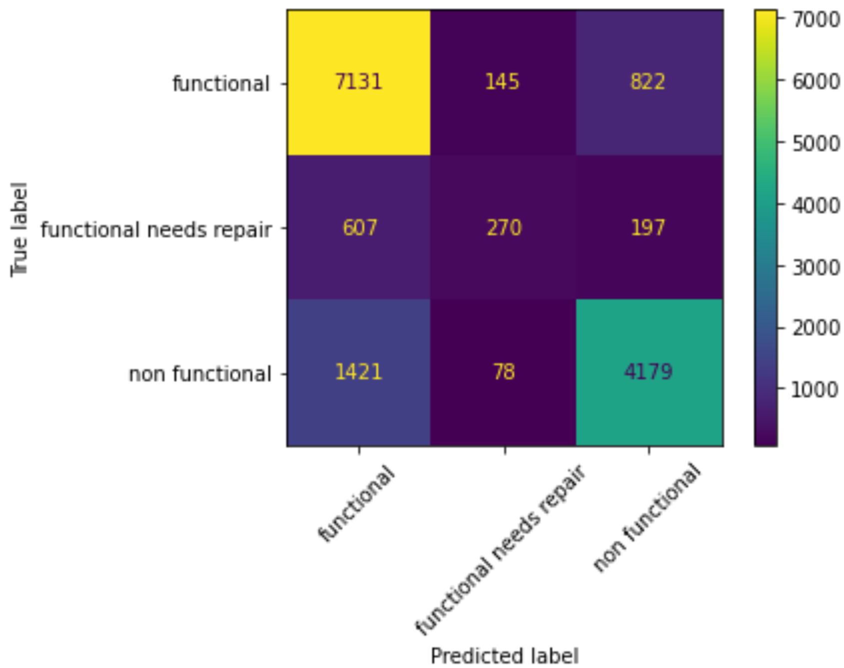
In [544]:

```
# Generate log_reg classification report
from sklearn.metrics import classification_report

print(classification_report(y_test, y_hat))
```

```
                         precision    recall  f1-score   support

             functional       0.78      0.88      0.83      8098
functional needs repair       0.55      0.25      0.34      1074
         non functional       0.80      0.74      0.77      5678

               accuracy                           0.78     14850
              macro avg       0.71      0.62      0.65     14850
           weighted avg       0.77      0.78      0.77     14850
```

In [545]:

```
plot_confusion_matrix(log_reg_pipe, X_test, y_test, xticks_rotatio
```



In [546]:
```
# Save model in Joblib
from joblib import Parallel, delayed
import joblib

import pickle

# Save the model as a pickle in a file
joblib.dump(log_reg_pipe, 'log_reg.pkl')

# Load the model from the file
#log_reg_from_joblib = joblib.load('log_reg.pkl')

# Use the loaded model to make predictions
#log_reg_from_joblib.predict(X_test)
```

Out[546]: ['log_reg.pkl']

3. Decision Tree Model with Parameter Tuning

Considering the dataset a decision tree would be a useful secondary model. Use hyperparameter tuning to improve upon the initial logistic regression model.

In [547]:
```
import category_encoders as ce


# create subpipe for numeric data

subpipe_num = Pipeline(steps=[('num_impute', SimpleImputer()),
                             ('ss', StandardScaler())])

# create subpipe for categorical data, use SimpleImputer for 'miss

subpipe_cat = Pipeline(steps=[('cat_impute', SimpleImputer(strateg
                               ('ohe', OneHotEncoder(sparse=False, h

# combine subpipes into ColumnTransformer

CT = ColumnTransformer(transformers=[('subpipe_num', subpipe_num,
                                     ('subpipe_cat', subpipe_cat, [



                             remainder='passthrough')

```

In [548]:
```
# Use a decision tree for the secondary model
dtc = DecisionTreeClassifier(random_state = 42)

dtc_pipe = Pipeline(steps=[('ct', CT),
                           ('dtc', dtc)])
```

In [549]:
```
1 dtc_pipe.fit(X_train, y_train)
```

Out[549]:
```
Pipeline(steps=[('ct',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('subpipe_num',
                                                  Pipeline(steps=[('n
um_impute',
                                                                    Si
mpleImputer()),
                                                                   ('s
s',
                                                                    St
andardScaler())]),
                                                  [0, 2, 4, 5, 12]),
                                                 ('subpipe_cat',
                                                  Pipeline(steps=[('c
at_impute',
                                                                    Si
mpleImputer(fill_value='missing',
strategy='constant')),
                                                                   ('o
he',
                                                                    On
eHotEncoder(handle_unknown='ignore',
sparse=False))]),
                                                  [1, 3, 6, 7, 8, 9,
10, 11, 13,
                                                   14, 15, 16, 17, 1
8, 19, 20,
                                                   21, 22, 23, 24, 2
5, 26])])),
                ('dtc', DecisionTreeClassifier(random_state=42))])
```

In [550]:
```
1 dtc_pipe.score(X_train, y_train)
```

Out[550]:
```
0.9984960718294051
```

In [551]:
```
1 dtc_pipe.score(X_test, y_test)
```

Out[551]:
```
0.7612121212121212
```

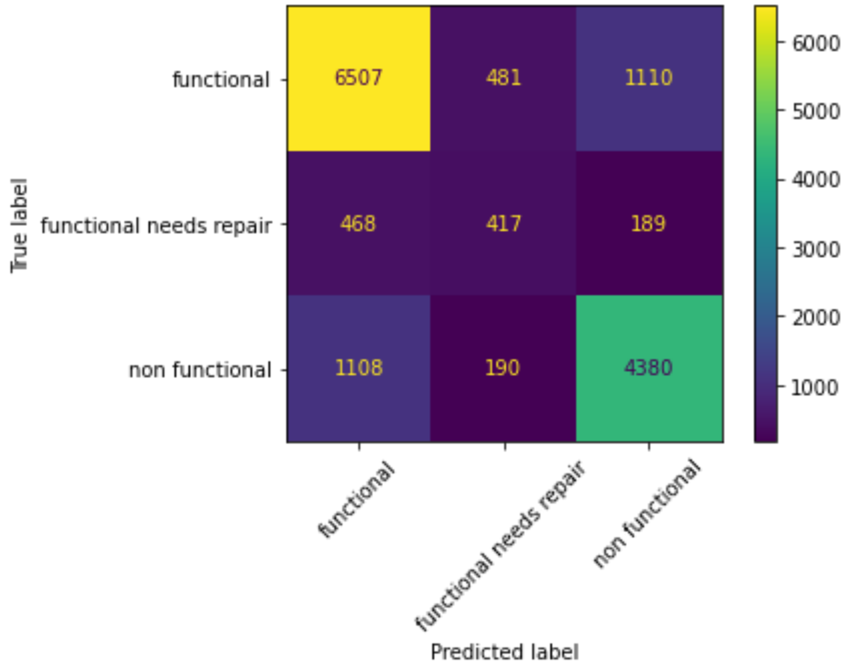
Evaluate Decision Tree Model

In [552]:
```
1 y_hat = dtc_pipe.predict(X_test)
```

In [553]:
```
print(classification_report(y_test, y_hat))
```

```
                          precision    recall  f1-score   support

              functional       0.81      0.80      0.80      8098
functional needs repair       0.38      0.39      0.39      1074
          non functional       0.77      0.77      0.77      5678

                accuracy                           0.76     14850
               macro avg       0.65      0.65      0.65     14850
            weighted avg       0.76      0.76      0.76     14850
```

In [554]:
```
plot_confusion_matrix(dtc_pipe, X_test, y_test, xticks_rotation=45
```



In [555]:
```
len(dtc_pipe.named_steps['dtc'].feature_importances_)
```

Out[555]: 5974

In [556]:
```
model_tree = dtc_pipe.named_steps['dtc']
model_tree.feature_importances_
```

Out[556]:
```
array([0.02232117, 0.05443548, 0.12866974, ..., 0.00177732, 0.0003740
2,
       0.00037427])
```

In [558]:
```
# Save the decision tree model as a pickle in a file
joblib.dump(dtc_pipe, 'dtc_pipe.pkl')
```

Out[558]: ['dtc_pipe.pkl']

Results

The decision tree model's accuracy was less than the logistic regression model and did not improve upon the logistic regression accuracy, though the f1-score for non-functional wells

Use gridsearch for hyperparameter tuning.

In [75]:

```
params = {}
params['dtc__criterion'] = ['gini', 'entropy']
params['dtc__min_samples_leaf'] = [1, 3, 5, 7, 10]
params['dtc__max_depth'] = [1,3,5,7,9]
params['dtc__splitter'] = ['best', 'random']

gs = GridSearchCV(estimator=dtc_pipe,
                  param_grid=params,
                  cv=3)
```

In [76]:
```
gs.fit(X_train, y_train)
```

Out[76]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('ct',
                                        ColumnTransformer(remainder='
passthrough',
                                                          transformer
s=[('subpipe_num',

Pipeline(steps=[('num_impute',

SimpleImputer()),

('ss',

StandardScaler())]),

[0, 2,

4, 5,

12]),

('subpipe_cat',

Pipeline(steps=[('cat_impute',

SimpleImputer(fill_value='missing',

strategy='constant')),

('ohe',

OneHotEncoder(handle_unknown='ignore',

sparse=False))]),

[1, 3,

6, 7,

8, 9,

10,

11,

13,

14,

15,

16,

17,
```

```
18,

19,

20,

21,

22,

23,

24,

25,

26])])),
                                        ('dtc',
                                         DecisionTreeClassifier(random
_state=42))]),
             param_grid={'dtc__criterion': ['gini', 'entropy'],
                         'dtc__max_depth': [1, 3, 5, 7, 9],
                         'dtc__min_samples_leaf': [1, 3, 5, 7, 10],
                         'dtc__splitter': ['best', 'random']})
```

In [77]:

```
# Identify the best parameters
gs.best_params_
```

Out[77]:

```
{'dtc__criterion': 'gini',
 'dtc__max_depth': 9,
 'dtc__min_samples_leaf': 5,
 'dtc__splitter': 'best'}
```

In [78]:
```
# Examine cross validation results
gs.cv_results_['mean_test_score']
```

Out[78]:
```
array([0.6424018 , 0.6424018 , 0.6424018 , 0.6424018 , 0.6424018 ,
       0.6424018 , 0.6424018 , 0.6424018 , 0.6424018 , 0.6424018 ,
       0.69427609, 0.69441077, 0.69427609, 0.69441077, 0.69429854,
       0.69443322, 0.69427609, 0.69445567, 0.69450056, 0.69461279,
       0.71270483, 0.70826038, 0.71261504, 0.70810325, 0.71265993,
       0.70808081, 0.71272727, 0.7081257 , 0.71261504, 0.70808081,
       0.72489338, 0.72282828, 0.72480359, 0.72255892, 0.72455668,
       0.72253648, 0.72453423, 0.72210999, 0.72430976, 0.72190797,
       0.73719416, 0.73476992, 0.73705948, 0.73429854, 0.73748597,
       0.73297419, 0.73643098, 0.73313131, 0.73542088, 0.73236813,
       0.6424018 , 0.6424018 , 0.6424018 , 0.6424018 , 0.6424018 ,
       0.6424018 , 0.6424018 , 0.6424018 , 0.6424018 , 0.6424018 ,
       0.69342312, 0.6935578 , 0.69342312, 0.6935578 , 0.69342312,
       0.6935578 , 0.69342312, 0.69360269, 0.69351291, 0.69362514,
       0.7006734 , 0.69723906, 0.70060606, 0.6973064 , 0.70056117,
       0.6973064 , 0.70042649, 0.69717172, 0.70038159, 0.69710438,
       0.71353535, 0.71380471, 0.71353535, 0.71360269, 0.71384961,
       0.71378227, 0.71367003, 0.7138945 , 0.71335578, 0.71411897,
       0.73158249, 0.7308642 , 0.73167228, 0.7308642 , 0.73156004,
       0.7308193 , 0.73182941, 0.73021324, 0.73113356, 0.73005612])
```

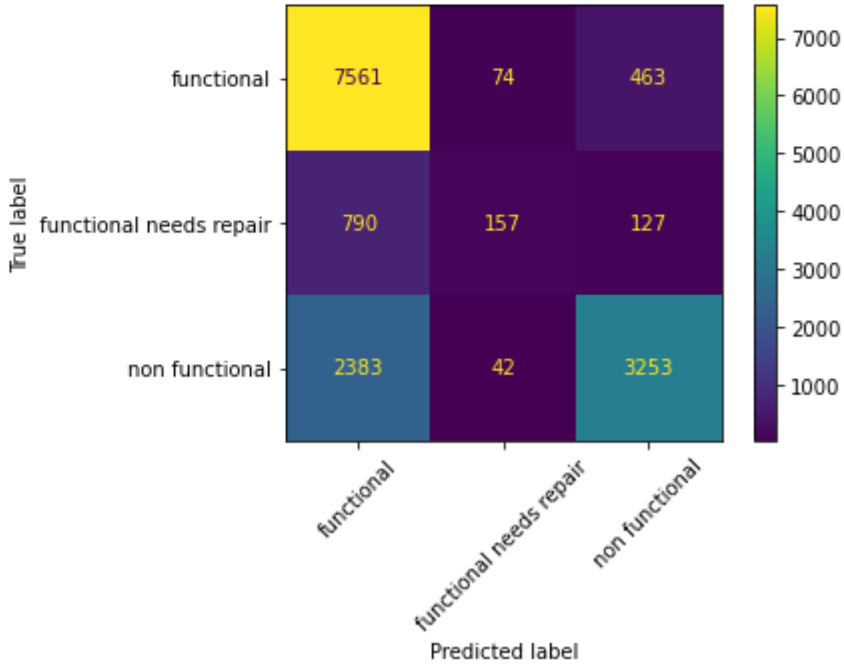
Evaluate decision tree gridsearch results

In [79]:
```
y_hat = gs.predict(X_test)
```

In [80]:
```
print(classification_report(y_test, y_hat))
```

```
                         precision    recall  f1-score   support

             functional       0.70      0.93      0.80      8098
functional needs repair       0.58      0.15      0.23      1074
         non functional       0.85      0.57      0.68      5678

               accuracy                           0.74     14850
              macro avg       0.71      0.55      0.57     14850
           weighted avg       0.75      0.74      0.72     14850
```

In [81]:
```
plot_confusion_matrix(gs, X_test, y_test, xticks_rotation = 45);
```



In [559]:
```
# Save the model as a pickle in a file
joblib.dump(gs, 'grid_search_dtc.pkl')
```

Out[559]: ['grid_search_dtc.pkl']

Results

While accuracy decreased overall, the precision score on non-functional wells improved from 77% to 85%. This could be a good model if we only focus on precision score for non-functioning wells. Wells that need repair precision score also improved by 20%, this opens a path to possibly identify wells that could soon be non-functioning.

4. Random Forest with SMOTE and Tuning

Use a random forest model to further explore whether the precision or recall score on non-functioning wells can be improved. Address class imbalance issues with SMOTE. Further tune the model using search tools for best hyperparameters.

In [82]:
```
# Instantiate a Random Forest Classifier

rfc = RandomForestClassifier(random_state=42)

# Instantiate SMOTE for class imbalance

sm = SMOTE(sampling_strategy = 'auto', random_state = 42)

# Create pipeline

rfc_model_pipe = ImPipeline(steps=[('ct', CT),
                              ('sm', sm),
                             ('rfc', rfc)])

```

In [83]:
```
rfc_model_pipe.fit(X_train, y_train)
```

Out[83]:
```
Pipeline(steps=[('ct',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('subpipe_num',
                                                  Pipeline(steps=[('n
um_impute',
                                                                   Si
mpleImputer()),
                                                                  ('s
s',
                                                                   St
andardScaler())]),
                                                  [0, 2, 4, 5, 12]),
                                                 ('subpipe_cat',
                                                  Pipeline(steps=[('c
at_impute',
                                                                   Si
mpleImputer(fill_value='missing',

strategy='constant')),
                                                                  ('o
he',
                                                                   On
eHotEncoder(handle_unknown='ignore',

sparse=False))]),
                                                  [1, 3, 6, 7, 8, 9,
10, 11, 13,
                                                   14, 15, 16, 17, 1
8, 19, 20,
                                                   21, 22, 23, 24, 2
5, 26])])),
                ('sm', SMOTE(random_state=42)),
                ('rfc', RandomForestClassifier(random_state=42))])
```

In [84]:
```
rfc_model_pipe.score(X_train, y_train)
```

Out[84]:
```
0.9984960718294051
```

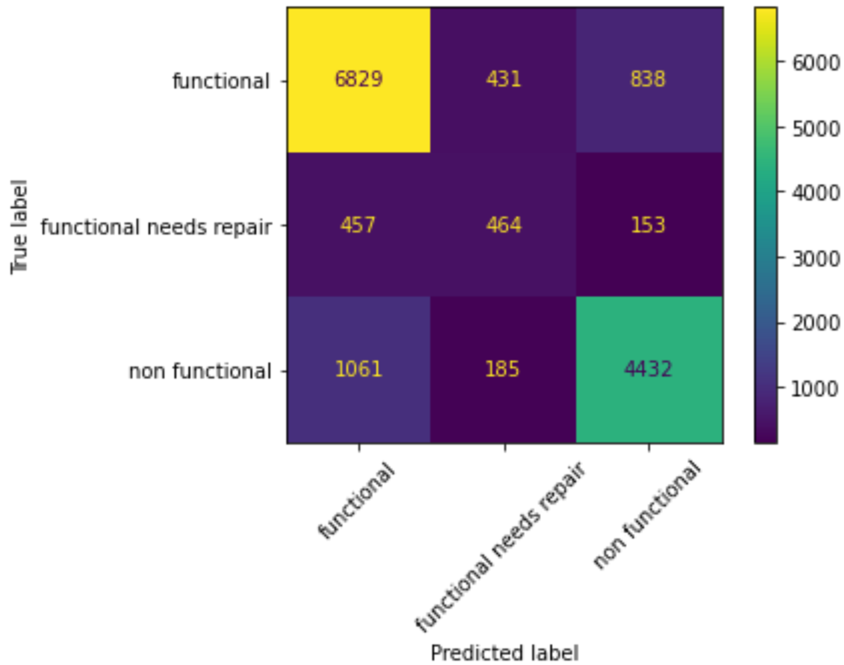
Evaluate results on Random Forest

In [85]:
```
y_hat_rfc = rfc_model_pipe.predict(X_test)
```

In [86]:
```
print(classification_report(y_test, y_hat_rfc))
```

```
                         precision    recall  f1-score   support

             functional       0.82      0.84      0.83      8098
functional needs repair       0.43      0.43      0.43      1074
         non functional       0.82      0.78      0.80      5678

               accuracy                           0.79     14850
              macro avg       0.69      0.69      0.69     14850
           weighted avg       0.79      0.79      0.79     14850
```

In [87]:
```
plot_confusion_matrix(rfc_model_pipe, X_test, y_test, xticks_rotat
```



In [560]:
```
# Save the random forest model as a pickle in a file
joblib.dump(rfc_model_pipe, 'rfc_model.pkl')
```

Out[560]: ['rfc_model.pkl']

Gridsearch for hyperparameter tuning

In [95]:

```
# Grid Search for better model criteria

params = {'rfc__n_estimators': [10],
          'rfc__criterion': ['gini'],
          'rfc__min_samples_leaf': [1, 5, 10],
          'rfc__max_depth': [1, 5, 9],
          'rfc__max_features': [9]
          }

gs_rfc = GridSearchCV(estimator=rfc_model_pipe,
                      param_grid=params, n_jobs = -1,
                      cv=3)
```

In [96]:
```
1 gs_rfc.fit(X_train, y_train)
```

Out[96]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('ct',
                                        ColumnTransformer(remainder='
passthrough',
                                                          transformer
s=[('subpipe_num',

Pipeline(steps=[('num_impute',

SimpleImputer()),

('ss',

StandardScaler())]),

[0, 2,

4, 5,

12]),

('subpipe_cat',

Pipeline(steps=[('cat_impute',

SimpleImputer(fill_value='missing',

strategy='constant')),

('ohe',

OneHotEncoder(handle_unknown='ignore',

sparse=False))]),

[1, 3,

6, 7,

8, 9,

10,

11,

13,

14,

15,

16,

17,
```

```
18,

19,

20,

21,

22,

23,

24,

25,

26])])),
                                        ('sm', SMOTE(random_state=4
2)),
                                        ('rfc',
                                         RandomForestClassifier(random
_state=42))]),
             n_jobs=-1,
             param_grid={'rfc__criterion': ['gini'],
                         'rfc__max_depth': [1, 5, 9], 'rfc__max_featu
res': [9],
                         'rfc__min_samples_leaf': [1, 5, 10],
                         'rfc__n_estimators': [10]})
```

In [103]:

```
# Best parameters for further tuning
gs_rfc.best_params_
```

Out[103]:

```
{'rfc__criterion': 'gini',
 'rfc__max_depth': 9,
 'rfc__max_features': 9,
 'rfc__min_samples_leaf': 5,
 'rfc__n_estimators': 10}
```

In [104]:

```
gs_rfc.score(X_train, y_train)
```

Out[104]:

```
0.5083726150392817
```

Evaluate gridsearch results

In [105]:

```
y_hat_gs_rfc = gs_rfc.predict(X_test)
```

In [106]:
```
print(classification_report(y_test, y_hat_gs_rfc))
```

```
                         precision    recall  f1-score   support

             functional       0.70      0.50      0.58      8098
functional needs repair       0.13      0.56      0.21      1074
         non functional       0.62      0.48      0.54      5678

               accuracy                           0.50     14850
              macro avg       0.48      0.51      0.44     14850
           weighted avg       0.63      0.50      0.54     14850
```

In [561]:
```
# Save the rfc gridsearch model model as a pickle in a file
joblib.dump(gs_rfc, 'gs_rfc.pkl')
```

Out[561]: ['gs_rfc.pkl']

Results summary on Random Forest Gridsearch

Accuracy decreased significantly, perhaps as a result of using 10 n_estimators rather than the default 100 to cut down on processing time. This model though suggests where to explore for max_depth, and samples leaf and split.

Use Randomized Search

In [137]:
```

from sklearn.model_selection import RandomizedSearchCV

# Based in previous gridsearch, optimize for max depth, min sample

random_grid = {
        'rfc__bootstrap': [True],
        'rfc__max_depth': [10, 20, 50, 100],
        'rfc__max_features': ['auto', 'sqrt'],
        'rfc__min_samples_leaf': [1, 2, 4],
        'rfc__min_samples_split': [2, 5, 10],
        'rfc__n_estimators': [10, 100]
}

random = RandomizedSearchCV(estimator = rfc_model_pipe,
                    param_distributions = random_grid, n_jobs = -1,
                    verbose = 2, random_state = 42, cv=3)
```

In [138]:
```
random.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent wo
rkers.
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 124.2min finish
ed
```

Out[138]:
```
RandomizedSearchCV(cv=3,
                   estimator=Pipeline(steps=[('ct',
                                              ColumnTransformer(remai
nder='passthrough',
                                                                trans
formers=[('subpipe_num',

Pipeline(steps=[('num_impute',

SimpleImputer()),

('ss',

StandardScaler())]),

[0,

2,

4,

5,

12]),

('subpipe_cat',

Pipeline(steps=[('cat_impute',

SimpleImputer(fill_value='missing',

strategy='constant')),

('ohe',

OneHotEncoder(handle_unknow...

20,

21,

22,

23,

24,
```

```
25,

26]))]),
                                              ('sm', SMOTE(random_stat
e=42)),
                                              ('rfc',
                                               RandomForestClassifier
(random_state=42))]),
                   n_jobs=-1,
                   param_distributions={'rfc__bootstrap': [True],
                                        'rfc__max_depth': [10, 20, 5
0, 100],
                                        'rfc__max_features': ['auto',
'sqrt'],
                                        'rfc__min_samples_leaf': [1,
2, 4],
                                        'rfc__min_samples_split': [2,
5, 10],
                                        'rfc__n_estimators': [10, 10
0]},
                   random_state=42, verbose=2)
```

In [140]:

```
# Best paramters from randomized search on RFC
random.best_params_
```

Out[140]:

```
{'rfc__n_estimators': 100,
 'rfc__min_samples_split': 5,
 'rfc__min_samples_leaf': 2,
 'rfc__max_features': 'auto',
 'rfc__max_depth': 100,
 'rfc__bootstrap': True}
```

Evaluate randomized search best parameter results

In [139]:

```
random.score(X_train, y_train)
```

Out[139]: 0.8312457912457912

In [141]:

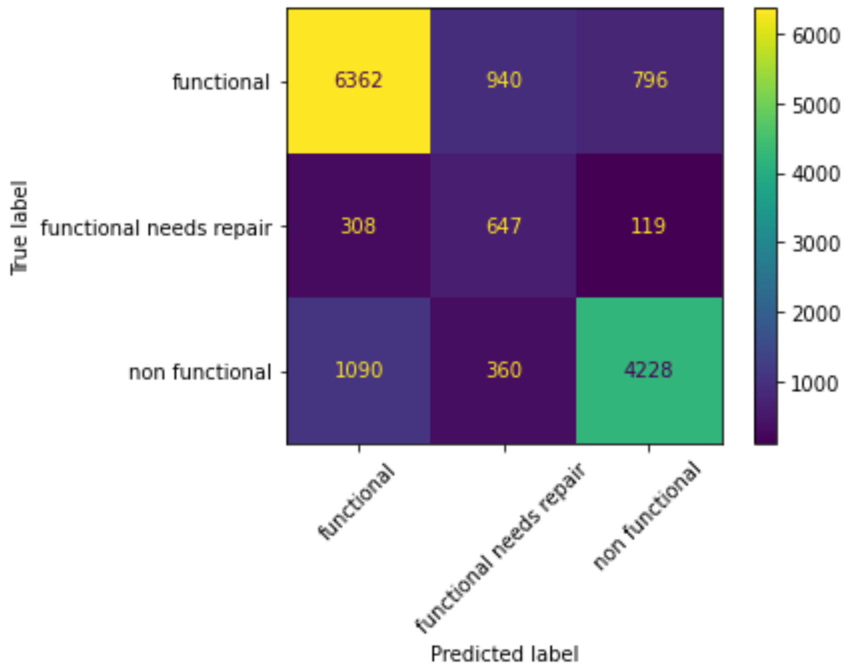
```
y_hat_random = random.predict(X_test)
```

In [142]:

```
print(classification_report(y_test, y_hat_random))
```

```
                         precision    recall  f1-score   support

             functional       0.82      0.79      0.80      8098
functional needs repair       0.33      0.60      0.43      1074
         non functional       0.82      0.74      0.78      5678

               accuracy                           0.76     14850
              macro avg       0.66      0.71      0.67     14850
           weighted avg       0.79      0.76      0.77     14850
```

In [569]:
```
plot_confusion_matrix(random, X_test, y_test, xticks_rotation = 45
```



In [562]:
```
# Save the model as a pickle in a file
joblib.dump(random, 'random_rfc.pkl')
```

Out[562]: ['random_rfc.pkl']

Gridsearch based on randomized results

In [571]:
```
# Based on randomized search conduct one more gridsearch
params = {
            'rfc__n_estimators': [100],
            'rfc__min_samples_leaf': [2,3],
            'rfc__max_depth': [100, 150],
            'rfc__min_samples_split': [3, 5, 7],
            'rfc__max_features': ['auto']
}

gs_rfc_2 = GridSearchCV(estimator=rfc_model_pipe,
                 param_grid=params, n_jobs = -1,
                 verbose = 2, cv = 3)

```

In [572]:
```
gs_rfc_2.fit(X_train, y_train)
```

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

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent wo
rkers.
[Parallel(n_jobs=-1)]: Done  36 out of  36 | elapsed: 129.6min finish
ed
```

Out[572]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('ct',
                                        ColumnTransformer(remainder='
passthrough',
                                                          transformer
s=[('subpipe_num',

Pipeline(steps=[('num_impute',

SimpleImputer()),

('ss',

StandardScaler())]),

[0, 2,

4, 5,

12]),

('subpipe_cat',

Pipeline(steps=[('cat_impute',

SimpleImputer(fill_value='missing',

strategy='constant')),

('ohe',

OneHotEncoder(handle_unknown='ign...

22,

23,

24,

25,

26])])),
                                       ('sm',
                                        SMOTE(n_jobs=-1, random_state
=42)),
                                       ('rfc',
                                        RandomForestClassifier(max_de
```

```
pth=100,
                                                                min_sa
mples_leaf=2,
                                                                min_sa
mples_split=3,
                                                                n_jobs
=-1,
                                                                random
_state=42))]),
             n_jobs=-1,
             param_grid={'rfc__max_depth': [100, 150],
                         'rfc__max_features': ['auto'],
                         'rfc__min_samples_leaf': [2, 3],
                         'rfc__min_samples_split': [3, 5, 7],
                         'rfc__n_estimators': [100]},
             verbose=2)
```

In [573]:

```
# Score the model on training data
gs_rfc_2.score(X_train, y_train)
```

Out[573]:

```
0.8340291806958474
```

In [574]:

```
# examine best paramters
gs_rfc_2.best_params_
```

Out[574]:

```
{'rfc__max_depth': 100,
 'rfc__max_features': 'auto',
 'rfc__min_samples_leaf': 2,
 'rfc__min_samples_split': 3,
 'rfc__n_estimators': 100}
```

In [575]:

```
# create predicted target using test set
y_hat_rfc_2 = gs_rfc_2.predict(X_test)
```

In [576]:

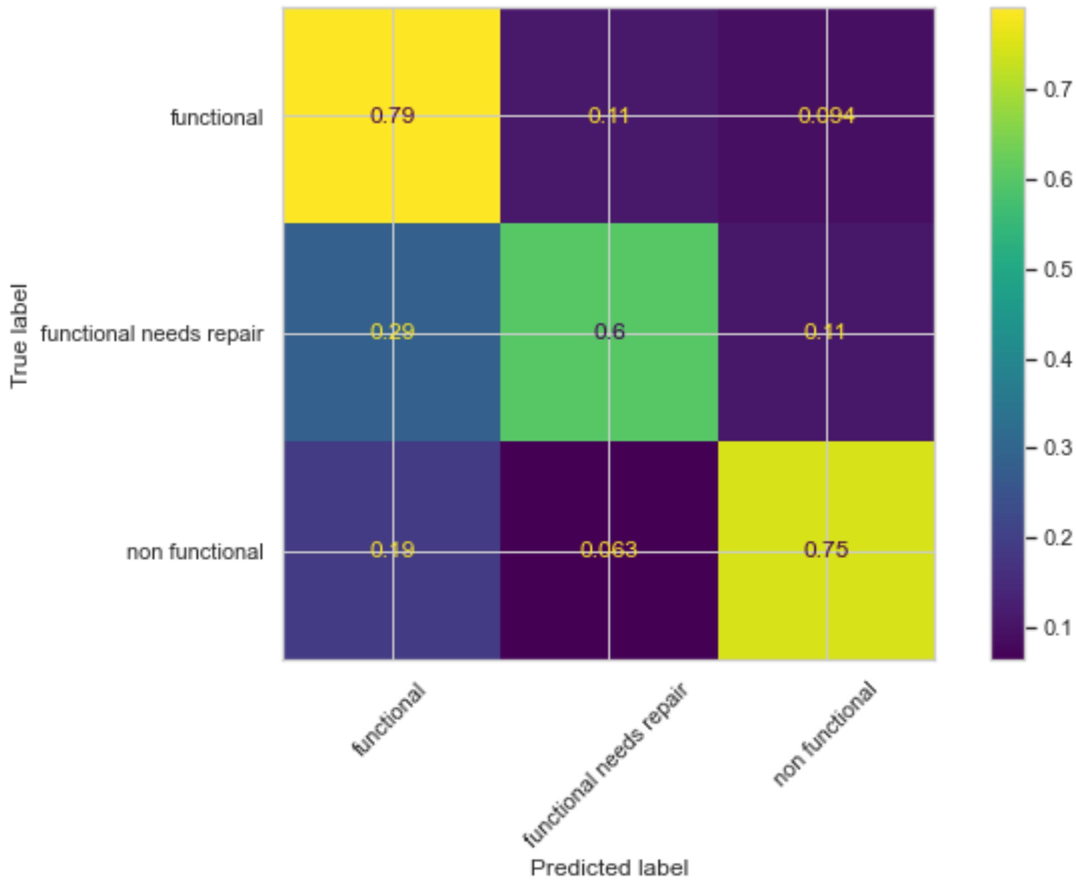
```
print(classification_report(y_test, y_hat_rfc_2))
```

```
                         precision    recall  f1-score   support

             functional       0.82      0.79      0.81      8098
functional needs repair       0.34      0.60      0.43      1074
         non functional       0.83      0.75      0.79      5678

               accuracy                           0.76     14850
              macro avg       0.66      0.71      0.67     14850
           weighted avg       0.79      0.76      0.77     14850
```

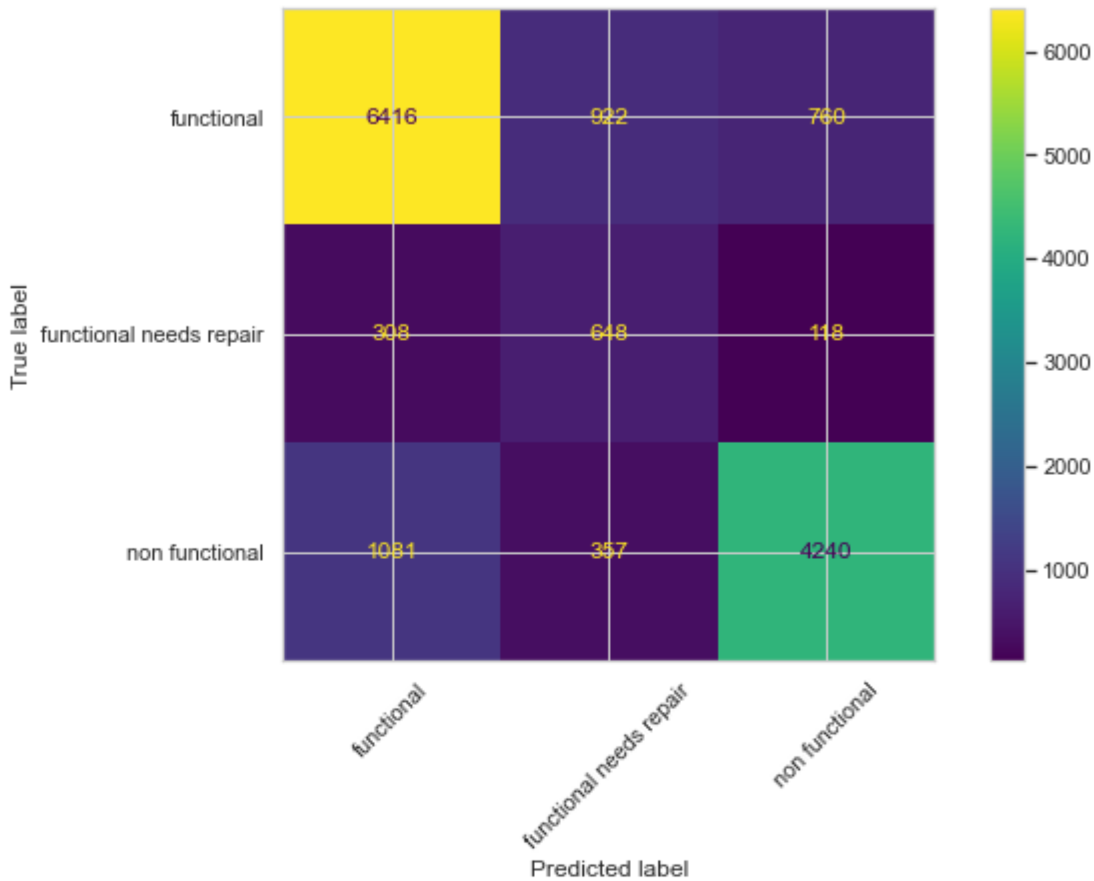
In [577]:

```
# select as final model
final_rfc_model = gs_rfc_2
```

In [787]:
```
# Plot confusion matrix with percentages
plot_confusion_matrix(final_rfc_model,
                      X_test, y_test,
                      xticks_rotation = 45,
                      normalize = 'true'
                     );
```



In [792]:
```
# Plot matrix with case numbers
plot_confusion_matrix(final_rfc_model,
                      X_test, y_test,
                      xticks_rotation = 45,

                     );

plt.savefig('final RFC model matrix')
```



In [579]:
```
# Save the model as a pickle in a file
joblib.dump(final_rfc_model, 'final_rfc_model.pkl')
```

Out[579]:
```
['final_rfc_model.pkl']
```

5. Gradient Boost Model

Compare a default parameter gradient boost model against the RFC final model and select final model.

In [184]:
```
# Gradient Boost model
gbc_model_pipe = Pipeline([('ct', CT), ('gbc', GradientBoostingCla

gbc_model_pipe.fit(X_train, y_train)
```

Out[184]:
```
Pipeline(steps=[('ct',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('subpipe_num',
                                                  Pipeline(steps=[('n
um_impute',
                                                                   Si
mpleImputer()),
                                                                  ('s
s',
                                                                   St
andardScaler())]),
                                                  [0, 2, 4, 5, 12]),
                                                 ('subpipe_cat',
                                                  Pipeline(steps=[('c
at_impute',
                                                                   Si
mpleImputer(fill_value='missing',

strategy='constant')),
                                                                  ('o
he',
                                                                   On
eHotEncoder(handle_unknown='ignore',

sparse=False))]),
                                                  [1, 3, 6, 7, 8, 9,
10, 11, 13,
                                                   14, 15, 16, 17, 1
8, 19, 20,
                                                   21, 22, 23, 24, 2
5, 26])])),
                ('gbc', GradientBoostingClassifier(random_state=4
2))])
```

In [185]:
```
gbc_model_pipe.score(X_train, y_train)
```

Out[185]:
```
0.7612570145903479
```

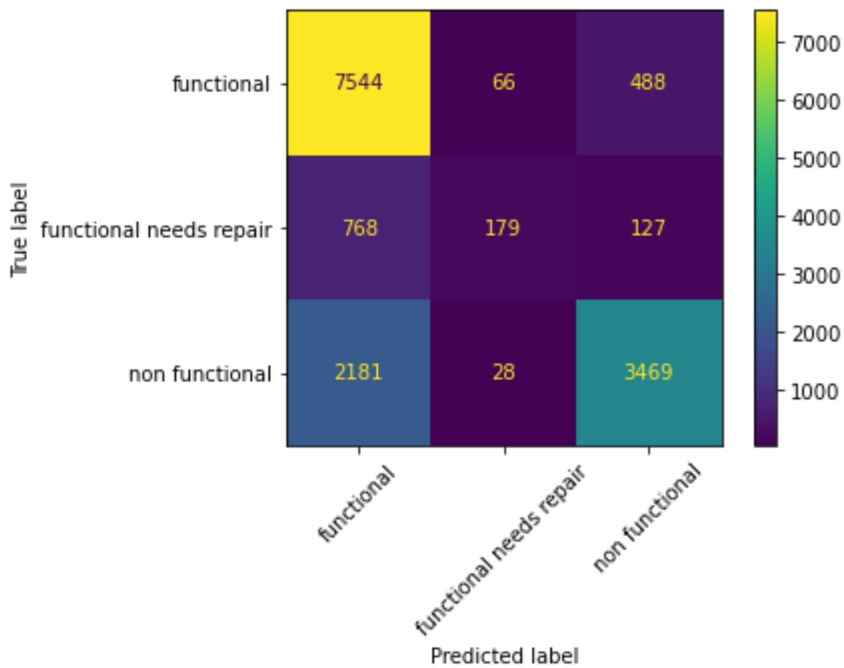
In [186]:
```
y_hat_gbc = gbc_model_pipe.predict(X_test)

print(classification_report(y_test, y_hat_gbc))
```

```
                         precision    recall  f1-score   support

             functional       0.72      0.93      0.81      8098
functional needs repair       0.66      0.17      0.27      1074
         non functional       0.85      0.61      0.71      5678

               accuracy                           0.75     14850
              macro avg       0.74      0.57      0.60     14850
           weighted avg       0.76      0.75      0.73     14850
```

In [193]:
```
gbc_model_pipe.named_steps['gbc']
```

Out[193]:
```
GradientBoostingClassifier(random_state=42)
```

In [568]:
```
plot_confusion_matrix(gbc_model_pipe, X_test, y_test, xticks_rotat
```



In [565]:
```
# Save the model as a pickle in a file
joblib.dump(gbc_model_pipe, 'gbc_model.pkl')
```

Out[565]:
```
['gbc_model.pkl']
```

6. Data Visualizations

Create three data visualizations to communicate findings to Water Aid.

In [797]:

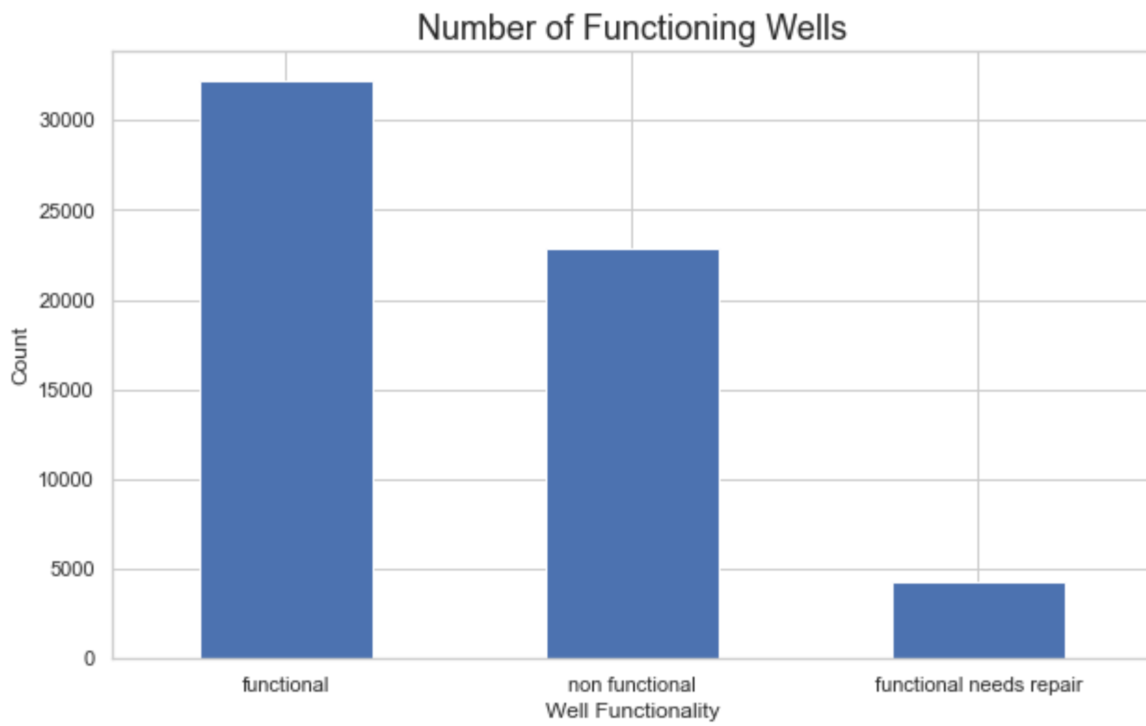
```
# Examine full dataframe columns
df.columns
```

Out[797]:

```
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_ye
ar',
       'extraction_type', 'extraction_type_group', 'extraction_type_c
lass',
       'management', 'management_group', 'payment', 'payment_type',
       'water_quality', 'quality_group', 'quantity', 'quantity_group
',
       'source', 'source_type', 'source_class', 'waterpoint_type',
       'waterpoint_type_group', 'status_group'],
      dtype='object')
```

In [816]:

```
# Visualize well status count from dataset

df.status_group.value_counts().plot(kind="bar")
plt.title("Number of Functioning Wells",fontsize= 18)
plt.xlabel("Well Functionality", fontsize = 12)
plt.xticks(rotation=0)
plt.ylabel("Count", fontsize = 12)

plt.savefig('Number of Functioning Wells.png')

plt.show();


```



In [799]:

```
# Plot four shared cross country water basins in the region
# Plot visual showing basins and functional wells
df_basin = df[df['basin'].isin(['Lake Nyasa', 'Lake Victoria', 'La
                                 'Ruvuma / Southern Coast',
                                 ])]
```

In [800]:

```
df_basin.basin.value_counts()
```

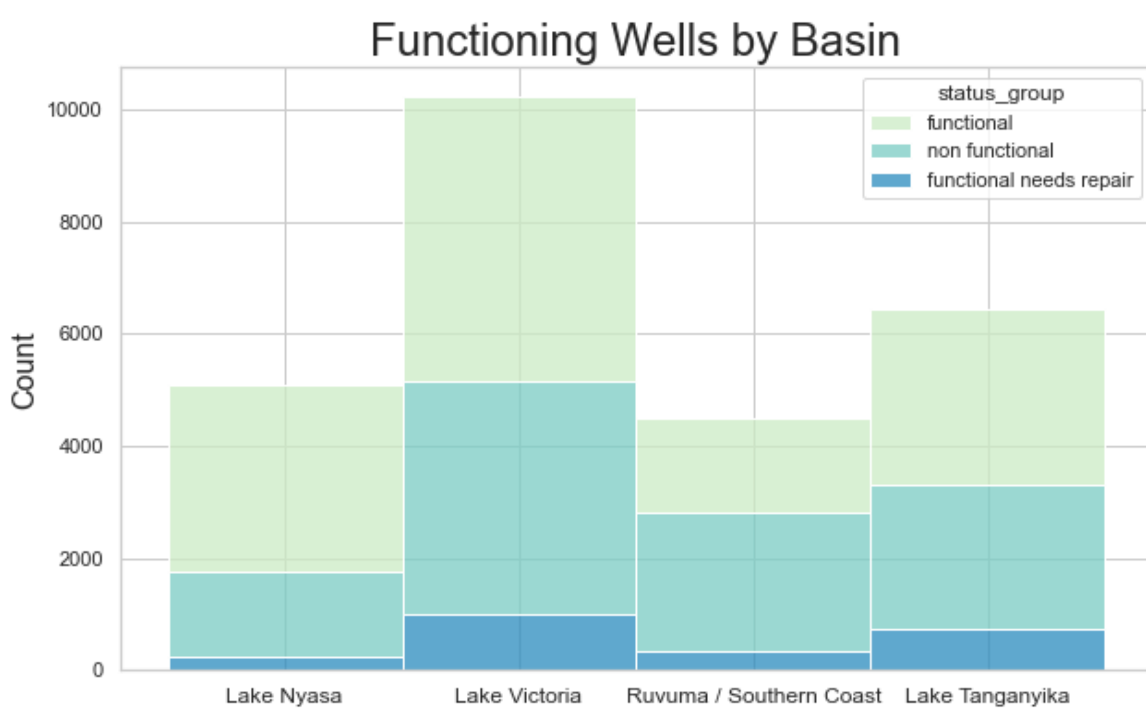
Out[800]:

```
Lake Victoria              10248
Lake Tanganyika             6432
Lake Nyasa                  5085
Ruvuma / Southern Coast     4493
Name: basin, dtype: int64
```

In [801]:
```
df_basin.status_group.value_counts()
```

Out[801]:
```
functional                  13201
non functional              10750
functional needs repair      2307
Name: status_group, dtype: int64
```

In [829]:
```
# Use Seaborn to and stacked histogram to show the four basins and

sns.set_theme()

sns.set(rc={"figure.figsize":(10, 6)})
sns.set_style('whitegrid')

sns.histplot(data = df_basin, x = 'basin', hue = 'status_group',
             bins = 10, binwidth = 6, palette = 'GnBu', legend = '
             multiple = 'stack')


plt.title("Functioning Wells by Basin",fontsize= 24)
plt.xlabel(None)
plt.ylabel("Count", fontsize = 16)
plt.xticks(rotation = 0, fontsize = 12)

plt.savefig('functioning wells by basin.png')

plt.show();


```



In [803]:
```
# Examine well status for two basin recommendations: Lake Victoria
df_victoria = df[df['basin'].isin(['Lake Victoria'])]

df_victoria.status_group.value_counts()
```

Out[803]:
```
functional                5100
non functional            4159
functional needs repair    989
Name: status_group, dtype: int64
```

In [804]:
```
# Create dataframe for Ruvuma Basin
df_ruvuma = df[df['basin'].isin(['Ruvuma / Southern Coast'])]

#Examine well function status for Ruvuma Basin
print(df_ruvuma.status_group.value_counts(normalize = True))
print()
print(df_ruvuma.status_group.value_counts())
```

```
non functional             0.555753
functional                 0.371689
functional needs repair    0.072557
Name: status_group, dtype: float64

non functional             2497
functional                 1670
functional needs repair     326
Name: status_group, dtype: int64
```

In [805]:
```
df_ruvuma.head()
```

Out[805]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	w
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	N
26	55012	500.0	2013-01-16	Sobodo	200	Kilolo Star	39.370777	-9.942532	
46	45111	20.0	2013-02-05	Lga	240	LGA	39.087415	-11.000604	M
91	62591	0.0	2013-01-20	Jica	212	Kokeni	38.962945	-10.476566	
98	33379	0.0	2013-02-19	Danida	1000	DWE	35.542173	-10.808853	

5 rows × 41 columns

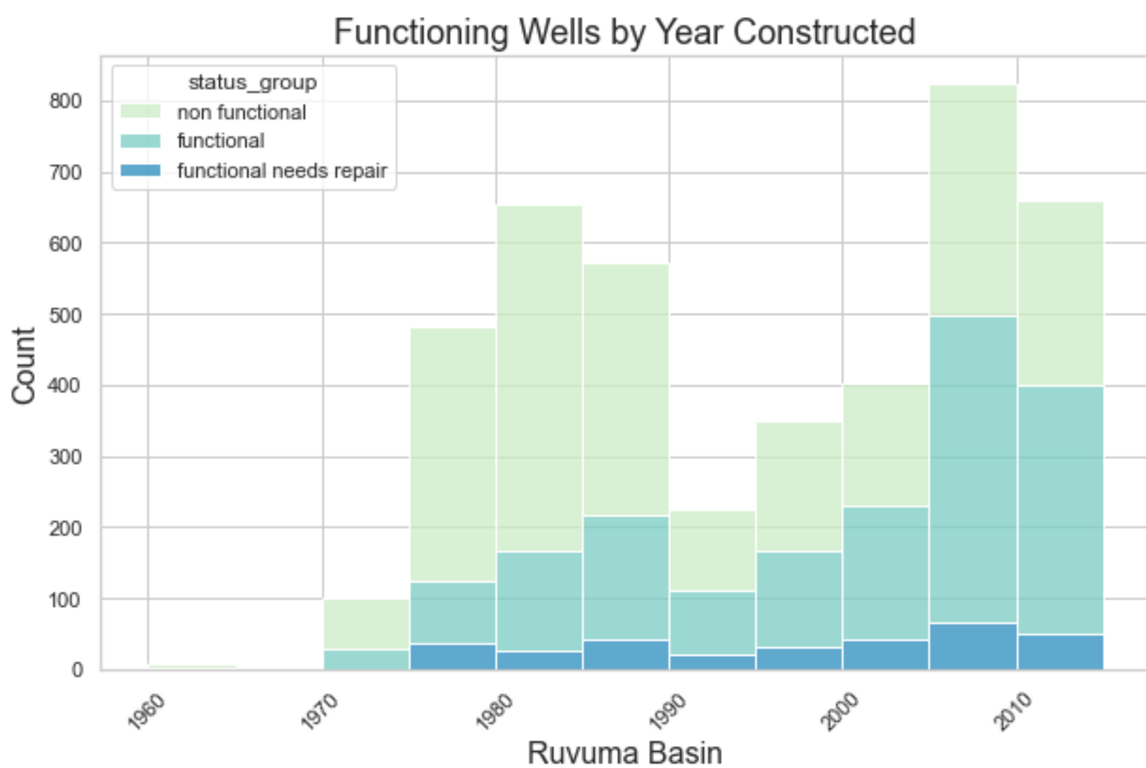
In [806]:
```
#examine descriptive statistics for Ruvuma
df_ruvuma.describe()
```

Out[806]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	regior
count	4493.000000	4493.000000	4493.000000	4493.000000	4493.000000	4493.000000	4493.(
mean	37322.257067	228.390385	410.640329	38.316789	-10.485215	0.124861	52.:
std	21489.456338	777.985990	338.566284	1.549237	0.591604	6.745120	38.‹
min	19.000000	0.000000	-90.000000	34.889771	-11.649440	0.000000	8.(
25%	18908.000000	0.000000	164.000000	37.244214	-10.850966	0.000000	10.(
50%	37228.000000	0.000000	342.000000	38.935668	-10.626269	0.000000	80.(
75%	55874.000000	50.000000	585.000000	39.448147	-10.250908	0.000000	90.(
max	74247.000000	15000.000000	1641.000000	40.345193	-8.496806	450.000000	99.(

In [807]:
```
# Build dataframe ruvuma basin with construction year
df_ruvuma_built = df_ruvuma[df_ruvuma.construction_year != 0]
```

In [818]:
```
# Create data visualization, histogram, for functioning wells in R
sns.set_theme()

sns.set(rc={"figure.figsize":(10, 6)})
sns.set_style('whitegrid')

sns.histplot(data = df_ruvuma_built, x = 'construction_year', hue
             bins = 20, binwidth = 5, palette = 'GnBu', legend = '
             multiple = 'stack')


plt.title("Functioning Wells by Year Constructed",fontsize= 18)
plt.xlabel('Ruvuma Basin', fontsize = 16)
plt.xticks(rotation=0)
plt.ylabel("Count", fontsize = 16)
plt.xticks(rotation = 45)

plt.savefig('functioning wells ruvuma.png')

plt.show()

;
```



Out[818]: ''

In [809]:
```
# Dataframe for older wells in Ruvuma, 1975 to 1990
df_ruvuma_old_wells = df_ruvuma.loc[(df_ruvuma.construction_year >
                                    (df_ruvuma.construction_year <=
```

In [810]:
```
1 # Percentage of wells in need of repair
2 df_ruvuma_old_wells.status_group.value_counts(normalize = True)
```

Out[810]:
```
non functional             0.699024
functional                 0.236646
functional needs repair    0.064331
Name: status_group, dtype: float64
```

Final Summary

The initial Logistic Regression model with default parameters delivered the following scores:

```
                              precision recall  f1-score   sup
   port

         functional              0.78      0.88      0.83      80
   98
         functional needs repair 0.55      0.25      0.34      10
   74
         non functional          0.80      0.74      0.77      56
   78
```

The final Random Forest Classifier model with class imbalance adjustments and hyperparamater tuning delivered the following scores:

```
                              precision recall  f1-score   sup
   port

         functional              0.82      0.79      0.81      80
   98
         functional needs repair 0.34      0.60      0.43      10
   74
         non functional          0.83      0.75      0.79      56
   78
```

The Random Forest Classifier was trained using both Randomized Search and Grid Search. Here are the final hyperparameter adjustments:

n_estimators = 100, (default)

max_depth = 100,

max_features = 'auto',

min_samples_leaf = 2,

min_samples_split = 3

The precision scores increased by 4% for functional wells and increased by 3% for non-functional wells. The precision score fell quite dramatically by 21% for wells in need of repair.

This may be due to wells in need of repair often being classified as functioning wells, their features appear to look much like functioning wells. Despite this the recall score for wells in need of repair improved dramatically, by 35%.

The improved model delivers trade offs. As precision scores increase for functional and non-functional wells, precision for wells in need of repair decreases. But, it needs to be noted, recall for wells in need of repair increases.

Water Aid's use of the model will be primarily for precision - true positive identification for functioning and non-functioning wells. They can still make use of the model for wells in need of repair, but the results for that class need to be understood in terms of recall - the ability of a model to find all the relevant cases within a data set.

Recommendations

1. Model Use

Wells in shared basins should make use of the model's precision metric to accurately identify non-functioning wells. Chances are 83% that they will be right which will help in making use of programming resources to repair the wells.

2. Basin Location

The model makes significant use of data in Tanzanian water basins that also span nearby countries. The Ruvuma Basin stretches from southern Tanzania to northern Mozambique. The Ruvuma basin contains more than 55% nonfunctioning wells and over 7% of wells need repair. Considering Water Aid has a presence in both countries, and efforts by other NGOs and governments of both countries to manage this space along transboundary lines, the Ruvuma basin offers an opportunity to make an impact using this model.

3. Well Age

In the Ruvuma Basin the proportion of older wells in need of repair compared to newer wells in need of repair is much higher. Wells built between 1975 to 1990 should be targeted first. These older non-functional wells account for nearly 70% of all wells built during this time frame.