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Tanzanian Water Wells Status Prediction

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1 Overview

Tanzania is a developing country that struggles to get clean water to its population of 59 million people. According to WHO, 1 in 6 people in Tanzania lack access to safe drinking water and 29 million don't have access to improved sanitation. The focus of this project is to build a classification model to predict the functionality of waterpoints in Tanzania given data provided by Taarifa and the Tanzanian Ministry of Water. The model was built from a dataset containing information about the source of water and status of the waterpoint (functional, functional but needs repairs, and non functional) using an iterative approach and can be found here (./data/training_set_values.csv). The dataset contains 60,000 waterpoints in Tanzania and the following features:

- `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 first sections focus on investigating, cleaning, wrangling, and reducing dimensionality for modeling. The next section contains 6 different classification models and evaluation of each, ultimately leading to us to select our best model for predicting waterpoint status based on the precision of the functional wells in the model. Finally, I will make recommendations to the Tanzanian Government and provide insight on predicting the status of waterpoints.

2 Business Problem

The Tanzanian government has a severe water crisis on their hands as a result of the vast number of non functional wells and they have asked for help. They want to be able to predict the statuses of which pumps are functional, functional but need repair, and non functional in order to improve

their maintenance operations and ensure that it's residents have access to safe drinking water. The data has been collected by and is provided by Taarifa and the Tanzanian Ministry of Water with the hope that the information provided by each waterpoint can aid understanding in which waterpoints will fail.

I have partnered with the Tanzanian government to build a classification model to predict the status of the waterpoints using the dataset provided. I will use the precision of the functional wells as my main metric for model selection, as a non functional well being predicted as a functional well would be more detrimental to their case, but will provide and discuss several metrics for each model.

3 Data Understanding

The dataset used for this analysis can be found here (./data/training_set_values.csv). It contains a wealth of information about waterpoints in Tanzania and the status of their operation. The target variable has 3 different options for it's status:

- `functional` - the waterpoint is operational and there are no repairs needed
- `functional needs repair` - the waterpoint is operational, but needs repairs
- `non functional` - the waterpoint is not operational

Below I will import the dataset and start my investigation of relevant information it may contain. Let's get started!

In [1]:

```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")

from sklearn.model_selection import train_test_split, GridSearchCV, cr
from sklearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE, SMOTENC

# Classification Models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
import xgboost as xgb
from sklearn.dummy import DummyClassifier
from xgboost.sklearn import XGBClassifier

from sklearn.metrics import plot_confusion_matrix, accuracy_score, f1_
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve, auc, roc_auc_score

# Scalers
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, label_binarize

# Categorical Create Dummies
from sklearn.preprocessing import OneHotEncoder
```

In [2]:
```
# Data Import Train Set
df_train_set = pd.read_csv('data/training_set_values.csv', index_col=
df_train_set
```

Out[2]:

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

In [3]:
```
# Data import Training set labels
df_train_labels = pd.read_csv('data/training_set_labels.csv', index_c
df_train_labels
```

Out[3]:

id	status_group
69572	functional
8776	functional
34310	functional
67743	non functional
19728	functional
...	...
60739	functional
27263	functional
37057	functional
31282	functional
26348	functional

59400 rows × 1 columns

In [4]:
```
#Merge datasets
df = pd.merge(df_train_labels, df_train_set, how = 'inner', on='id')
```

In [5]:
```
#Reset index
df.reset_index(inplace=True)
df.head()
```

Out[5]:

	id	status_group	amount_tsh	date_recorded	funder	gps_height	installer	longitude	la
0	69572	functional	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.8
1	8776	functional	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.1
2	34310	functional	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.8
3	67743	non functional	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.1
4	19728	functional	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.8

5 rows × 41 columns

In [6]:
```
# Check datatypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   status_group           59400 non-null  object 
 2   amount_tsh             59400 non-null  float64
 3   date_recorded          59400 non-null  object 
 4   funder                 55765 non-null  object 
 5   gps_height             59400 non-null  int64  
 6   installer              55745 non-null  object 
 7   longitude              59400 non-null  float64
 8   latitude               59400 non-null  float64
 9   wpt_name               59400 non-null  object 
 10  num_private            59400 non-null  int64  
 11  basin                  59400 non-null  object 
 12  subvillage             59029 non-null  object 
 13  region                 59400 non-null  object 
```

In [7]:
```
#Get stats on numeric columns
df.describe()
```

Out[7]:

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

In [8]:
```
#Check for duplicates
sum(df.duplicated())
```

Out[8]: 0

In [9]:
```
# Print all value counts to make observations
for col in df.columns:
    print(df[col].value_counts())
```

```
2047     1
72310    1
49805    1
51852    1
62091    1
        ..
46396    1
36155    1
34106    1
38200    1
0        1
Name: id, Length: 59400, dtype: int64
functional                 32259
non functional             22824
functional needs repair     4317
Name: status_group, dtype: int64
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
2011-03-15    572
2011-03-17    558
2013-02-03    546
2011-03-14    520
2011-03-16    513
             ...
2011-09-14      1
2011-09-28      1
2002-10-14      1
2011-09-05      1
2011-09-26      1
Name: date_recorded, Length: 356, dtype: int64
Government Of Tanzania      9084
Danida                      3114
Hesawa                      2202
Rwssp                       1374
World Bank                  1349
                            ...
Kwa Mzee Waziri                1
Nyabibuye Islamic Center       1
Iom                            1
San Pellegrino                 1
Tquick Wings                   1
Name: funder, Length: 1897, dtype: int64
 0       20438
```

```
-15         60
-16         55
-13         55
-20         52
          ...
 2285        1
 2424        1
 2552        1
 2413        1
 2385        1
Name: gps_height, Length: 2428, dtype: int64
DWE                            17402
Government                      1825
RWE                             1206
Commu                           1060
DANIDA                          1050
                               ...
Friedkin conservation fund         1
MIAB                               1
Indiv                              1
Omar Ally                          1
MAJ MUGUMU                         1
Name: installer, Length: 2145, dtype: int64
0.000000     1812
37.540901       2
33.010510       2
39.093484       2
32.972719       2
              ...
37.579803       1
33.196490       1
34.017119       1
33.788326       1
30.163579       1
Name: longitude, Length: 57516, dtype: int64
-2.000000e-08    1812
-6.985842e+00       2
-3.797579e+00       2
-6.981884e+00       2
-7.104625e+00       2
                  ...
-5.726001e+00       1
-9.646831e+00       1
-8.124530e+00       1
-2.535985e+00       1
-2.598965e+00       1
Name: latitude, Length: 57517, dtype: int64
none                           3563
Shuleni                        1748
Zahanati                        830
Msikitini                       535
Kanisani                        323
                               ...
Kwa Serijo Mlawa                  1
Kwa Anyandile Kasyupa             1
Shule Ya Msingi Kipungulu         1
Kwa Jasoni Mwalwaka               1
```

```
Mwiono B                          1
Name: wpt_name, Length: 37400, dtype: int64
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
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
Madukani     508
Shuleni      506
Majengo      502
Kati         373
Mtakuja      262
            ...
Mashinoda      1
Maluga         1
Saata          1
Igekemaja      1
Mwiono B       1
Name: subvillage, Length: 19287, dtype: int64
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
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
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
Njombe          2503
Arusha Rural    1252
Moshi Rural     1251
Bariadi         1177
Rungwe          1106
                ...
Moshi Urban       79
```

```
Kigoma Urban      71
Arusha Urban      63
Lindi Urban       21
Nyamagana          1
Name: lga, Length: 125, dtype: int64
Igosi        307
Imalinyi     252
Siha Kati    232
Mdandu       231
Nduruma      217
            ...
Chinugulu      1
Kapilula       1
Ukata          1
Mlimani        1
Linda          1
Name: ward, Length: 2092, dtype: int64
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
True     51011
False     5055
Name: public_meeting, dtype: int64
GeoData Consultants Ltd    59400
Name: recorded_by, dtype: int64
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
K                             682
None                          644
Borehole                      546
Chalinze wate                 405
M                             400
                             ...
Mbatakero mradi wa Maji shu     1
Nabaiye pipe broken             1
Kizota                          1
QWUICKWIN                       1
```

```
IKTM 3 water supply              1
Name: scheme_name, Length: 2696, dtype: int64
True     38852
False    17492
Name: permit, dtype: int64
0       20709
2010     2645
2008     2613
2009     2533
2000     2091
2007     1587
2006     1471
2003     1286
2011     1256
2004     1123
2012     1084
2002     1075
1978     1037
1995     1014
2005     1011
1999      979
1998      966
1990      954
1985      945
1980      811
1996      811
1984      779
1982      744
1994      738
1972      708
1974      676
1997      644
1992      640
1993      608
2001      540
1988      521
1983      488
1975      437
1986      434
1976      414
1970      411
1991      324
1989      316
1987      302
1981      238
1977      202
1979      192
1973      184
2013      176
1971      145
1960      102
1967       88
1963       85
1968       77
1969       59
1964       40
1962       30
```

```
1961       21
1965       19
1966       17
Name: construction_year, dtype: int64
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
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
gravity         26780
handpump        16456
other            6430
submersible      6179
motorpump        2987
rope pump         451
wind-powered      117
Name: extraction_type_class, dtype: int64
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
user-group    52490
commercial     3638
parastatal     1768
other           943
unknown         561
Name: management_group, dtype: int64
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
never pay     25348
per bucket     8985
monthly        8300
unknown        8157
on failure     3914
annually       3642
other          1054
Name: payment_type, dtype: int64
soft                  50818
salty                  4856
unknown                1876
milky                   804
coloured                490
salty abandoned         339
fluoride                200
fluoride abandoned       17
Name: water_quality, dtype: int64
good        50818
salty        5195
unknown      1876
milky         804
colored       490
fluoride      217
Name: quality_group, dtype: int64
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: quantity, dtype: int64
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: quantity_group, dtype: int64
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
spring                   17021
shallow well             16824
borehole                 11949
river/lake               10377
rainwater harvesting      2295
dam                        656
other                      278
Name: source_type, dtype: int64
groundwater    45794
surface        13328
unknown          278
Name: source_class, dtype: int64
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
communal standpipe    34625
hand pump             17488
other                  6380
improved spring         784
cattle trough           116
dam                       7
Name: waterpoint_type_group, dtype: int64
```

In [10]:
```
# Check null values
df.isna().sum()
```

Out[10]:
```
id                        0
status_group              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 [11]:
```
# Check unique values for categorical data
obj_df = df.select_dtypes(include=['object'])
obj_df.nunique()
```

Out[11]:
```
status_group               3
date_recorded            356
funder                  1897
installer               2145
wpt_name               37400
basin                      9
subvillage             19287
region                    21
lga                      125
ward                    2092
public_meeting             2
recorded_by                1
scheme_management         12
scheme_name             2696
permit                     2
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
```

3.1 Initial Observations

3.1.1 Missing Values

scheme_name has the most missing values, followed by **funder**, **installer**, **public_meeting**, **scheme_management**, and **permit** with ~3,000 null values, and then **subvillage** with 371 null values. Several of these columns will be deleted as they appear to duplicate other columns, and I will investigate **installer**, **permit**, and **subvillage** further.

3.1.2 Data types

- **wpt_name**, **subvillage**, **ward**, **scheme_name**, **installer**, **funder**, and **date_recorded** are categorical features that have unique values in the thousands. This will be a problem with dummy variables, will likely remove or feature engineer.
- I will drop **recorded_by** as it has the same value for all rows.

- **num_private** is not defined on the DrivenData site, and it is not obvious what the feature indicates.
- **id** column will be dropped.
- **public_meeting** and **permit** are boolean.
- **construction_year**, **latitude**, **longitude**, **gps_height**, **amount_tsh**, and **population** all have thousands of rows of 0 entered. I will drop rows for most of these variables that have 0 entered, and will have to investigate further for real data on some columns.

3.1.3 Duplicate and Similar Data

The following columns all contain duplicate or similar data, will remove features that will cause multicollinearity:

- **extraction_type**, **extraction_type_group**, and **extraction_type_class**
- **payment** and **payment_type**
- **water_quality** and **quality_group**
- **quanitity** and **quantity_group**
- **source** and **source_type**
- **waterpoint_type** and **waterpoint_type_group**
- **region** and **region_code**

4 Data Cleaning

In this section, I will clean the dataset by removing similar and unnecessary columns and trim the dataset of remaining null values. I will also further investigate whether some columns contain the same information if it was not immediately obvious. There are several rows containing 0 enteries in some column information. I will investigate whether I believe the data to be real instead of a placeholder.

4.1 Drop duplicate and columns with similar information

I will keep **extraction_type_class** and remove **extraction_type** and **extraction_type_group** as it's columns values appear to be the most relevant for the project. **scheme_name** will be dropped for it's many null values. Other columns will be removed at this point due to irrelavancy, duplicates, null values, and some others will have to be investigated after the first drop.

In [12]:
```
# Columns to be dropped
dropped_columns = ['extraction_type', 'extraction_type_group', 'payme
                   'quantity_group', 'source', 'waterpoint_type_group
                   'id', 'subvillage', 'wpt_name', 'ward', 'funder',
                   'region_code', 'district_code', 'lga', 'scheme_man
```

In [13]:
```
df = df.drop(dropped_columns, axis=1)
```

In [14]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 19 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   status_group           59400 non-null  object 
 1   amount_tsh             59400 non-null  float64
 2   gps_height             59400 non-null  int64  
 3   installer              55745 non-null  object 
 4   longitude              59400 non-null  float64
 5   latitude               59400 non-null  float64
 6   basin                  59400 non-null  object 
 7   region                 59400 non-null  object 
 8   population             59400 non-null  int64  
 9   permit                 56344 non-null  object 
 10  construction_year      59400 non-null  int64  
 11  extraction_type_class  59400 non-null  object 
 12  management             59400 non-null  object 
 13  management_group       59400 non-null  object 
 14  payment_type           59400 non-null  object 
 15  water_quality          59400 non-null  object 
 16  quantity               59400 non-null  object 
 17  source_type            59400 non-null  object 
 18  waterpoint_type        59400 non-null  object 
dtypes: float64(3), int64(3), object(13)
memory usage: 8.6+ MB
```

4.2 Dealing with null values

In [15]:
```
1 #Check for nulls
2 df.isna().sum()
```

Out[15]:
```
status_group               0
amount_tsh                 0
gps_height                 0
installer               3655
longitude                  0
latitude                   0
basin                      0
region                     0
population                 0
permit                  3056
construction_year          0
extraction_type_class      0
management                 0
management_group           0
payment_type               0
water_quality              0
quantity                   0
source_type                0
waterpoint_type            0
dtype: int64
```

In [16]:
```
# Drop all remaining null values from our dataset
df = df.dropna()
```

In [17]:
```
#Check to see that it worked
df.isna().sum()
```

Out[17]:
```
status_group            0
amount_tsh              0
gps_height              0
installer               0
longitude               0
latitude                0
basin                   0
region                  0
population              0
permit                  0
construction_year       0
extraction_type_class   0
management              0
management_group        0
payment_type            0
water_quality           0
quantity                0
source_type             0
waterpoint_type         0
dtype: int64
```

In [18]:
```
# Convert boolean permit to integers
df['permit'] = df['permit'].astype(int)
```

In [19]:
```
# Check to see that it worked
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 55102 entries, 0 to 59399
Data columns (total 19 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   status_group           55102 non-null  object
 1   amount_tsh             55102 non-null  float64
 2   gps_height             55102 non-null  int64
 3   installer              55102 non-null  object
 4   longitude              55102 non-null  float64
 5   latitude               55102 non-null  float64
 6   basin                  55102 non-null  object
 7   region                 55102 non-null  object
 8   population             55102 non-null  int64
 9   permit                 55102 non-null  int64
 10  construction_year      55102 non-null  int64
 11  extraction_type_class  55102 non-null  object
 12  management             55102 non-null  object
 13  management_group       55102 non-null  object
```

4.3 Investigate management and management_group

I need to investigate these 2 columns further to see if they contain similar information.

In [20]:
```
1 df['management'].value_counts()
```

Out[20]:
```
vwc                 37416
wug                  6314
water board          2705
wua                  2307
private operator     1891
parastatal           1588
water authority       825
other                 733
company               656
unknown               491
other - school         99
trust                  77
Name: management, dtype: int64
```

In [21]:
```
1 df['management_group'].value_counts()
```

Out[21]:
```
user-group    48742
commercial     3449
parastatal     1588
other           832
unknown         491
Name: management_group, dtype: int64
```

The most data is contained in the user-group subcategory of **management_group**. I will groupby to investigate if the information is similar.

In [22]:
```
1 df.loc[df['management_group']=='user-group']['management'].value_count
```

Out[22]:
```
vwc            37416
wug             6314
water board     2705
wua             2307
Name: management, dtype: int64
```

The data is identical to the data contained in the management column in the subcategory of 'user-group'. I will drop **management_group** from our features.

In [23]:
```
1 #Drop column
2 df = df.drop('management_group', axis=1)
```

In [24]:
```
#Check to see that it worked
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 55102 entries, 0 to 59399
Data columns (total 18 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   status_group           55102 non-null  object 
 1   amount_tsh             55102 non-null  float64
 2   gps_height             55102 non-null  int64  
 3   installer              55102 non-null  object 
 4   longitude              55102 non-null  float64
 5   latitude               55102 non-null  float64
 6   basin                  55102 non-null  object 
 7   region                 55102 non-null  object 
 8   population             55102 non-null  int64  
 9   permit                 55102 non-null  int64  
 10  construction_year      55102 non-null  int64  
 11  extraction_type_class  55102 non-null  object 
 12  management             55102 non-null  object 
 13  payment_type           55102 non-null  object 
 14  water_quality          55102 non-null  object 
 15  quantity               55102 non-null  object 
 16  source_type            55102 non-null  object 
 17  waterpoint_type        55102 non-null  object 
dtypes: float64(3), int64(4), object(11)
memory usage: 8.0+ MB
```

In [25]:
```
for col in df.columns:
    print(df[col].value_counts())
```

```
functional                29885
non functional            21381
functional needs repair    3836
Name: status_group, dtype: int64
0.0        37811
500.0       3071
50.0        2333
1000.0      1442
20.0        1427
           ...
38000.0        1
1400.0         1
8500.0         1
6300.0         1
26.0           1
Name: amount_tsh, Length: 95, dtype: int64
 0       18310
-15         54
 303        51
```

After our first round of cleaning, there are several features we need to examine further:

- **status_group** is an unbalanced target, may need to look into further during modeling and apply SMOTE.

- There are several columns with thousands of 0 entries - **amount_tsh**, **gps_height**, **longitude**, **latitude**, **population**, **construction_year**.

4.4 Construction year

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

Out[26]:
```
0       18392
2008     2568
2009     2490
2010     2427
2000     1565
2007     1557
2006     1447
2003     1276
2011     1211
2004     1107
2002     1064
1978     1027
2012     1025
2005      983
1995      978
1999      950
1985      941
1998      921
1984      777
```

In [27]:
```
# Finding mean and median without zero values
df.loc[df['construction_year']!=0].describe()
```

Out[27]:

	amount_tsh	gps_height	longitude	latitude	population	permit	const
count	36710.000000	36710.000000	36710.000000	36710.000000	36710.000000	36710.000000	3
mean	471.881843	982.395015	36.015003	-6.358975	268.881694	0.717379	
std	3074.841656	623.784917	2.609370	2.762486	542.812926	0.450280	
min	0.000000	-63.000000	29.607122	-11.649440	0.000000	0.000000	
25%	0.000000	351.000000	34.671850	-8.855908	30.000000	0.000000	
50%	0.000000	1116.500000	36.691907	-6.351197	150.000000	1.000000	
75%	200.000000	1471.000000	37.896261	-3.731978	304.000000	1.000000	
max	250000.000000	2770.000000	40.345193	-1.042375	30500.000000	1.000000	

In [28]:
```
#Replace 0 values in construction_year with 1950 to aid visualization
df['construction_year'].replace(to_replace = 0, value = 1950, inplace=
```

In [29]:
```
#Check to see if it worked
df['construction_year'].value_counts()
```

Out[29]:

1950	18392
2008	2568
2009	2490
2010	2427
2000	1565
2007	1557
2006	1447
2003	1276
2011	1211
2004	1107
2002	1064
1978	1027
2012	1025
2005	983
1995	978
1999	950
1985	941
1998	921
1984	777
1996	766
1982	741
1972	705
1994	703
1974	675
1990	666
1980	647
1992	632
1997	612
1993	595
2001	530
1988	520
1983	487
1975	437
1986	431
1976	411
1991	322
1989	316
1970	310
1987	297
1981	237
1977	199
1979	192
1973	183
2013	173
1971	145
1963	84
1967	83
1968	68
1969	59
1960	45
1964	40
1962	29
1961	20
1965	19

```
1966       17
Name: construction_year, dtype: int64
```

It is unfortunate that there are 19,000 entries with 0 for the **construction_year**. These may be natural and spring fed sources that were never "constructed". I chose to replace the 0 values with 1950, so they are still the "oldest" in the dataset, but will aid in visualizing the functionality of the pumps by the year they were made.

4.5 Latitude/Longitude zeros

In [30]:
```
df.longitude.value_counts()
```

Out[30]:
```
0.000000     1793
32.984790       2
37.540901       2
37.328905       2
37.252194       2
               ...
39.002868       1
37.095964       1
36.658462       1
33.116994       1
38.592731       1
Name: longitude, Length: 53261, dtype: int64
```

In [31]:
```
# Investigate longitude entries that are 0
df.loc[df['longitude'] == 0]
```

Out[31]:

	status_group	amount_tsh	gps_height	installer	longitude	latitude	basin	region
21	functional	0.0	0	DWE	0.0	-2.000000e-08	Lake Victoria	Shinyanga
53	non functional	0.0	0	Government	0.0	-2.000000e-08	Lake Victoria	Mwanza
168	functional	0.0	0	WVT	0.0	-2.000000e-08	Lake Victoria	Shinyanga
177	non functional	0.0	0	DWE	0.0	-2.000000e-08	Lake Victoria	Shinyanga
253	functional needs repair	0.0	0	DWE	0.0	-2.000000e-08	Lake Victoria	Mwanza
...	...	...	...	...	...	...	...	...
59189	functional needs repair	0.0	0	DWE	0.0	-2.000000e-08	Lake Victoria	Shinyanga

The 0s that are entered into the longitude column are also 0s in gps_height and -2e8 for latitude columns. I will drop these values from the dataset.

In [32]:
```
# Drop rows with 0 entered in longitude column
df = df.loc[df['longitude'] != 0]
```

In [33]:
```
# Check to see if it worked
df.describe()
```

Out[33]:

	amount_tsh	gps_height	longitude	latitude	population	permit	const
count	53309.000000	53309.000000	53309.000000	53309.000000	53309.000000	53309.000000	5
mean	337.580181	692.509670	35.186804	-5.849440	188.814515	0.702508	
std	2714.547122	691.264883	2.670974	2.806529	474.147131	0.457159	
min	0.000000	-90.000000	29.607122	-11.649440	0.000000	0.000000	
25%	0.000000	0.000000	33.167340	-8.441371	0.000000	0.000000	
50%	0.000000	438.000000	35.295878	-5.144420	45.000000	1.000000	
75%	40.000000	1322.000000	37.353028	-3.359390	240.000000	1.000000	
max	250000.000000	2770.000000	40.345193	-0.998464	30500.000000	1.000000	

In [34]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 53309 entries, 0 to 59399
Data columns (total 18 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   status_group           53309 non-null  object 
 1   amount_tsh             53309 non-null  float64
 2   gps_height             53309 non-null  int64  
 3   installer              53309 non-null  object 
 4   longitude              53309 non-null  float64
 5   latitude               53309 non-null  float64
 6   basin                  53309 non-null  object 
 7   region                 53309 non-null  object 
 8   population             53309 non-null  int64  
 9   permit                 53309 non-null  int64  
 10  construction_year      53309 non-null  int64  
 11  extraction_type_class  53309 non-null  object 
 12  management             53309 non-null  object 
 13  payment_type           53309 non-null  object 
 14  water_quality          53309 non-null  object 
 15  quantity               53309 non-null  object 
 16  source_type            53309 non-null  object 
 17  waterpoint_type        53309 non-null  object 
dtypes: float64(3), int64(4), object(11)
memory usage: 7.7+ MB
```

Looks like it all worked! I believe the **amount_tsh** and **population** 0 values are real so I will leave all data as is for vanilla models.

4.6 Installer - Several different spellings for same installer

In [35]:
```
#Check unique values after inital cleaning
df.nunique()
```

Out[35]:
```
status_group               3
amount_tsh                95
gps_height              2426
installer               2024
longitude              53260
latitude               53262
basin                      9
region                    21
population              1026
permit                     2
construction_year         55
extraction_type_class      7
management                12
payment_type               7
water_quality              8
quantity                   5
source_type                7
waterpoint_type            7
dtype: int64
```

Upon checking the unique values for our categorical variables after trimming the dataset, installer still has 2024 unique entries, which will be a problem when we create dummies. We will need to cut down the amount of unique entries to not overload our model.

In [36]:
```
#Investigate 2024 unique values for installer
# pd.set_option("display.max_rows", None)
df['installer'].value_counts()
```

Out[36]:
```
DWE                          16214
Government                    1633
RWE                           1178
Commu                         1060
DANIDA                        1049
                             ...
Wahidi                           1
mchina                           1
Mwigicho                         1
FRESH WATER PLC ENGLAND          1
MAJ MUGUMU                       1
Name: installer, Length: 2024, dtype: int64
```

There are several entries with typos and different variations of the same installer. I will attempt to fix some of the clerical errors and narrow down the amount of unique identifiers we will use for our model.

In [37]:

```
# Correct variations and misspellings in the installer column
df['installer'] = df['installer'].replace(to_replace = ('Central gover
                                          'Cental Government','Tanzani
                                          'Centra Government', 'centra
                                          'TANZANIA GOVERNMENT','Centi
                                          'Tanzanian Government', 'Tan

df['installer'] = df['installer'].replace(to_replace = ('District COUN
                                          'Counc','District council',
                                          'Council', 'COUN', 'Distri',
                                         value = 'District Council')

df['installer'] = df['installer'].replace(to_replace = ('villigers',
                                          'Villi', 'Village Council',
                                          'Village community', 'Villag
                                          'Villege Council', 'Village
                                          'Villager', 'Village Technic
                                          'Village community members',
                                          'Village govt', 'VILLAGERS',

df['installer'] = df['installer'].replace(to_replace = ('District Water
                                          'Distric Water Department'),

df['installer'] = df['installer'].replace(to_replace = ('FinW', 'Fini
                                          'Finwater', 'FINN WATER', 'F
                                         value ='Fini Water')

df['installer'] = df['installer'].replace(to_replace = ('RC CHURCH',
                                          'RC church', 'RC CATHORIC',

df['installer'] = df['installer'].replace(to_replace = ('world vision
                                          'WORLD VISION', 'World Visi

df['installer'] = df['installer'].replace(to_replace = ('Unisef','Unic

df['installer'] = df['installer'].replace(to_replace = 'DANID', value

df['installer'] = df['installer'].replace(to_replace =('Commu', 'Commu
                                          'Adra /Community', 'Communit
                                         value ='Community')

df['installer'] = df['installer'].replace(to_replace = ('GOVERNMENT',
                                          'Gover', 'Gove', 'Governme',

df['installer'] = df['installer'].replace(to_replace = ('Hesawa', 'hes

df['installer'] = df['installer'].replace(to_replace = ('JAICA', 'JICA
                                         value ='Jaica')

df['installer'] = df['installer'].replace(to_replace = ('KKKT _ Konde
                                         value ='KKKT')

df['installer'] = df['installer'].replace(to_replace = '0', value ='Un
```

In [38]:
```
df['installer'].value_counts().head(20)
```

Out[38]:
```
DWE                   16214
Government             2468
Community              1791
DANIDA                 1601
HESAWA                 1180
RWE                    1178
District Council       1173
Central Government     1115
KKKT                   1102
Fini Water              952
Unknown                 780
TCRS                    702
World Vision            660
CES                     610
RC Church               484
Villagers               482
LGA                     408
WEDECO                  397
TASAF                   371
```

4.7 Reduce Dimensionality for Installer

In [39]:
```
# Keep only top 20 installers as unique values
installer_20 = df.installer.value_counts(normalize=True).head(20).inde


df['installer'] = [type_ if type_ in installer_20
                        else "OTHER" for type_ in df['installer']]
```

In [40]:
```
1 df.installer.value_counts()
```

Out[40]:
```
OTHER                19283
DWE                  16214
Government            2468
Community             1791
DANIDA                1601
HESAWA                1180
RWE                   1178
District Council      1173
Central Government    1115
KKKT                  1102
Fini Water             952
Unknown                780
TCRS                   702
World Vision           660
CES                    610
RC Church              484
Villagers              482
LGA                    408
WEDECO                 397
TASAF                  371
Jaica                  358
Name: installer, dtype: int64
```

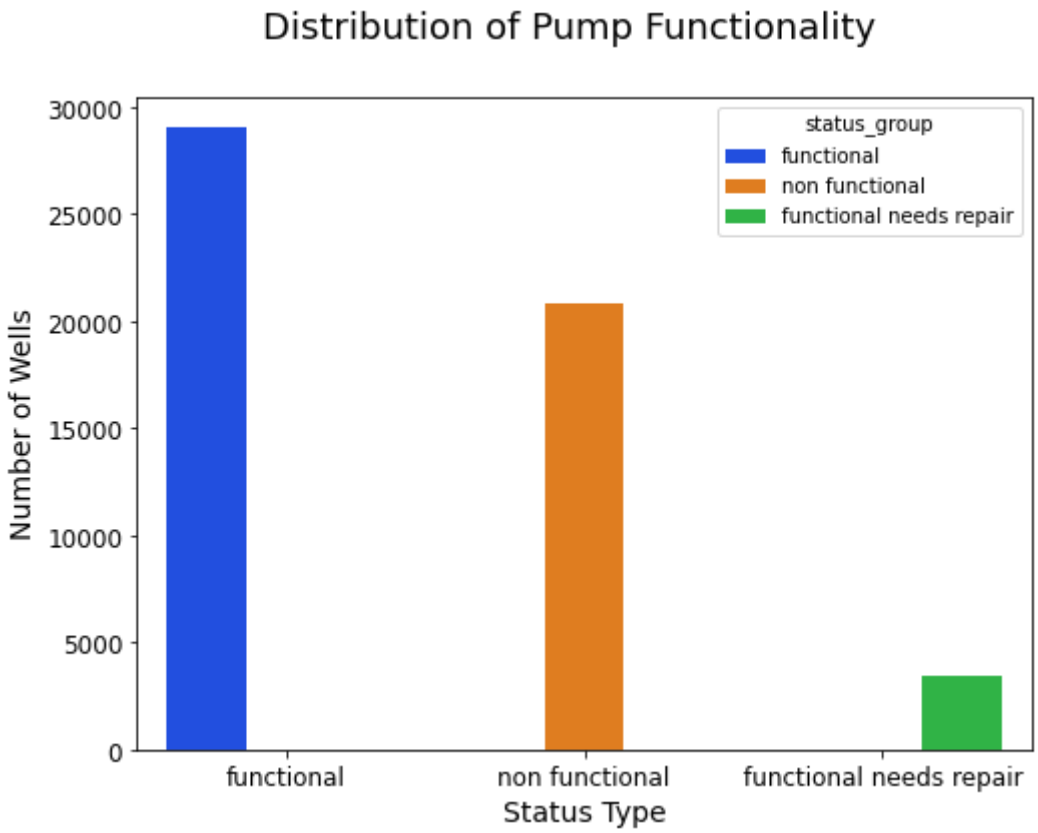
To reduce the dimensionality of the dataset, I made an "Other" category for installer if they were not in the top 20 installers of the dataset.

5 Modified Features Exploration

5.1 Column EDA

5.1.1 Target Feature Distribution

In [41]:
```
fig, ax = plt.subplots(figsize=(8,6))
ax = sns.countplot(x='status_group', hue="status_group", palette='bri
fig.suptitle('Distribution of Pump Functionality', fontsize=18)
plt.xlabel("Status Type", fontsize=14)
plt.ylabel("Number of Wells", fontsize=14)
plt.tick_params(labelsize='large')
plt.show()

fig.savefig('./images/function.jpeg');
```



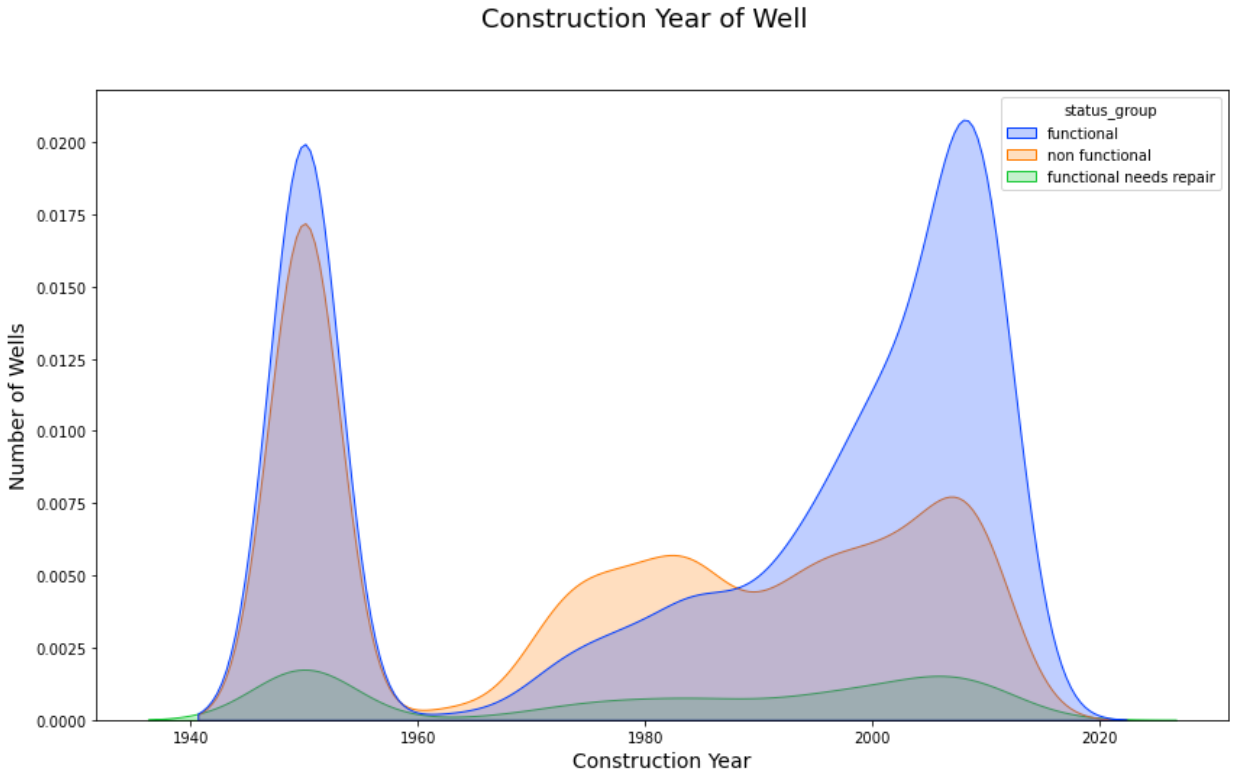
In [42]:
```
df['status_group'].value_counts()
```

Out[42]:
```
functional                 29026
non functional             20829
functional needs repair     3454
Name: status_group, dtype: int64
```

We have the most functional wells at ~29,000, followed by non functional wells at ~21,000, and the minority class, functional needs repair at ~3,500.

5.1.2 Construction year

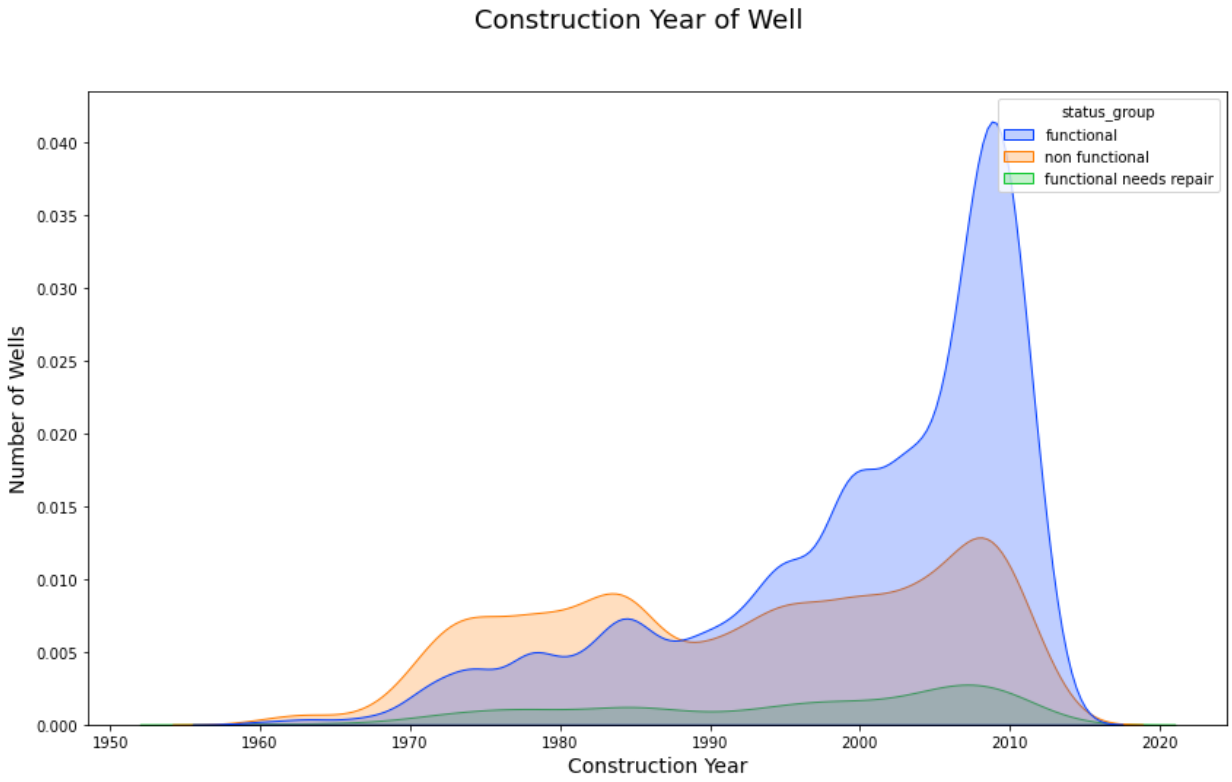
In [43]:
```
fig, ax = plt.subplots(figsize=(14,8))
ax = sns.kdeplot(data=df, x='construction_year', hue='status_group', 
fig.suptitle('Construction Year of Well', fontsize=18)
plt.xlabel("Construction Year", fontsize=14)
plt.ylabel("Number of Wells", fontsize=14)
plt.show();
```



There is large amount of data in the year 1950 which were entered as 0 in the dataset, these may be natural sources and our distribution is normal for these sources. However, we can see the correlation of an older pump being more likely to be non functional and more functional newer pumps.

In [44]:
```
# Create df without entries in year 1950
const_year_df = df.loc[df['construction_year'] != 1950]
```

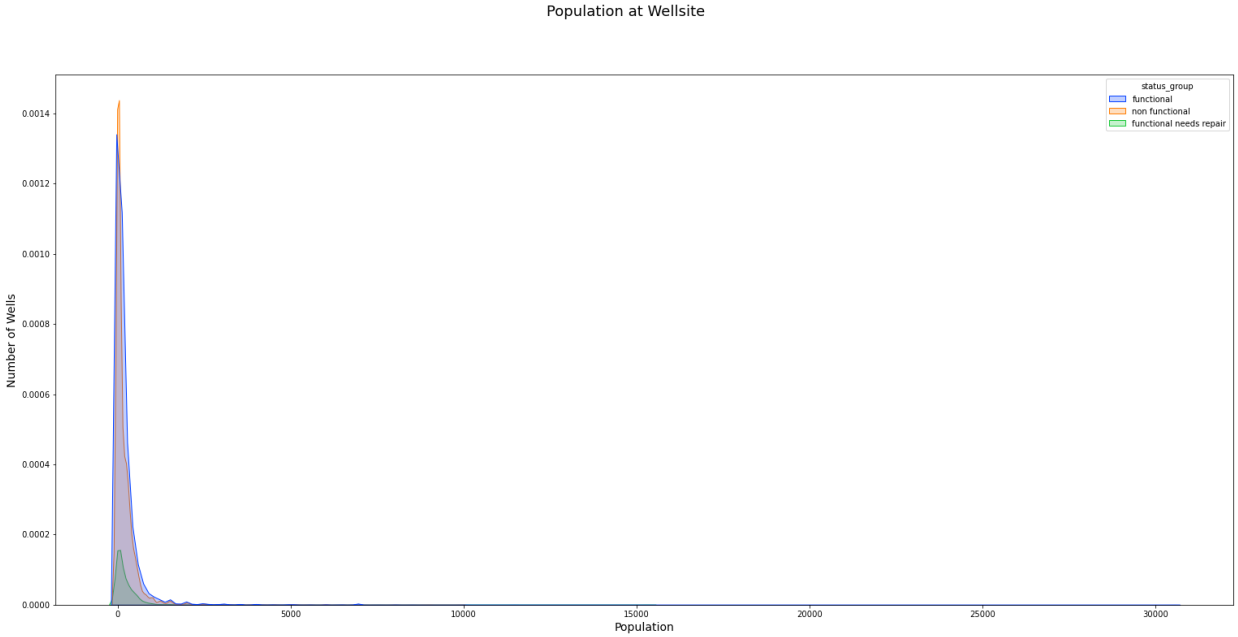
In [45]:
```
# Save without waterpoints from year 1950
fig, ax = plt.subplots(figsize=(14,8))
ax = sns.kdeplot(data=const_year_df, x='construction_year', hue='statu
fig.suptitle('Construction Year of Well', fontsize=18)
plt.xlabel("Construction Year", fontsize=14)
plt.ylabel("Number of Wells", fontsize=14)
plt.show()

fig.savefig('./images/year_function.jpeg');
```



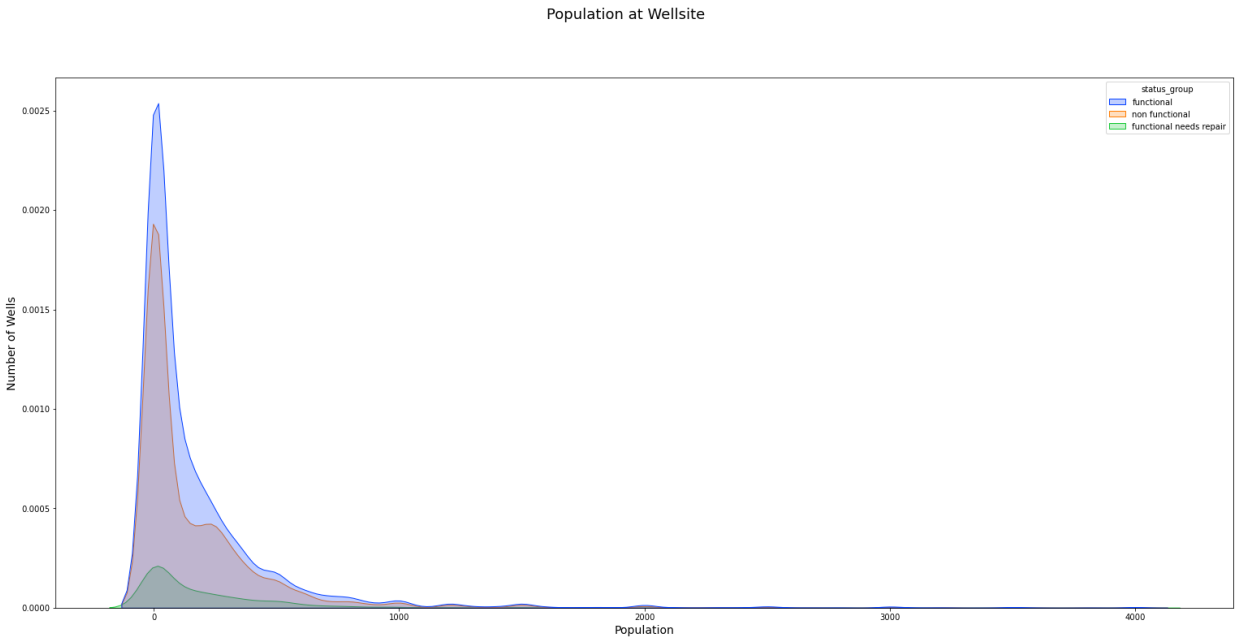
There are more non functional pumps than functional if they were built before 1988, but the rate of functionality keeps increasing after 1988.

5.1.3 Population

In [46]:
```
fig, ax = plt.subplots(figsize=(26,12))
ax = sns.kdeplot(data=df, x='population', hue='status_group', palette=
fig.suptitle('Population at Wellsite', fontsize=18)
plt.xlabel("Population", fontsize=14)
plt.ylabel("Number of Wells", fontsize=14)
plt.show()
```



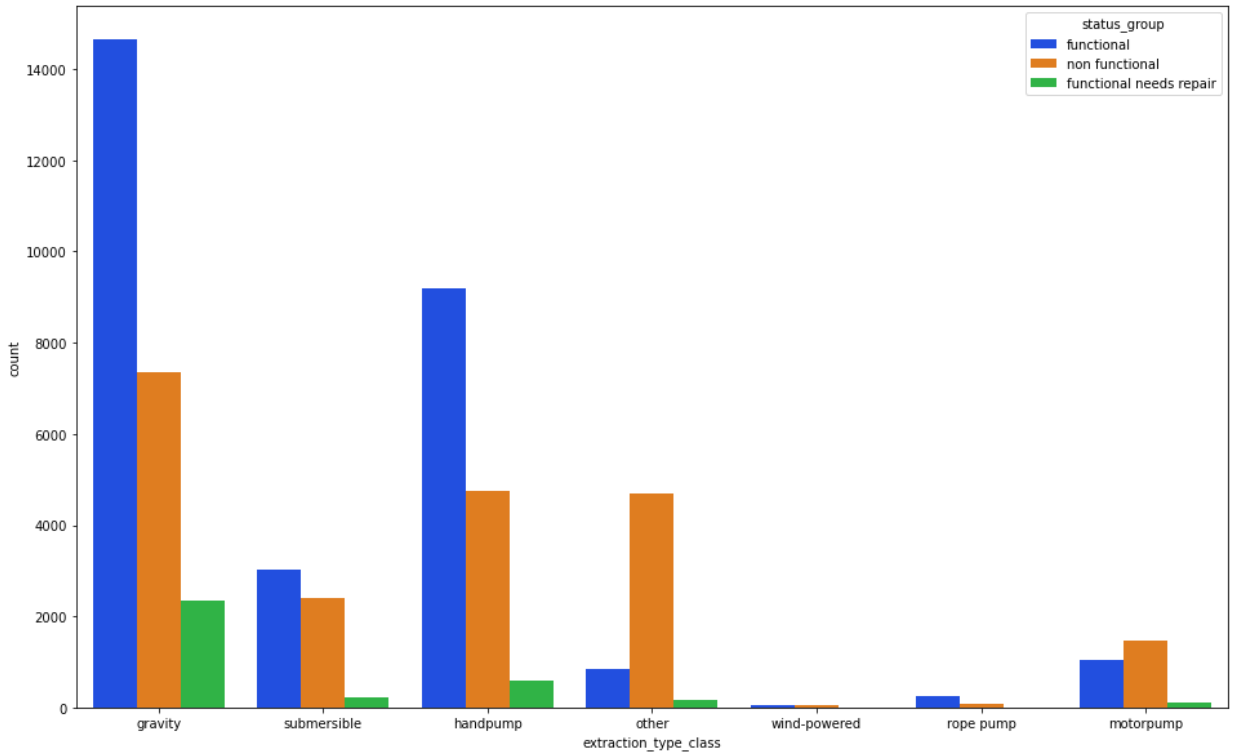
In [47]:
```
# Get a closer look
pop_df = df.loc[df['population'] <= 4000]

fig, ax = plt.subplots(figsize=(26,12))
ax = sns.kdeplot(data=pop_df, x='population', hue='status_group', pale
fig.suptitle('Population at Wellsite', fontsize=18)
plt.xlabel("Population", fontsize=14)
plt.ylabel("Number of Wells", fontsize=14)
plt.show()
```



Overall, the distribution of pump functionality is similar across all population ranges and there isn't a lot of separation, with there being more functional wells than any other class. There isn't too much to draw from these graphs about population and functionality.

5.1.4 Extraction_type_class

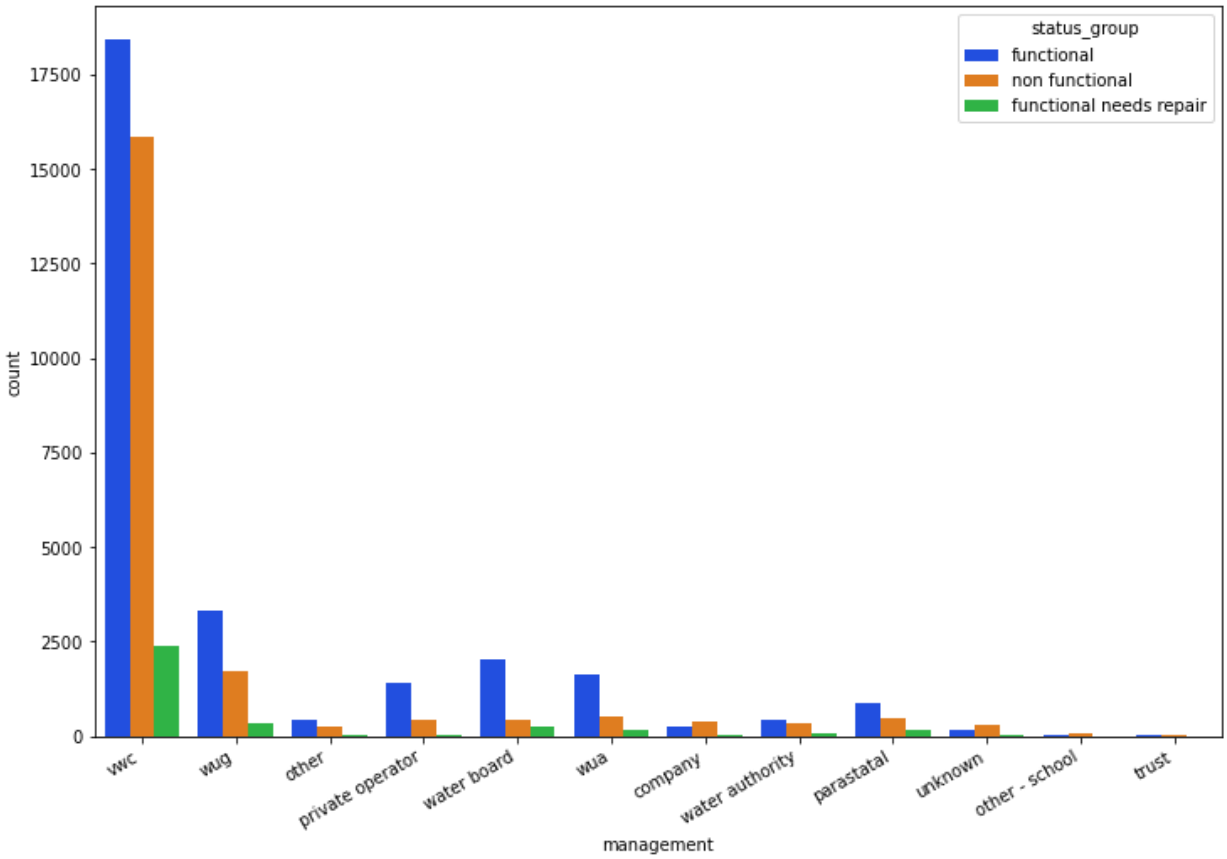
In [48]:
```
1 plt.figure(figsize=(16,10))
2 ax = sns.countplot(x='extraction_type_class', hue='status_group', pale
```



Other type and motorpump are especially non functioning. Gravity and handpump are the 2 largest types, and both have more functioning, but half non functioning.

5.1.5 Management

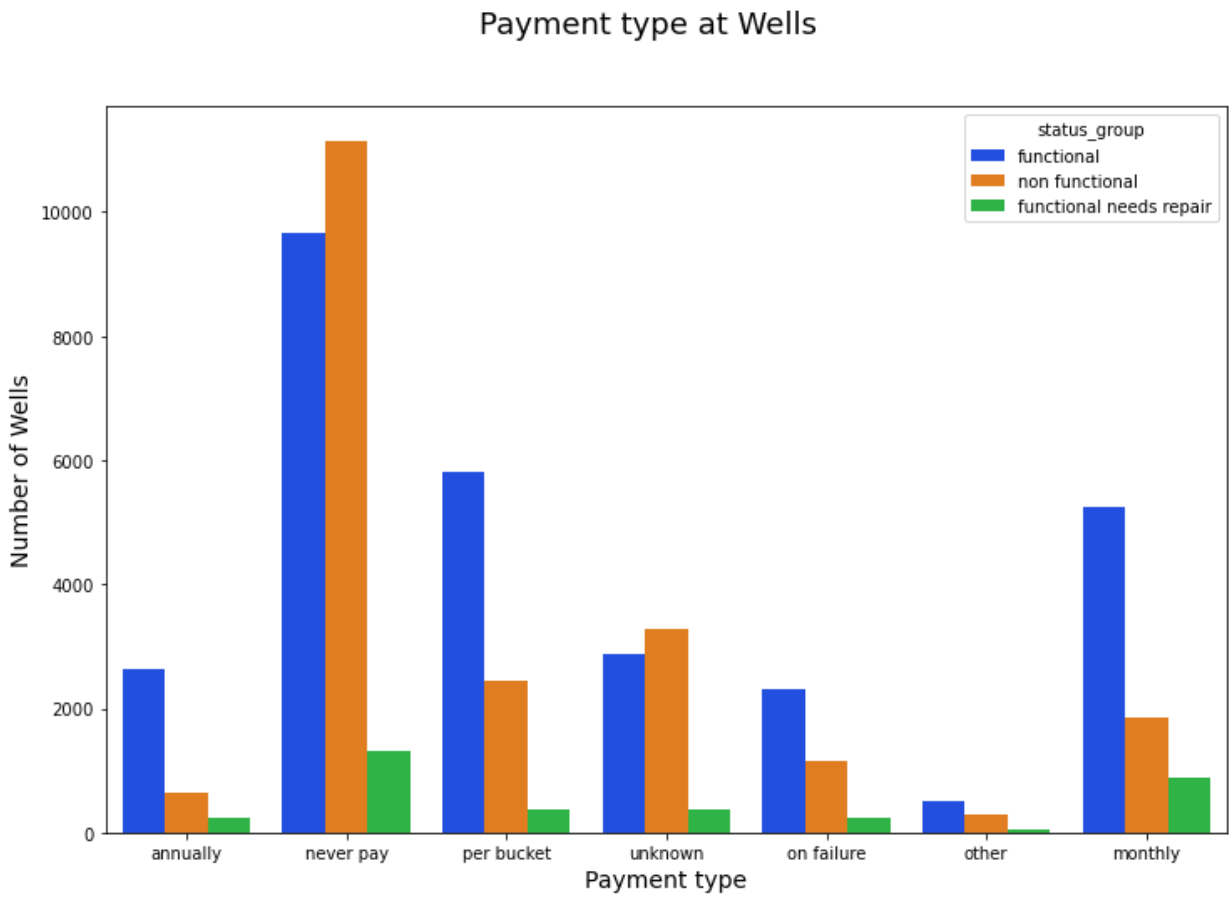
In [49]:
```
plt.figure(figsize=(12,8))
ax = sns.countplot(x='management', hue='status_group', palette='bright
plt.xticks(rotation=30, ha='right');
```



water board, wua, and private operators have a high rate of functionality.

5.1.6 Payment_type

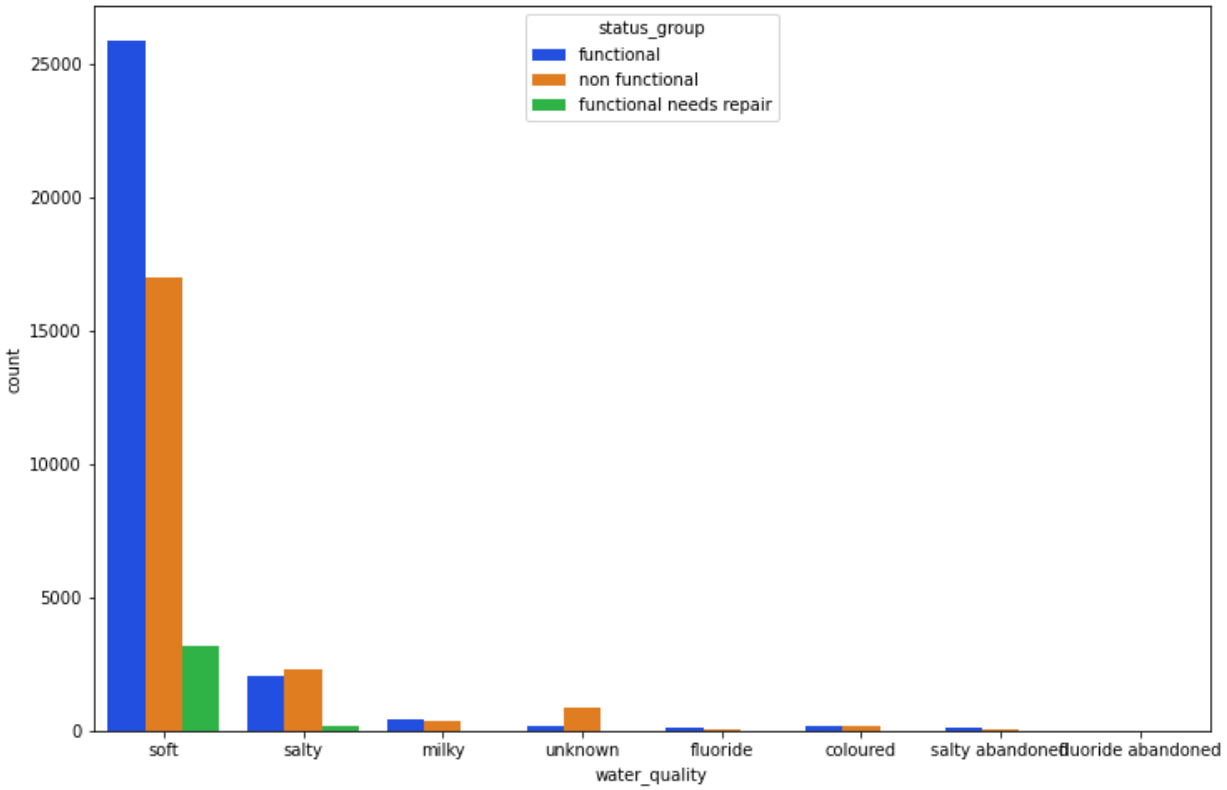
In [50]:
```
fig, ax = plt.subplots(figsize=(12,8))
ax = sns.countplot(x='payment_type', hue="status_group", palette='bri

fig.suptitle('Payment type at Wells', fontsize=18)
plt.xlabel("Payment type", fontsize=14)
plt.ylabel("Number of Wells", fontsize=14)
plt.show()

fig.savefig('./images/payment_function.jpeg');
```



Never pay pumps have more non functioning waterpoints than functioning waterpoints. Some form of payment increases the functionality of the waterpoints.

5.1.7 Water quality

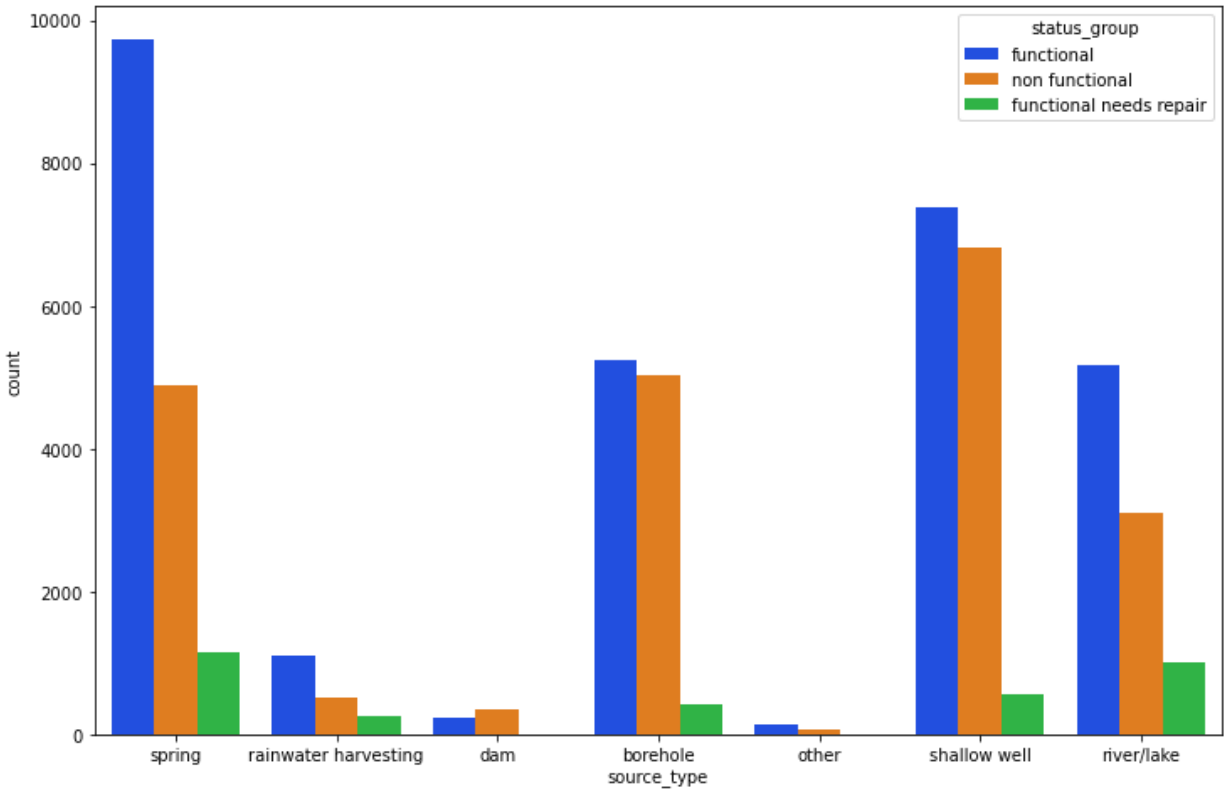
In [51]:
```
plt.figure(figsize=(12,8))
ax = sns.countplot(x='water_quality', hue='status_group', palette='br
```



Soft water quality has a high rate of functional waterpoints, salty has a high rate of non functional waterpoints.

5.1.8 Source type

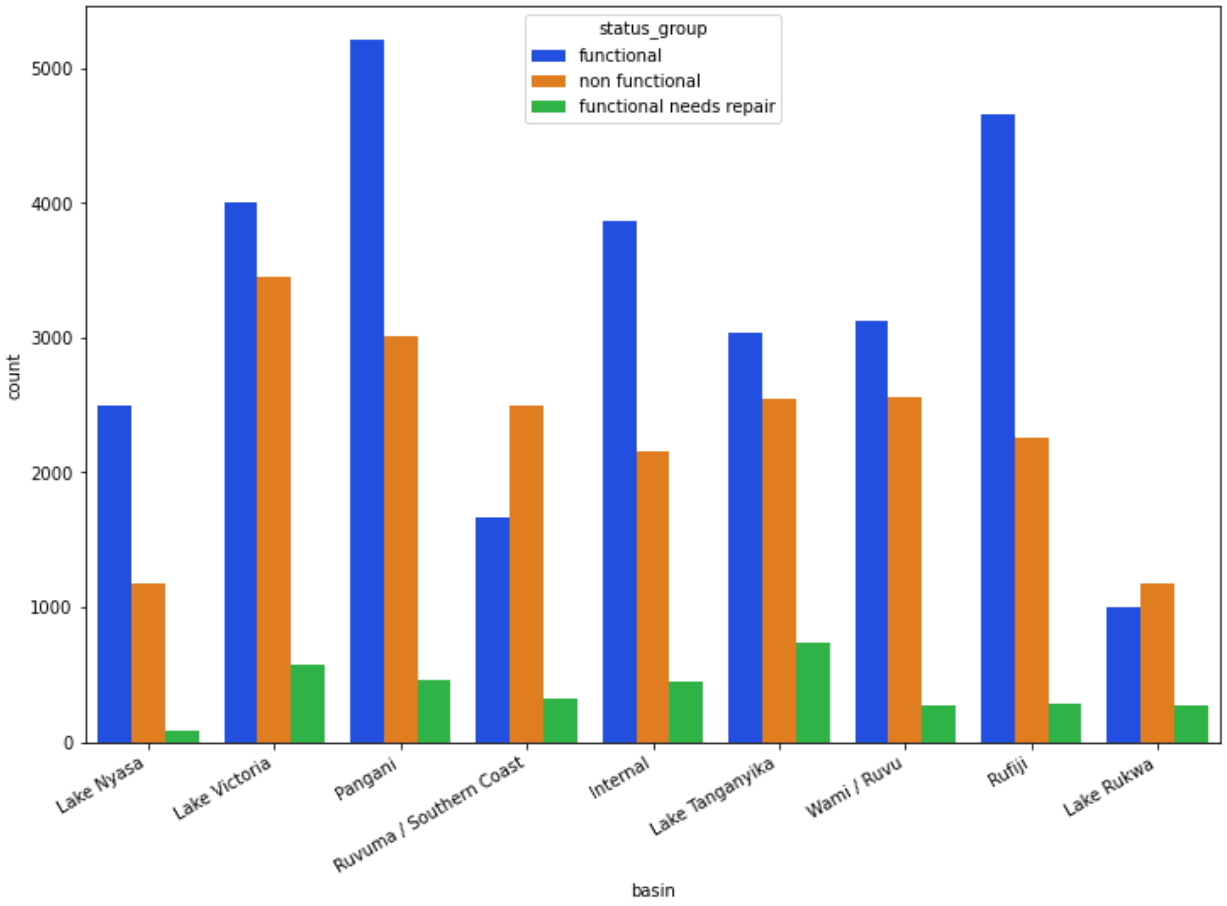
In [52]:
```
plt.figure(figsize=(12,8))
ax = sns.countplot(x='source_type', hue='status_group', palette='brigl
```



Even distribution of functional and nonfunctional boreholes. Many more functional springs and rivers than non functional.

5.1.9 Basin

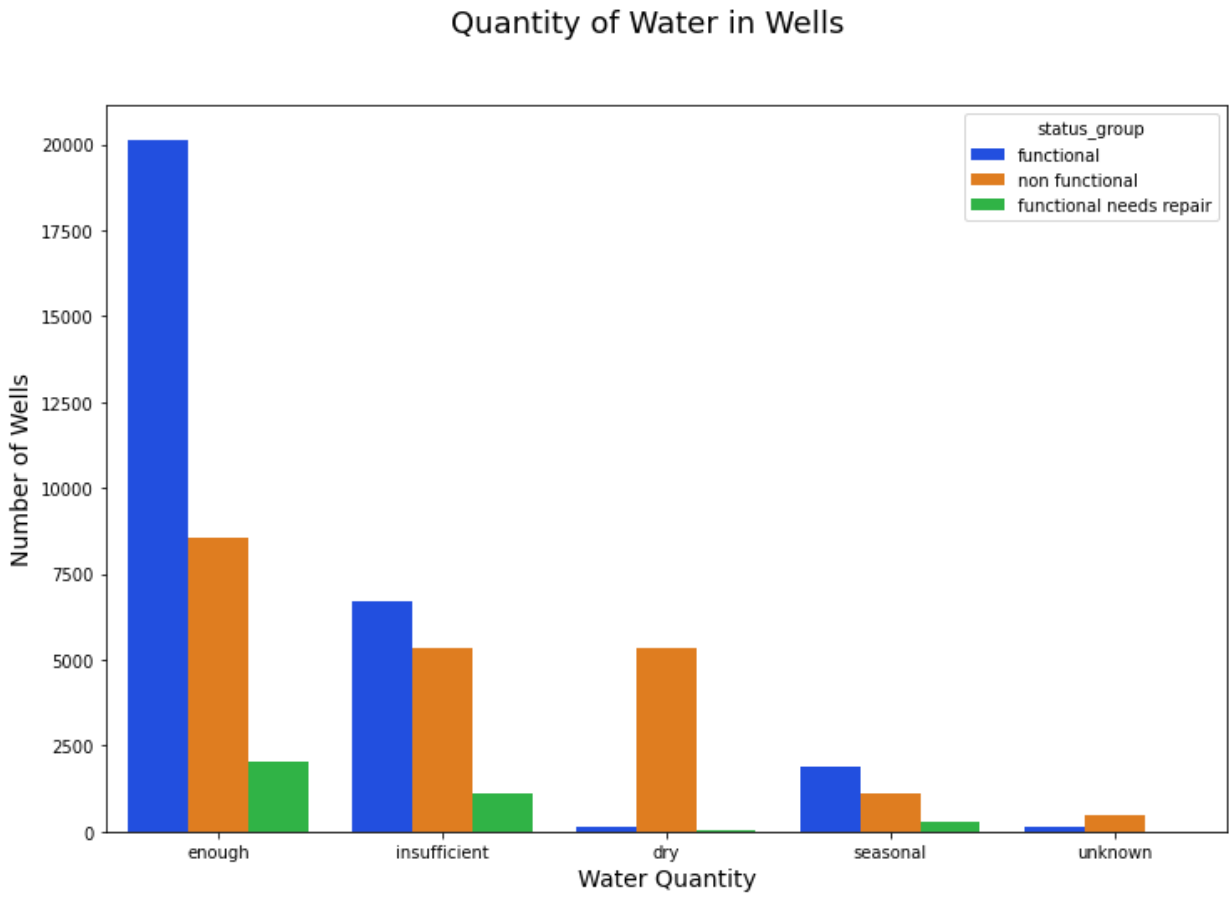
In [53]:
```
plt.figure(figsize=(12,8))
ax = sns.countplot(x='basin', hue='status_group', palette='bright', da
plt.xticks(rotation=30, ha='right');
```



The Ruvuma/Southern Coast and Lake Rukwa basins have more non functioning wells than functional.

5.1.10 Quantity

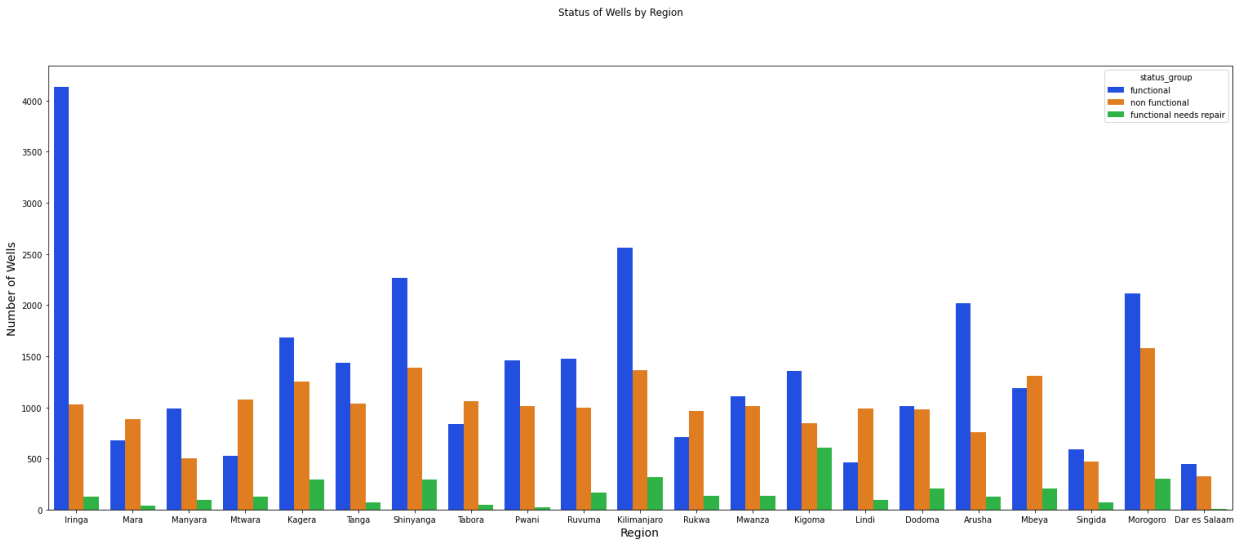
In [54]:
```
fig, ax = plt.subplots(figsize=(12,8))
ax = sns.countplot(x='quantity', hue="status_group", palette='bright'
fig.suptitle('Quantity of Water in Wells', fontsize=18)
plt.xlabel("Water Quantity", fontsize=14)
plt.ylabel("Number of Wells", fontsize=14)
plt.show()

fig.savefig('./images/quantity_function.jpeg');
```



Dry waterpoints have a high chance of being non functional, as expected. If the waterpoint has enough water, there is a high chance of functionality.

5.1.11 Region

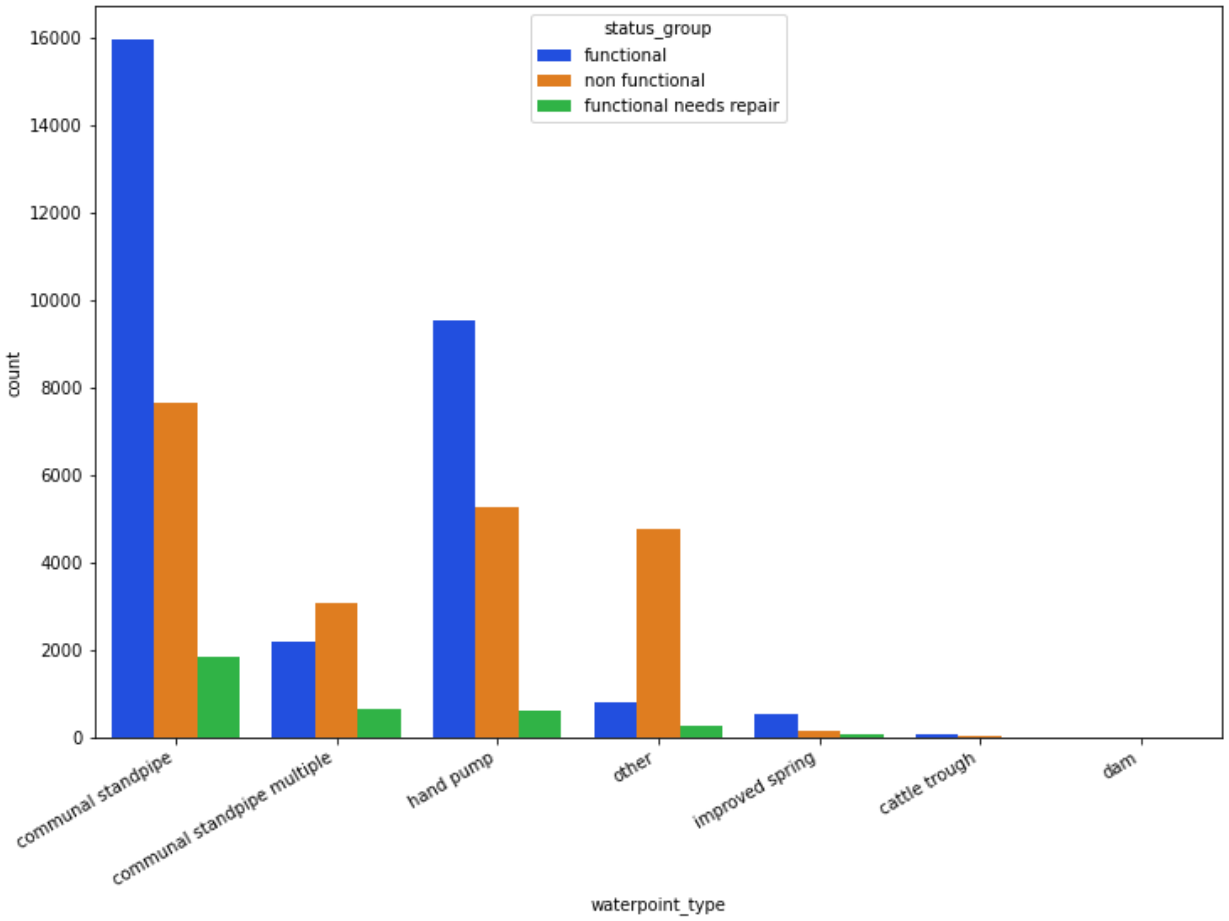
In [55]:
```
fig, ax = plt.subplots(figsize=(26,10))
ax = sns.countplot(x='region', hue="status_group", palette='bright', c

fig.suptitle('Status of Wells by Region')
plt.xlabel("Region", fontsize=14)
plt.ylabel("Number of Wells", fontsize=14)
plt.show()

fig.savefig('./images/region_function.jpeg');
```



The Iringa region has a very high rate of functioning wells, followed by Kilimanjaro, Arusha, and Shinyanga. The worst regions for well perfomance are Mtwara, Mara, Rukwa, and Lindi.

5.1.12 Waterpoint type

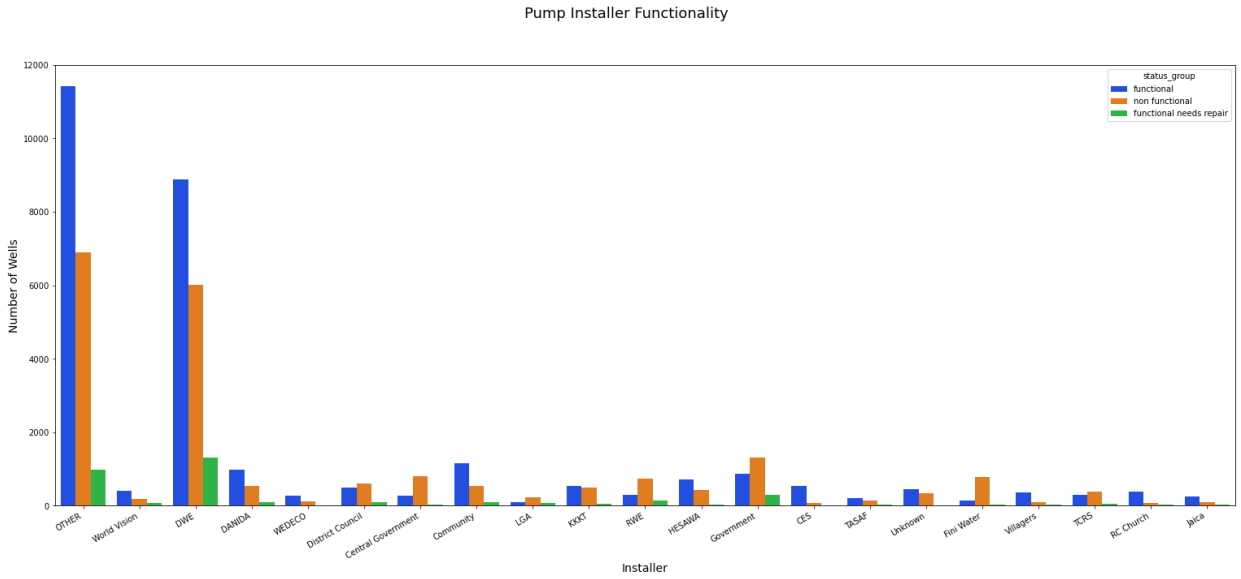
In [56]:
```
plt.figure(figsize=(12,8))
ax = sns.countplot(x='waterpoint_type', hue='status_group', palette='
plt.xticks(rotation=30, ha='right');
```



Other and communal standpipe multiple have the highest rate of being non functioning.

5.1.13 Installer

In [57]:
```
fig, ax = plt.subplots(figsize=(26,10))
ax = sns.countplot(x='installer', hue="status_group", palette='bright

fig.suptitle('Pump Installer Functionality', fontsize=18)
plt.xlabel("Installer", fontsize=14)
plt.ylabel("Number of Wells", fontsize=14)
plt.xticks(rotation=30, ha='right')
plt.show()

fig.savefig('./images/installer_function.jpeg');
```



The government, Fini Water, RWE, and Distict Council have a high rate of non functioning wells. Other is out largest category.

5.2 Well Function map

In [58]:
```
import folium
from folium.plugins import FloatImage
```

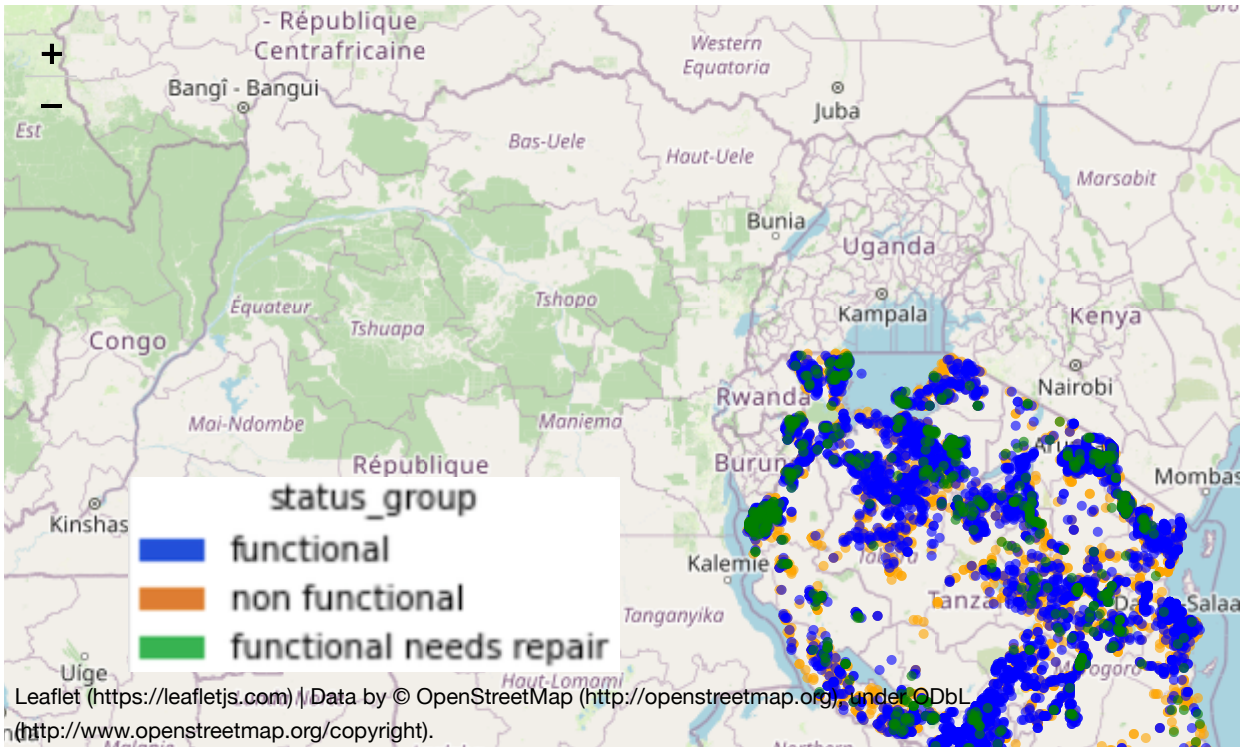
In [59]:
```
# Create 3 dataframes for each status_group
df_f = df[df['status_group'] == 'functional']
df_nf = df[df['status_group'] == 'non functional']
df_fnr = df[df['status_group'] == 'functional needs repair']
```

In [60]:

```
# Create lists of latitude and longitude values
lat_f = [x for x in df_f['latitude']]
long_f = [x for x in df_f['longitude']]

lat_nf = [x for x in df_nf['latitude']]
long_nf = [x for x in df_nf['longitude']]

lat_fnr = [x for x in df_fnr['latitude']]
long_fnr = [x for x in df_fnr['longitude']]

lat_long_f = [(lat_f[i], long_f[i]) for i in range(len(lat_f))]
lat_long_nf = [(lat_nf[i], long_nf[i]) for i in range(len(lat_nf))]
lat_long_fnr = [(lat_fnr[i], long_fnr[i]) for i in range(len(lat_fnr)
```

In [61]:
```
#Create map
this_map = folium.Map()

# Loop through 3 dataframes and plot point for each coordinate
for coord in lat_long_nf[::5]:
    folium.CircleMarker(location=[coord[0], coord[1]], opacity=0.6, co
for coord in lat_long_f[::5]:
    folium.CircleMarker(location=[coord[0], coord[1]], opacity=0.6, co
for coord in lat_long_fnr[::5]:
    folium.CircleMarker(location=[coord[0], coord[1]], opacity=0.6, co



#Set the zoom to fit our bounds
this_map.fit_bounds(this_map.get_bounds())

# Add legend
FloatImage('./images/legend.png', bottom=10, left=10).add_to(this_map


this_map
```

Out[61]:



As we saw above, there is a high rate of non functional waterpoints in the southeast corner of Tanzania in Mtwara and Lindi, as well as up north in Mara, and the southwest in Rukwa. We can see the cluster of high functional wells in Iringa, Shinyanga, Kilimanjaro, and Arusha. There is a cluster of functional but need repair waterpoints in Kigoma.

5.3 Create df['status'] with status_group in integer format

In [62]:
```
# Change status_group/target values to numeric values
df['status'] = df.status_group.map({"non functional":0, "functional ne
df.head()
```

Out[62]:

	status_group	amount_tsh	gps_height	installer	longitude	latitude	basin	region	popul
0	functional	6000.0	1390	OTHER	34.938093	-9.856322	Lake Nyasa	Iringa	
1	functional	0.0	1399	OTHER	34.698766	-2.147466	Lake Victoria	Mara	
2	functional	25.0	686	World Vision	37.460664	-3.821329	Pangani	Manyara	
3	non functional	0.0	263	OTHER	38.486161	-11.155298	Ruvuma / Southern Coast	Mtwara	
4	functional	0.0	0	OTHER	31.130847	-1.825359	Lake Victoria	Kagera	

In [63]:
```
df = df.drop('status_group', axis=1)
```

In [64]:
```
df.shape
```

Out[64]:
```
(53309, 18)
```

6 Modeling

6.1 Data Preprocessing

Following we will create our dummy variables for our categorical columns and perform train test split to prepare for modeling.

In [65]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 53309 entries, 0 to 59399
Data columns (total 18 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   amount_tsh             53309 non-null  float64
 1   gps_height             53309 non-null  int64  
 2   installer              53309 non-null  object 
 3   longitude              53309 non-null  float64
 4   latitude               53309 non-null  float64
 5   basin                  53309 non-null  object 
 6   region                 53309 non-null  object 
 7   population             53309 non-null  int64  
 8   permit                 53309 non-null  int64  
 9   construction_year      53309 non-null  int64  
 10  extraction_type_class  53309 non-null  object 
 11  management             53309 non-null  object 
 12  payment_type           53309 non-null  object 
 13  water_quality          53309 non-null  object 
 14  quantity               53309 non-null  object 
 15  source_type            53309 non-null  object 
 16  waterpoint_type        53309 non-null  object 
 17  status                 53309 non-null  int64  
dtypes: float64(3), int64(5), object(10)
memory usage: 10.2+ MB
```

6.1.1 Create dummies

In [66]:
```
# Create lists of categorical and continuous columns
cat_col = ['installer','basin','region','extraction_type_class','manag
           'quantity','source_type','waterpoint_type']
cont_col = ['amount_tsh','gps_height','longitude','latitude','populati
```

In [67]:
```
#Create dummies
dummy_df = pd.get_dummies(df,columns=cat_col,drop_first=True)

dummy_df.shape
```

Out[67]: (53309, 102)

6.1.2 Separate target and perform train test split

In [68]:
```
y = dummy_df['status']
X = dummy_df.drop(['status'], axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0
```

6.1.3 Model Statistics Function

Precision will be our main metric used to track model performance, but we will calculate accuracy,

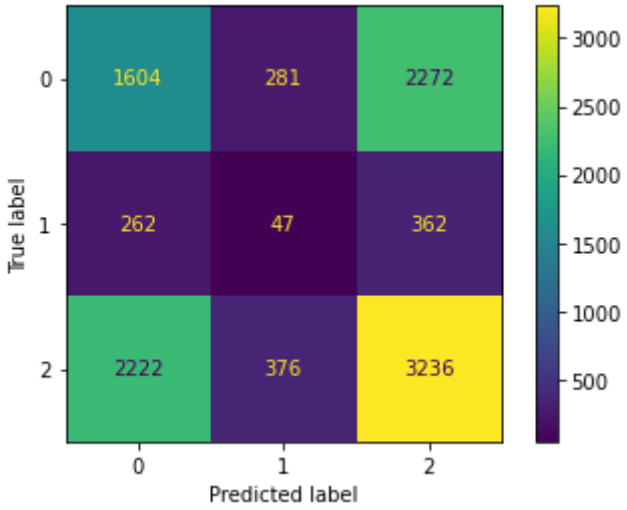
recall, and f1 score to provide more detail using sklearn's *classification_report()* function.

In [69]:
```
# function to track model metrics and plot confusion matrix

def model_score(model, X, y_pred, y_true):
    target_names= ['non func', 'func need repair', 'functional']
    print(classification_report(y_true, y_pred, target_names=target_na

    #Confusion matrix
    return plot_confusion_matrix(model, X, y_true, display_labels=tar
```

6.2 Dummy Classifier Model

In [70]:
```
dummy = DummyClassifier(random_state=42)
dummy.fit(X_train, y_train)
print(dummy.score(X_test, y_test))

plot_confusion_matrix(dummy, X_test, y_test);
```

```
0.4583567810917276
```

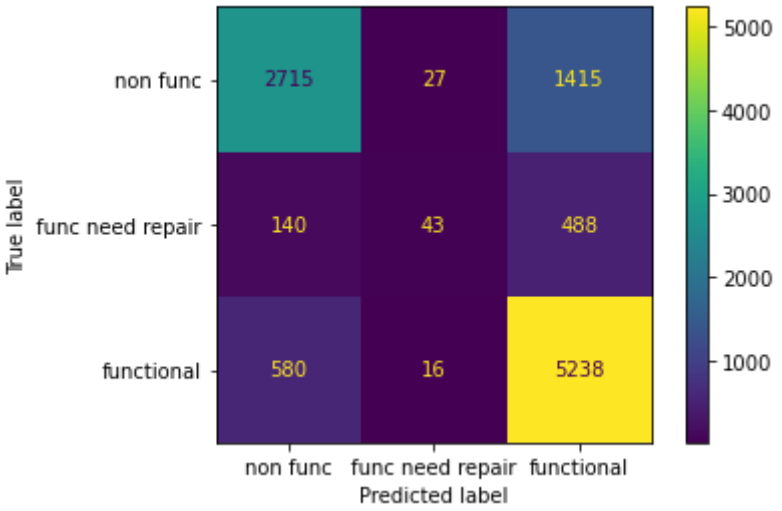


Our baseline dummy model performed very poorly with an accuracy score of 46%. Our data is heavily imbalanced, which explains how our ternary model performed close to 50%.

6.3 Logistic Regression

In [71]:
```
# Make pipe
pipe_lr = Pipeline([('ss', StandardScaler()),
                    ('lr', LogisticRegression())])
# Fit and predict
pipe_lr.fit(X_train, y_train)
test_preds = pipe_lr.predict(X_test)

print("Test data model score:")
lr_score = model_score(pipe_lr, X_test, test_preds, y_test)
```

```
Test data model score:
                  precision    recall  f1-score   support

        non func       0.79      0.65      0.72      4157
func need repair       0.50      0.06      0.11       671
      functional       0.73      0.90      0.81      5834

        accuracy                           0.75     10662
       macro avg       0.67      0.54      0.55     10662
    weighted avg       0.74      0.75      0.73     10662
```



Our logistic regression model is improved to 75% accuracy over the dummy model. This model struggled to predict wells that were functional but needed repairs, likely due to class imbalances. The precision of the functional class is 73%.

6.4 K Nearest Neighbors

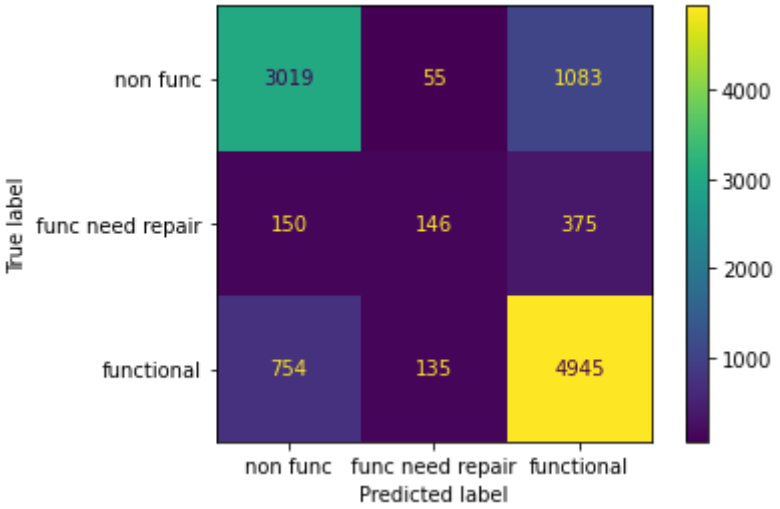
Below I will run GridSearch with my Pipeline to create a K Nearest Neighbors model. I ran GridSearch to find the best parameters, and have then commented out the code to save computing time while still showing the process. The same process is repeated for all following models of running GridSearch and commenting out code.

In [72]:
```
# GridSearch
knn = KNeighborsClassifier()
grid = {
    'n_neighbors' : [5, 10, 15, 20, 25, 40]
}

#knn_grid_search = GridSearchCV(knn, grid, cv=3)
#knn_grid_search.fit(X_train, y_train)

#knn_grid_search.best_params_
```

In [73]:
```
# Narrow down parameters for 2nd gridsearch
knn = KNeighborsClassifier()
grid = {
    'n_neighbors' : [7, 8, 9, 10, 11, 12, 13]
}

#knn_grid_search = GridSearchCV(knn, grid, cv=3)
#knn_grid_search.fit(X_train, y_train)

#knn_grid_search.best_params_
```

In [74]:
```
# Make pipe
pipe_knn = Pipeline([('ss', StandardScaler()),
                     ('knn', KNeighborsClassifier(n_neighbors=9))])
#Fit and predict
pipe_knn.fit(X_train, y_train)
test_preds = pipe_knn.predict(X_test)

print("Test data model score:")
knn_score = model_score(pipe_knn, X_test, test_preds, y_test)
```

```
Test data model score:
                  precision    recall  f1-score   support

        non func       0.77      0.73      0.75      4157
func need repair       0.43      0.22      0.29       671
      functional       0.77      0.85      0.81      5834

        accuracy                           0.76     10662
       macro avg       0.66      0.60      0.62     10662
    weighted avg       0.75      0.76      0.75     10662
```



In [75]:
```
# Check for training and test sets
# Predict on training and test sets
training_preds = pipe_knn.predict(X_train)
test_preds = pipe_knn.predict(X_test)

# Accuracy of training and test sets
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 80.14%
Validation accuracy: 76.06%
```

The K Nearest Neighbors model outperformed the Logistic Regression model. Number of neighbors was hypertuned by running and GridSearch and optimal parameters were put into our pipe. Our K Nearest Neighbors model is not overfitting as the accuracy of training and test sets are 80.23% and 76.03%, respectively. The precision of the functional class is 77%, which is a huge improvement from our Logistic Regression model at 73%.

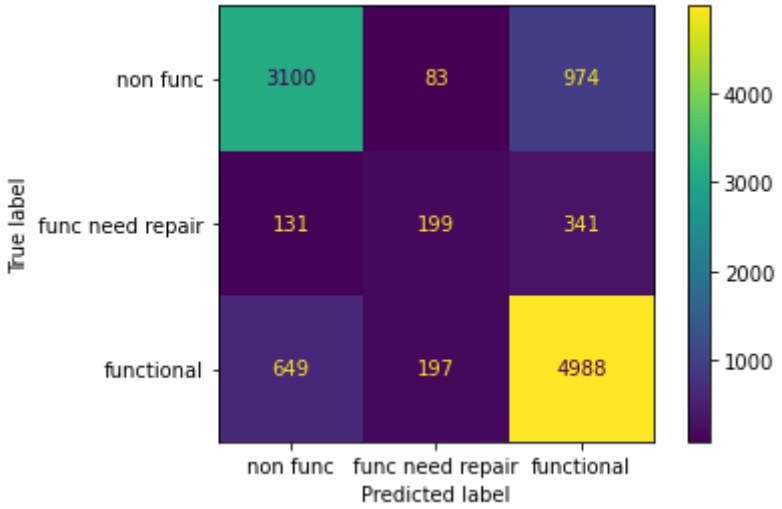
6.5 Decision Tree Model

In [76]:

```
# GridSearch commented out to show process
dt = DecisionTreeClassifier()
dt_grid = {
    'criterion' : ['entropy', 'gini'],
    'max_depth': [10, 20, 30, 40, 50, 60, None],
    'min_samples_split' : [1, 2, 5, 10, 20, 30],
    'min_impurity_decrease' : [0.0, 0.1, 0.2, 0.3, 0.4, 0.5],
    'min_impurity_split' : [None, 0.1, 0.2, 0.3, 0.4, 0.5],
}

#dt_tree = GridSearchCV(estimator=dt, param_grid=dt_grid, cv=5)
#dt_tree.fit(X_train, y_train)

#print(f'Best parameters are {dt_tree.best_params_}')
#print(f'Best score {dt_tree.best_score_}')  #0.768565112
#print(f'Best estimator score {dt_tree.best_estimator_.score(X_test, )
```

In [77]:
```
# Make pipe
pipe_dt = Pipeline([('ss', StandardScaler()),
                    ('dt', DecisionTreeClassifier(criterion='gini', ma
                                                  min_samples_split=2
#Fit and Predict
pipe_dt.fit(X_train, y_train)
test_preds = pipe_dt.predict(X_test)

print("Test data model score:")
dt_score = model_score(pipe_dt, X_test, test_preds, y_test)
```

```
Test data model score:
                  precision    recall  f1-score   support

        non func       0.80      0.75      0.77      4157
func need repair       0.42      0.30      0.35       671
      functional       0.79      0.85      0.82      5834

        accuracy                           0.78     10662
       macro avg       0.67      0.63      0.65     10662
    weighted avg       0.77      0.78      0.77     10662
```



In [78]:
```
# Predict on training and test sets
training_preds = pipe_dt.predict(X_train)
test_preds = pipe_dt.predict(X_test)

# Accuracy of training and test sets
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 89.16%
Validation accuracy: 77.72%
```

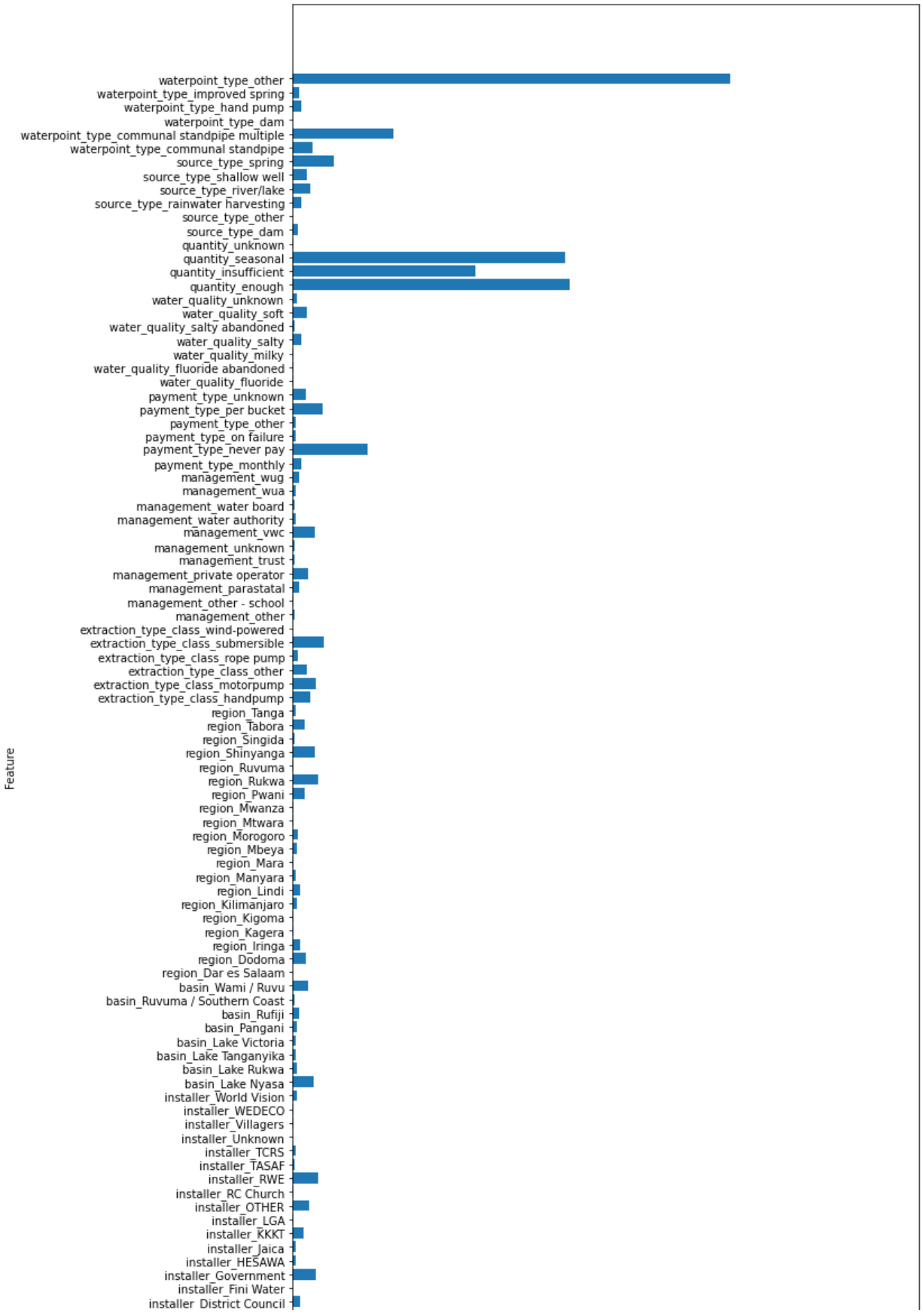
Our decision tree model once again improved our functional class precision scores to 79%, but the model is highly overfitting with training accuracy at 89% and test accuracy at 78%.

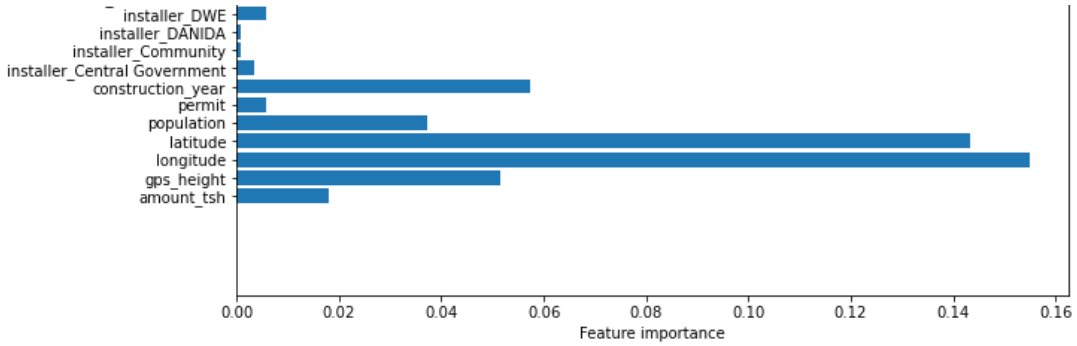
6.5.1 Function to plot feature importances

In [79]:
```
def plot_feature_importances(model):
    n_features = X_train.shape[1]
    plt.figure(figsize=(10,25))
    plt.barh(range(n_features), model.feature_importances_, align='ce
    plt.yticks(np.arange(n_features), X_train.columns.values)
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')
```

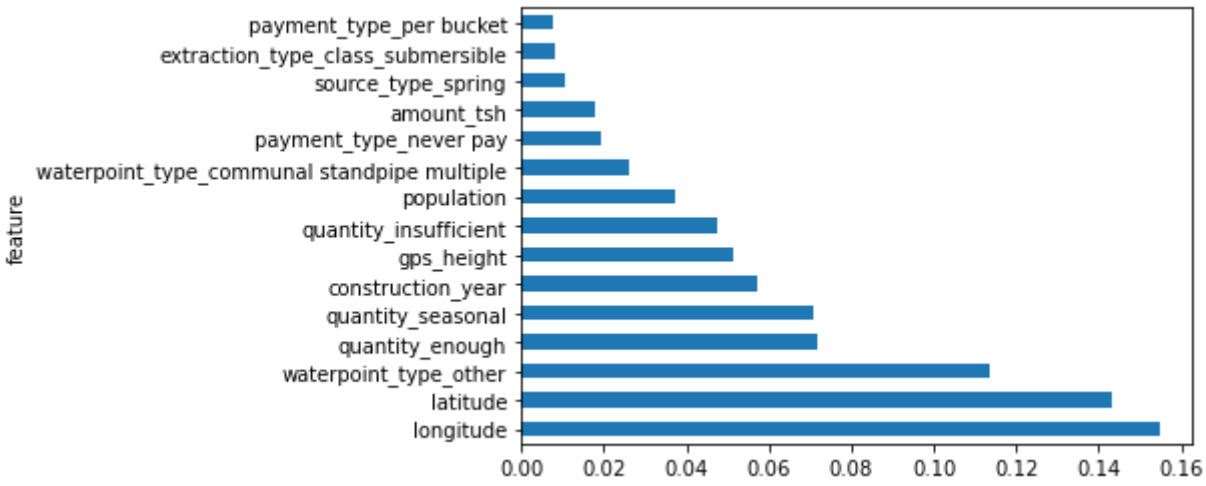
6.5.2 Decision Tree Feature Importances

In [80]:
```
# Instantiate and fit a DecisionTreeClassifier with optimal parameters
tree_clf = DecisionTreeClassifier(criterion='gini', max_depth=20, min_
tree_clf.fit(X_train, y_train)

plot_feature_importances(tree_clf)
```





In [81]:
```
# Top features
feature_importances=pd.DataFrame(columns=['feature','importance'])

feature_importances['feature']= X_train.columns

feature_importances['importance']=tree_clf.feature_importances_

feature_importances= feature_importances.set_index('feature')

feature_importances['importance'].sort_values(ascending = False).head
```



Our decision tree model showed longitude, latitude, waterpoint type other, and enough quantity being the most important features.

6.6 Random Forests

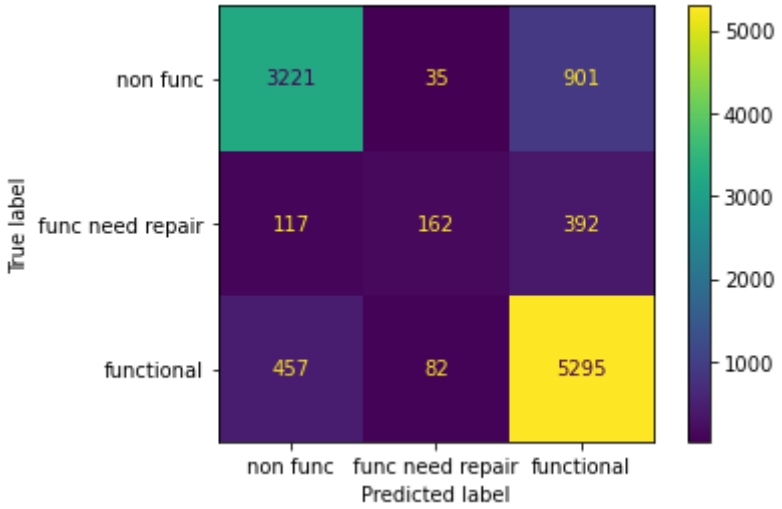
In [82]:

```
#Instantiate RandomForestClassifier
forest = RandomForestClassifier(n_estimators=100, max_depth= 5)
forest.fit(X_train, y_train)

#scores on folds
scores = cross_val_score(estimator=forest, X=X_train, y=y_train, cv=5
print(np.mean(scores))

#scores on on test
score = forest.score(X_test, y_test)
print(score)

# grid search on random forest

#grid = {
#    'criterion' : ['entropy', 'gini'],
#    'max_depth': [5,10,15,20, None],
#    'min_impurity_decrease' : [0.0, 0.1, 0.2, 0.3,0.4, 0.5], #values
#    'min_impurity_split' : [None, 0.1, 0.2, 0.3, 0.4, 0.5], #values
#}
#gs_forest = GridSearchCV(estimator=forest, param_grid=grid, cv=5)
#gs_forest.fit(X_train, y_train)

#print(f'Best parameters are {gs_forest.best_params_}')
#print(f'Best score {gs_forest.best_score_}')
#print(f'Best estimator score {gs_forest.best_estimator_.score(X_test,
```

```
0.6919362242082286
0.6956480960420184
```

In [83]:
```
# Make pipeline with tuned hyperparameters
pipe_rf = Pipeline([('ss', StandardScaler()),
                    ('RF', RandomForestClassifier(bootstrap=True, crit
# Fit and predict
pipe_rf.fit(X_train, y_train)
test_preds = pipe_rf.predict(X_test)

# Print metrics
print("Test data model score:")
rf_score = model_score(pipe_rf, X_test, test_preds, y_test)
```

```
Test data model score:
                  precision    recall  f1-score   support

        non func       0.85      0.77      0.81      4157
func need repair       0.58      0.24      0.34       671
      functional       0.80      0.91      0.85      5834

        accuracy                           0.81     10662
       macro avg       0.74      0.64      0.67     10662
    weighted avg       0.81      0.81      0.80     10662
```



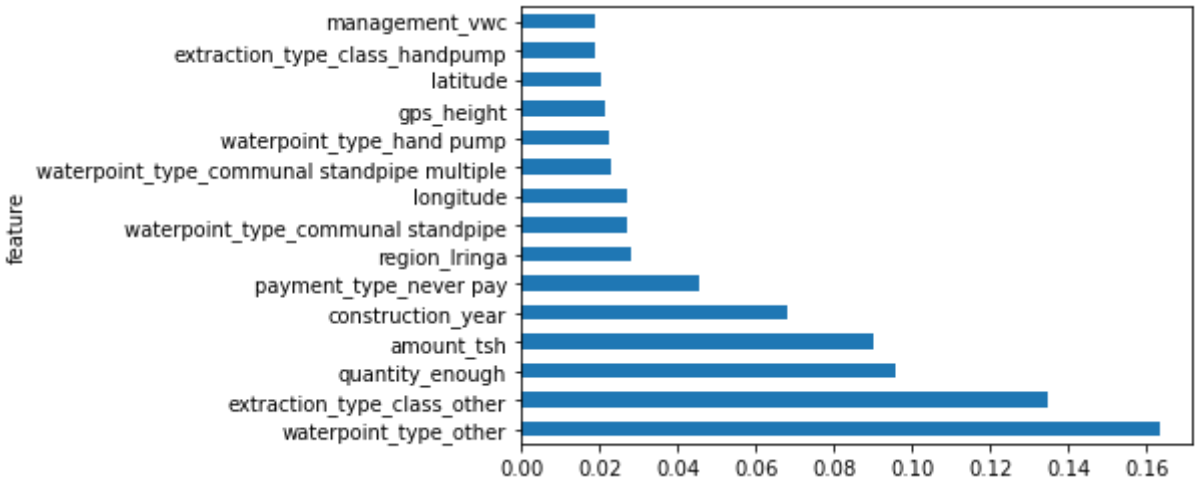
In [84]:
```
# Predict on training and test sets
training_preds = pipe_rf.predict(X_train)
test_preds = pipe_rf.predict(X_test)

# Accuracy of training and test sets
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 93.47%
Validation accuracy: 81.39%
```

Upon running GridSearch with our Random Forests Pipeline, we have once again improved from our baseline accuracy to 80% precision for the functional class over the Decision Tree model at 79%. The model is still overfitting the training data, as the training accuracy is 93.5% and the test accuracy is 81.4%, but this is our best performing model so far.

6.6.1 Random Forests Feature Importances

In [85]:
```
# Top features
feature_importances=pd.DataFrame(columns=['feature','importance'])

feature_importances['feature']= X_train.columns

feature_importances['importance']=forest.feature_importances_

feature_importances= feature_importances.set_index('feature')

feature_importances['importance'].sort_values(ascending = False).head
```

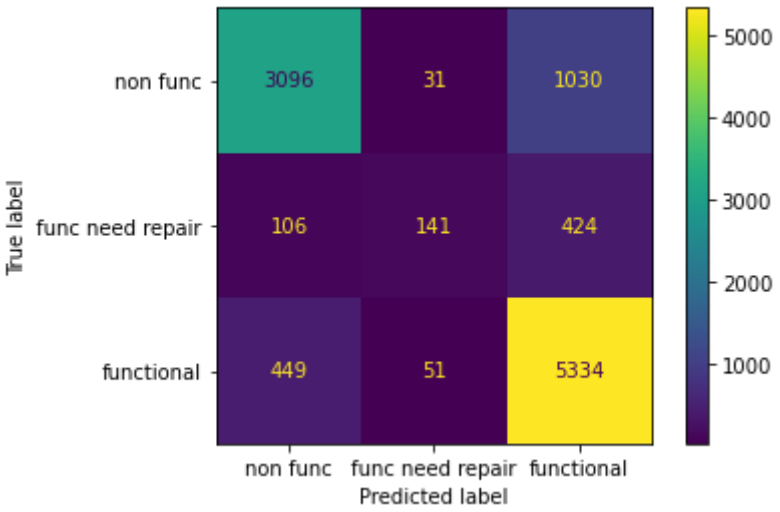


Our random forests model show waterpoint_type other, enough quantity, extraction_type_class_other, and amount_tsh being the most important features to the model.

6.7 XG Boost

In [86]:
```
# Instantiate XGBClassifier
xgb = XGBClassifier()

# Fit XGBClassifier
xgb.fit(X_train, y_train)

print("Test data model score:")
xgb_model_score = model_score(xgb, X_test, test_preds, y_test)
```

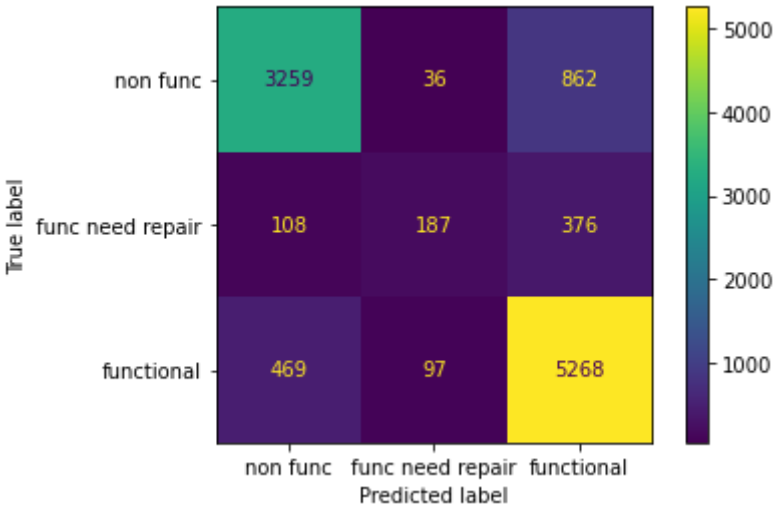
```
Test data model score:
                  precision    recall  f1-score   support

        non func       0.85      0.77      0.81      4157
func need repair       0.58      0.24      0.34       671
      functional       0.80      0.91      0.85      5834

        accuracy                           0.81     10662
       macro avg       0.74      0.64      0.67     10662
    weighted avg       0.81      0.81      0.80     10662
```



In [87]:
```
# Gridsearch commented out
# xgb = XGBClassifier()
# grid = {
#     'learning_rate': [0.1, 0.2],
#     'max_depth': [4, 6, 8, 10],
#     'xmin_child_weight': [1, 2],
#     'subsample': [0.5, 0.7],
#     'n_estimators': [100, 250, 500],
#}

#gs_xgb = GridSearchCV(estimator=xgb, param_grid=grid, cv=5)
#gs_xgb.fit(X_train, y_train)

#print(f'Best parameters are {gs_xgb.best_params_}')
#print(f'Best score {gs_xgb.best_score_}')
#print(f'Best estimator score {gs_xgb.best_estimator_.score(X_test, y_
```

In [88]:
```
# Instantiate xg Boost Classifier pipeline with tuned hyperparameters
pipe_xgb = Pipeline([('ss', StandardScaler()),
                     ('xgb', XGBClassifier(learning_rate=0.1, max_dept
                      n_estimators=250, subsample=0.7))])

pipe_xgb.fit(X_train, y_train)
test_preds = pipe_xgb.predict(X_test)

print("Test data model score:")
dt_score = model_score(pipe_xgb, X_test, test_preds, y_test)
```

```
Test data model score:
                  precision    recall  f1-score   support

        non func       0.85      0.78      0.82      4157
func need repair       0.58      0.28      0.38       671
      functional       0.81      0.90      0.85      5834

        accuracy                           0.82     10662
       macro avg       0.75      0.66      0.68     10662
    weighted avg       0.81      0.82      0.81     10662
```



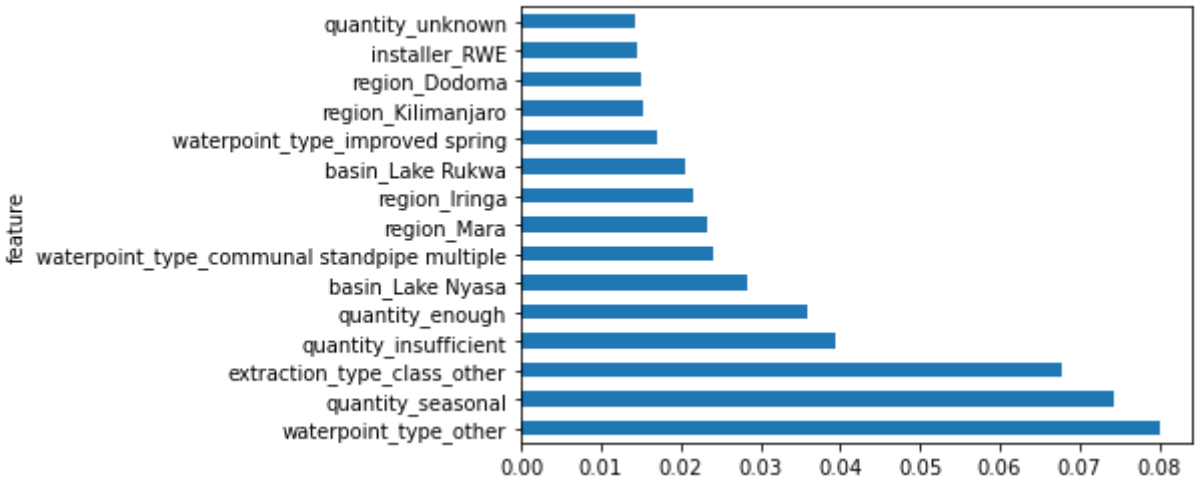
In [89]:
```
# Predict on training and test sets
training_preds = pipe_xgb.predict(X_train)
test_preds = pipe_xgb.predict(X_test)

# Accuracy of training and test sets
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 92.57%
Validation accuracy: 81.73%
```

Our best performing model ended up being the XG Boost model with tuned hyperparameters, although the random forests model was not far behind with 80% precision for the functional wells class. The model has overfitted the training data with a training accuracy of 92.57% and test accuracy at 81.73%, but this model boasted the highest precision score for the functional wells class at 81%.

6.7.1 XGB Feature Importances

In [90]:
```
feature_importances=pd.DataFrame(columns=['feature','importance'])

feature_importances['feature']= X_train.columns

feature_importances['importance']=xgb.feature_importances_

feature_importances= feature_importances.set_index('feature')

feature_importances['importance'].sort_values(ascending = False).head
```



Our XG Boost model shows the most important features to be waterpoint_type_other, quantity_seasonal, extraction_type_class_other, and quantity_insufficient.

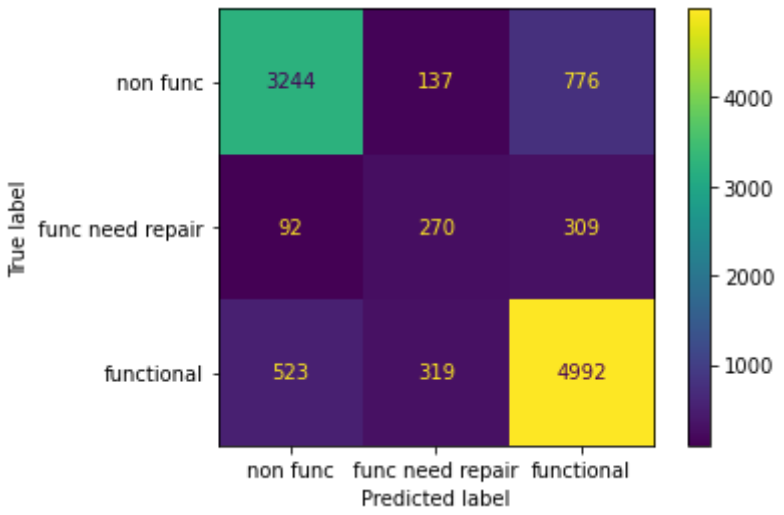
6.7.2 SMOTE and XGBoost

In [91]:
```
# Apply SMOTE oversampling

oversample = SMOTE(sampling_strategy = 'auto', n_jobs = -1)

X_train_smote, y_train_smote = oversample.fit_resample(X_train, y_tra

print(y_train.value_counts())
print(y_train_smote.value_counts())
```

```
2    23192
0    16672
1     2783
Name: status, dtype: int64
2    23192
1    23192
0    23192
Name: status, dtype: int64
```

In [92]:
```
# Instatiate XGB pipeline with SMOTE preprocessing
xgb_smote = Pipeline([('ss', StandardScaler()),
                      ('xgb smote', XGBClassifier(learning_rate=0.1, r
                        n_estimators=250, subsample=0.7))])
xgb_smote.fit(X_train_smote, y_train_smote)
test_preds = xgb_smote.predict(X_test)

print("Test data model score:")
dt_score = model_score(xgb_smote, X_test, test_preds, y_test)
```

```
Test data model score:
                  precision    recall  f1-score   support

        non func       0.84      0.78      0.81      4157
func need repair       0.37      0.40      0.39       671
      functional       0.82      0.86      0.84      5834

        accuracy                           0.80     10662
       macro avg       0.68      0.68      0.68     10662
    weighted avg       0.80      0.80      0.80     10662
```



In [93]:
```
# Predict on training and test sets
training_preds = xgb_smote.predict(X_train)
test_preds = xgb_smote.predict(X_test)

# Accuracy of training and test sets
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 91.8%
Validation accuracy: 79.78%
```

Our XG Boost model with SMOTE prepreprocessing gave us worse accuracy and more overfitting that the non SMOTE XG Boost model. However, the precision of the functional class was the same as our non SMOTE XG Boost at 81%, but due to more overfitting, we will take the XG Boost model as our final model.

6.8 ROC AUC Analysis

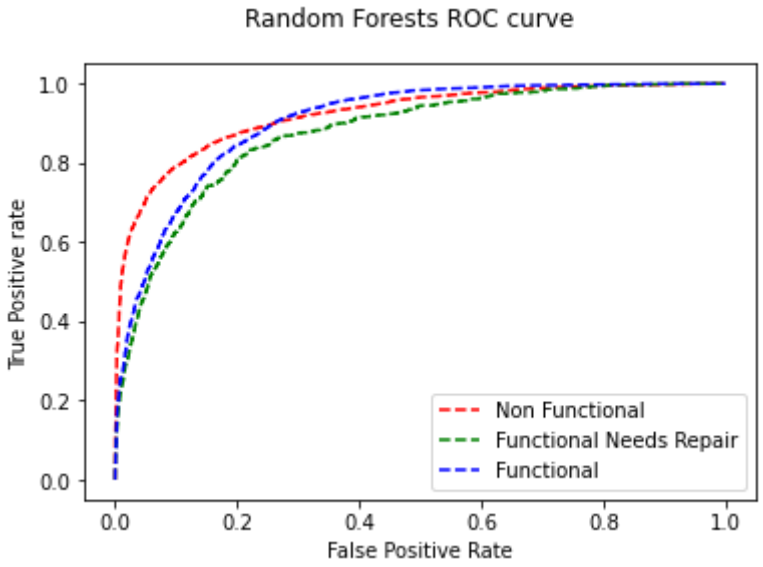
In [94]:

```
# Binarize for multiclass problem
y_multi_test = label_binarize(y_test, classes=[0, 1, 2])

# Predict probability for each model
dt_model_pred_proba = pipe_dt.predict_proba(X_test)
rf_model_pred_proba = pipe_rf.predict_proba(X_test)
knn_model_pred_proba = pipe_knn.predict_proba(X_test)
log_model_pred_proba = pipe_lr.predict_proba(X_test)
dummy_model_pred_proba = dummy.predict_proba(X_test)
xgb_model_pred_proba = pipe_xgb.predict_proba(X_test)

# Calculate AUC ROC score using predicted probablity for each model
dt_test = roc_auc_score(y_multi_test, dt_model_pred_proba, multi_class
rf_auc = roc_auc_score(y_multi_test, rf_model_pred_proba, multi_class=
knn_auc = roc_auc_score(y_multi_test, knn_model_pred_proba, multi_cla
log_model_auc = roc_auc_score(y_multi_test, log_model_pred_proba, mult
dummy_auc = roc_auc_score(y_multi_test, dummy_model_pred_proba, multi_
xgb_auc = roc_auc_score(y_multi_test, xgb_model_pred_proba, multi_cla

print(f'The AUC score for our baseline model is: {round(dummy_auc, 4)}
print(f'The AUC score for our decision tree model is: {round(dt_test,
print(f'The AUC score for our random forest model is: {round(rf_auc, 
print(f'The AUC score for our k nearest neighbor model is: {round(knn_
print(f'The AUC score for our logistic regression model is: {round(log
print(f'The AUC score for our XG Boost model is: {round(xgb_auc, 4)}'
```

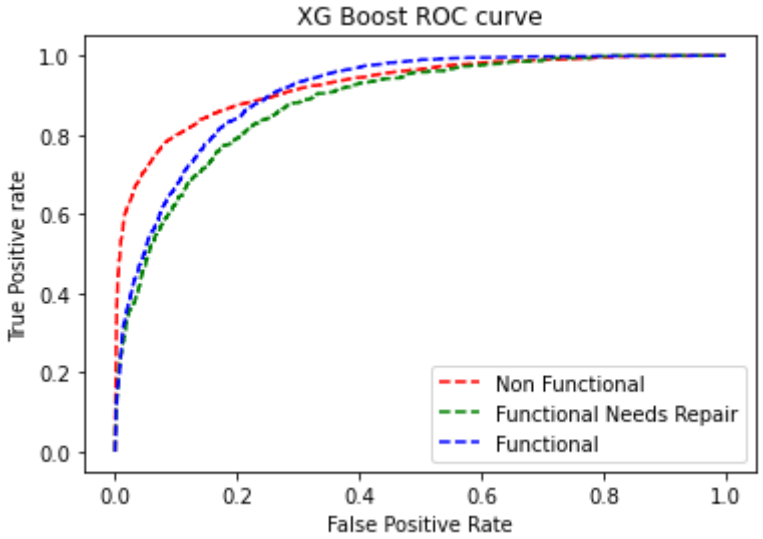
```
The AUC score for our baseline model is: 0.5029
The AUC score for our decision tree model is: 0.7615
The AUC score for our random forest model is: 0.9
The AUC score for our k nearest neighbor model is: 0.8496
The AUC score for our logistic regression model is: 0.8309
The AUC score for our XG Boost model is: 0.9042
```

In [95]:

```
fig, ax = plt.subplots()

# Create dictionary
n_class = 3

fpr = {}
tpr = {}
thresh ={}

# Iterate through each class to create roc_curve
for i in range(n_class):
    fpr[i], tpr[i], thresh[i] = roc_curve(y_test, rf_model_pred_proba

# plotting
plt.plot(fpr[0], tpr[0], linestyle='--',color='red', label='Non Functi
plt.plot(fpr[1], tpr[1], linestyle='--',color='green', label='Functio
plt.plot(fpr[2], tpr[2], linestyle='--',color='blue', label='Functiona
plt.suptitle('Random Forests ROC curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive rate')
plt.legend(loc='best')
plt.savefig('./images/roc_rf.png');
```



In [96]:
```
# Iterate through each class to create roc_curve
for i in range(n_class):
    fpr[i], tpr[i], thresh[i] = roc_curve(y_test, xgb_model_pred_proba

# plotting
plt.plot(fpr[0], tpr[0], linestyle='--',color='red', label='Non Functi
plt.plot(fpr[1], tpr[1], linestyle='--',color='green', label='Functio
plt.plot(fpr[2], tpr[2], linestyle='--',color='blue', label='Functiona
plt.title('XG Boost ROC curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive rate')
plt.legend(loc='best')
plt.savefig('./images/roc_xgb.png');
```



Before performing the ROC AUC curves analysis, our best performing model was our XG Boost model, followed closely by our Random Forest model. The AUC of each model showed the same results again with XG Boost (AUC = 90.5%) outperforming all other models, followed closely by our Random Forests (AUC = 89.9%) model.

7 Conclusions

XG Boost was our top performing model, although Random Forests was not far behind. The poor performance of the K Nearest Neighbors, Decision Tree, and Logistic Regression models indicate that the data is not easily separable. Our XG Boost model performs with an 81.73% testing accuracy and precision for the functional class at 81%. It also had the highest f1 score of any model at 81% and the highest AUC scores at 90.5%.

Based on my findings, I am confident to partner with the Tanzanian government to help solve their water crisis by predicting water pump failure. As we illustrated above, there is a high rate of non functional waterpoints in the southeast corner of Tanzania in Mtwara and Lindi, as well as up north in Mara, and the southwest in Rukwa. These areas need immediate attention as the situations here are critical. There are a high number of functional wells in Iringa, Shinyanga, Kilimanjaro, and Arusha. There is a cluster of functional but need repair waterpoints in Kigoma, these should be addressed to prevent failure which can be more expensive to repair.

Several of our models showed one of it's most important features to be quantity enough for the waterpoint. There are over 8,000 waterpoints that have enough water in them but are non functional. These are a high priority to address as well since there is water present. Wells with no fees are more likely to be non functional. Payment provides incentive and means to keep wells functional. The Government, District Council, and Fini Water all have a high rate of pump failure. Investigate why these installers have such a high rate of failure or use other installers.

Future work for this project involve improving the quality of the data moving forward. Better data trained in our model will improve the predictions. We will also monitor the wells and update the model regularly to continuously improve our strategy.