In [154]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import datetime as dt

from sklearn.model_selection import (train_test_split,
                                      cross_val_score,
                                     GridSearchCV)

from sklearn.metrics import (accuracy_score,
                             f1_score, precision_score,
                             confusion_matrix,
                             classification_report,
                             confusion_matrix, roc_curve, auc)

from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from sklearn.tree import DecisionTreeClassifier
```

Business Problem

Tanzania has had a problem with available water to the general populace for many years.

The Tanzanian government has hired us to figure out a way to imporve methods in identifying non-functioning water wells.

We will be trying to detect which key features will help up identify the status of these wells.

Column Descriptions

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

In [2]:
```
independants = pd.read_csv("Data/Training_Set_Values.csv")
independants.head()
```

Out[2]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_r
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	Zah
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Mal
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	Zah Nanyu
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	Sh

5 rows × 40 columns

In [3]:
```
dependants = pd.read_csv("Data/Training_Set_Labels.csv")
dependants.head()
```

Out[3]:

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

Looks like these are our independant and dependant variables. Going to merge them together for a df.

In [4]:
```
df = independants.merge(dependants, how='outer')
df.head()
```

Out[4]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_r
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	Zah
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Mal
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	Zah Nanyu
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	Sh

5 rows × 41 columns

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 41 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 
 40  status_group           59400 non-null  object 
dtypes: float64(3), int64(7), object(31)
memory usage: 19.0+ MB
```

Data Cleaning and Exploration

In [6]:
```
##Dropping id since it's irrelevant
df = df.drop("id", axis=1)
```

In [7]:
```
df.duplicated().sum()
```

Out[7]: 36

In [8]:
```
#Dropping duplicate rows
df.drop_duplicates(keep="first", inplace=True)
```

In [9]:
```
df.duplicated().sum()
```

Out[9]: 0

In [10]:
```
df.isna().sum()
```

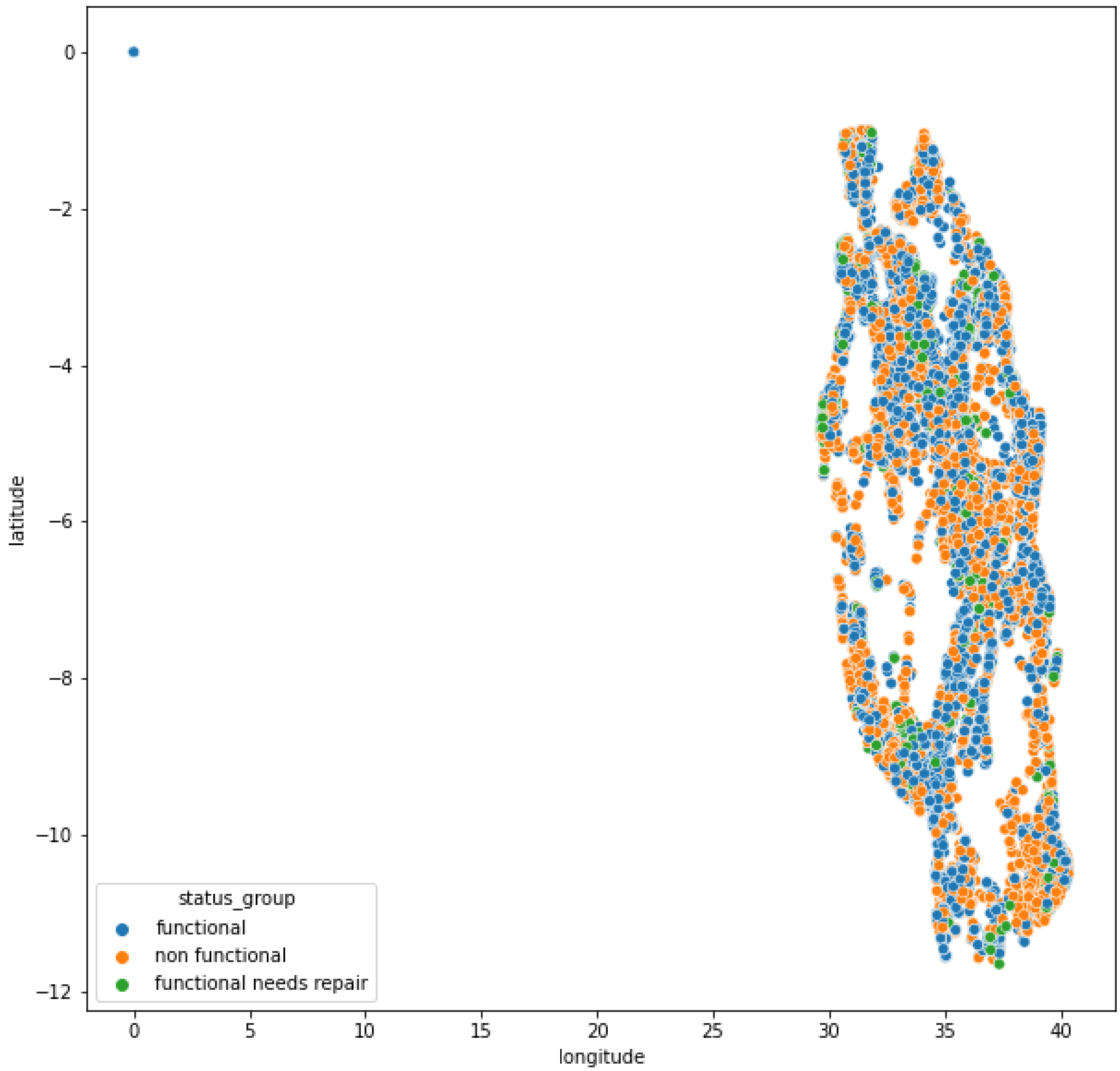
Out[10]:
```
amount_tsh                   0
date_recorded                0
funder                    3635
gps_height                   0
installer                 3655
longitude                    0
latitude                     0
wpt_name                     0
num_private                  0
basin                        0
subvillage                 371
region                       0
region_code                  0
district_code                0
lga                          0
ward                         0
population                   0
public_meeting            3314
recorded_by                  0
scheme_management         3877
scheme_name              28139
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
status_group                 0
dtype: int64
```

scheme_name is missing about half it's values. Dropping it

In [11]:
```
df = df.drop("scheme_name", axis=1)
```

In [12]:
```
plt.figure(figsize = (10,10))
sns.scatterplot(x='longitude',y='latitude',hue='status_group',data=df)
```

Out[12]:
```
<AxesSubplot:xlabel='longitude', ylabel='latitude'>
```



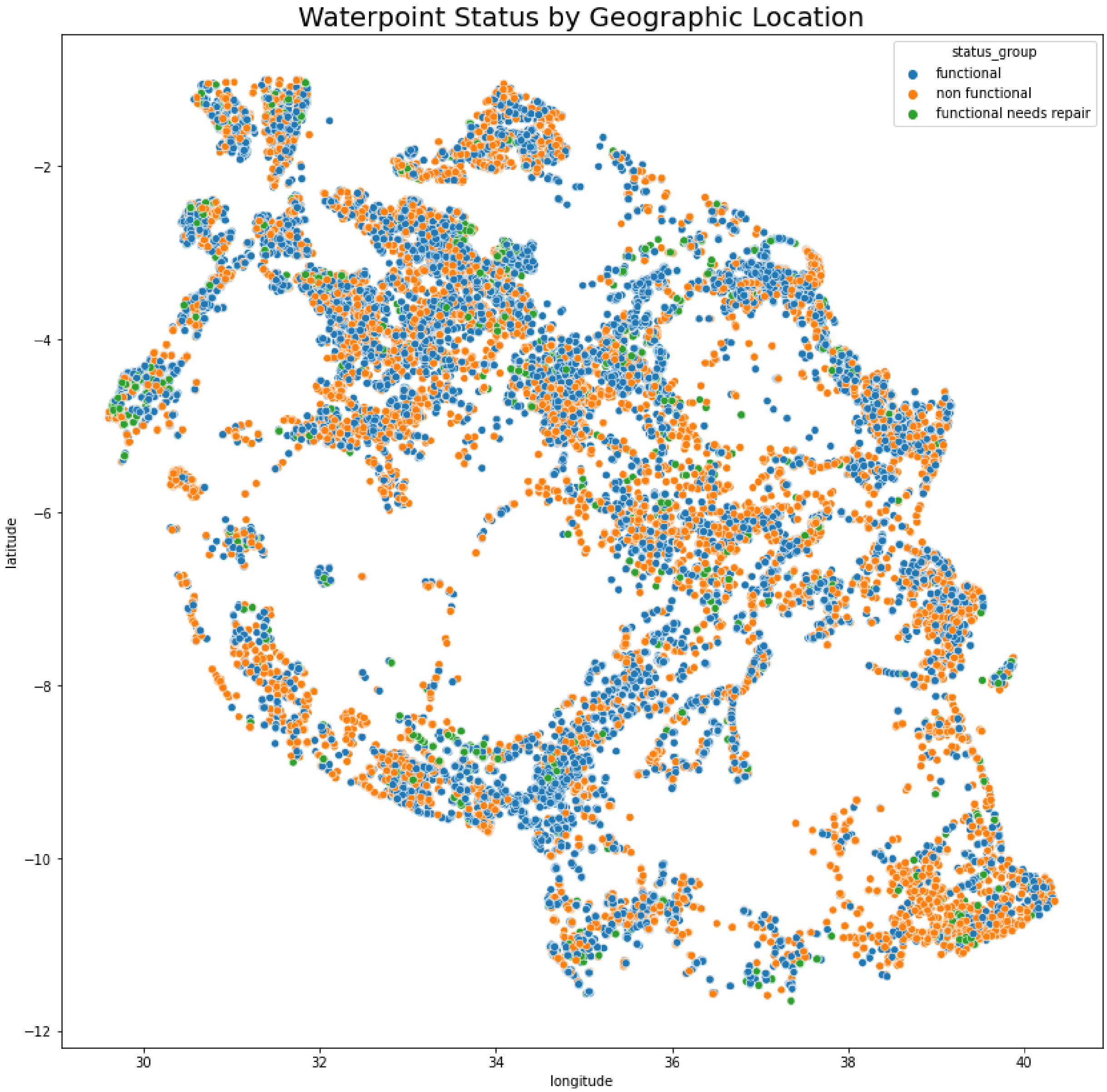
Looks like 0 longitude and latitude is used as a placeholder for unknown locations. Let's remove the rows

In [13]:
```
df = df[df.longitude > 0]
```

In [14]:
```
df.longitude.value_counts()
```

Out[14]:
```
39.090448    2
39.086287    2
39.086183    2
39.098514    2
39.093095    2
            ..
37.579803    1
33.196490    1
34.017119    1
33.788326    1
35.005922    1
Name: longitude, Length: 57515, dtype: int64
```

In [15]:
```
plt.figure(figsize = (14,14))
sns.scatterplot(x='longitude', y='latitude', hue='status_group', data=df)
plt.title('Waterpoint Status by Geographic Location', fontsize=20)
plt.savefig('Location Map')
```



In [16]:
```
df.info()
```

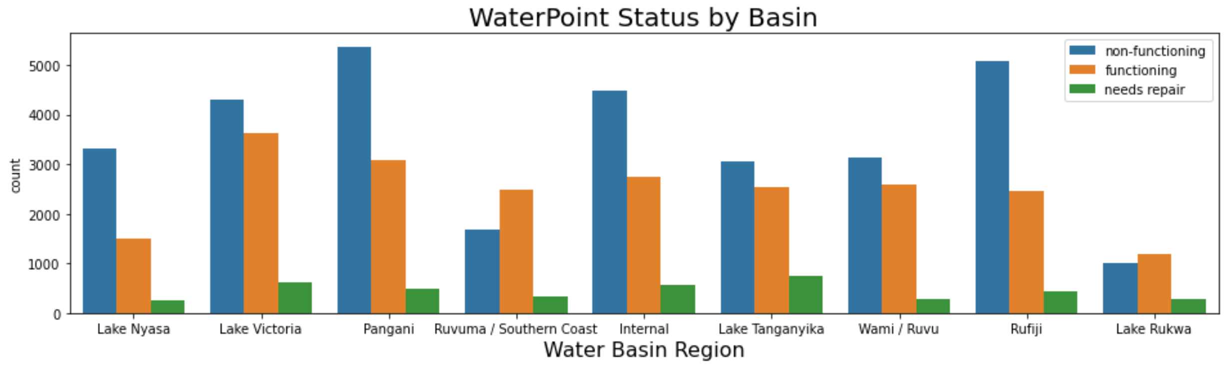
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 57587 entries, 0 to 59399
Data columns (total 39 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   amount_tsh             57587 non-null  float64
 1   date_recorded          57587 non-null  object 
 2   funder                 53965 non-null  object 
 3   gps_height             57587 non-null  int64  
 4   installer              53951 non-null  object 
 5   longitude              57587 non-null  float64
 6   latitude               57587 non-null  float64
 7   wpt_name               57587 non-null  object 
 8   num_private            57587 non-null  int64  
 9   basin                  57587 non-null  object 
 10  subvillage             57216 non-null  object 
 11  region                 57587 non-null  object 
 12  region_code            57587 non-null  int64  
 13  district_code          57587 non-null  int64  
 14  lga                    57587 non-null  object 
 15  ward                   57587 non-null  object 
 16  population             57587 non-null  int64  
 17  public_meeting         54611 non-null  object 
 18  recorded_by            57587 non-null  object 
 19  scheme_management      53837 non-null  object 
 20  permit                 54531 non-null  object 
 21  construction_year      57587 non-null  int64  
 22  extraction_type        57587 non-null  object 
 23  extraction_type_group  57587 non-null  object 
 24  extraction_type_class  57587 non-null  object 
 25  management             57587 non-null  object 
 26  management_group       57587 non-null  object 
 27  payment                57587 non-null  object 
 28  payment_type           57587 non-null  object 
 29  water_quality          57587 non-null  object 
 30  quality_group          57587 non-null  object 
 31  quantity               57587 non-null  object 
 32  quantity_group         57587 non-null  object 
 33  source                 57587 non-null  object 
 34  source_type            57587 non-null  object 
 35  source_class           57587 non-null  object 
 36  waterpoint_type        57587 non-null  object 
 37  waterpoint_type_group  57587 non-null  object 
 38  status_group           57587 non-null  object 
dtypes: float64(3), int64(6), object(30)
memory usage: 17.6+ MB
```

In [17]:
```
#date_recorded is an object. Chnaging to datetime
df['date_recorded'] = pd.to_datetime(df['date_recorded'])
df['date_recorded'] = df['date_recorded'].map(dt.datetime.toordinal)
```

In [18]:
```
df.date_recorded.head()
```

Out[18]:
```
0    734210
1    734933
2    734924
3    734896
4    734331
Name: date_recorded, dtype: int64
```

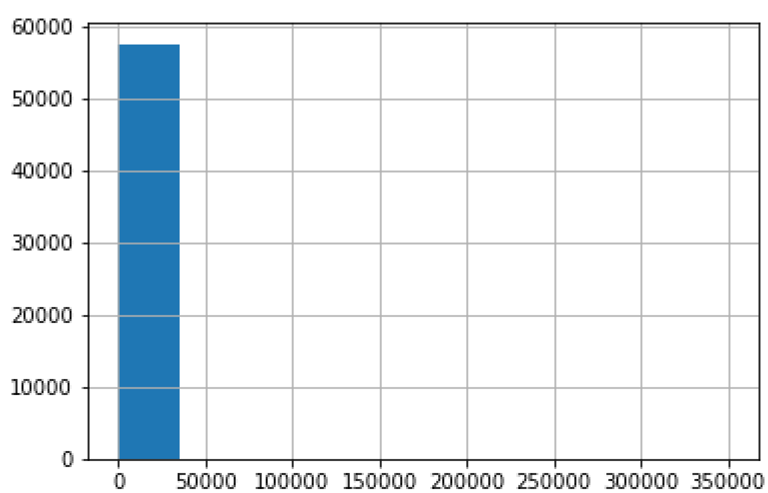
In [19]:
```

plt.figure(figsize=(16,4))
ax = sns.countplot(x="basin", hue='status_group', data=df)
plt.xlabel('Water Basin Region', fontsize=16)
plt.title("WaterPoint Status by Basin", fontsize=20)
labels = ['non-functioning', 'functioning', 'needs repair']
plt.legend(labels)
plt.show()
```



Continuous variable cleaning

In [20]:
```
df.amount_tsh.hist()
```

Out[20]:
```
<AxesSubplot:>
```



In [21]:
```
df.amount_tsh.value_counts(normalize=True)
```

Out[21]:
```
0.0         0.691580
500.0       0.053866
50.0        0.042926
1000.0      0.025839
20.0        0.025405
              ...
8500.0      0.000017
6300.0      0.000017
220.0       0.000017
138000.0    0.000017
12.0        0.000017
Name: amount_tsh, Length: 98, dtype: float64
```

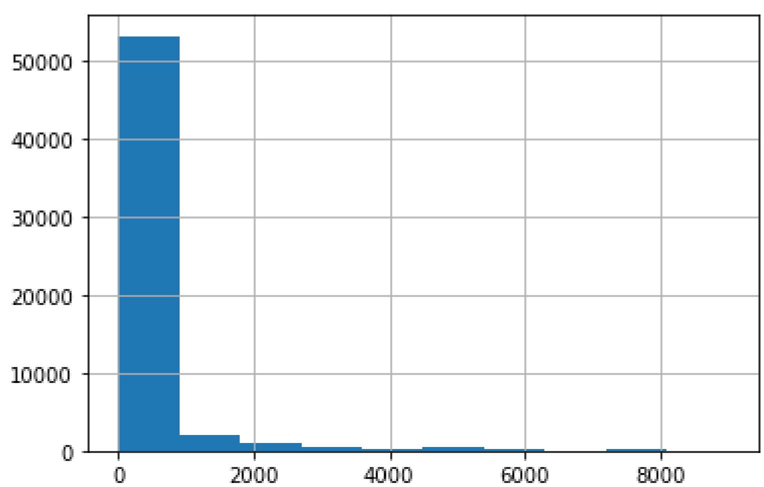
Most values are 0. Seems to be some outliers making the hist hard to read. Removing outliers

In [22]:
```
amount_tsh_std = df.amount_tsh.mean() + df.amount_tsh.std()*3
amount_tsh_std
# Showing how many we are removing for reference
print("Outliers:", df.amount_tsh[df['amount_tsh'] > amount_tsh_std].count())
# Remove outliers from the data
df = df[df['amount_tsh'] < amount_tsh_std]
```

```
Outliers: 237
```

In [23]:
```
df.amount_tsh.hist()
```

Out[23]:
```
<AxesSubplot:>
```



In [24]:
```
df.describe()
```

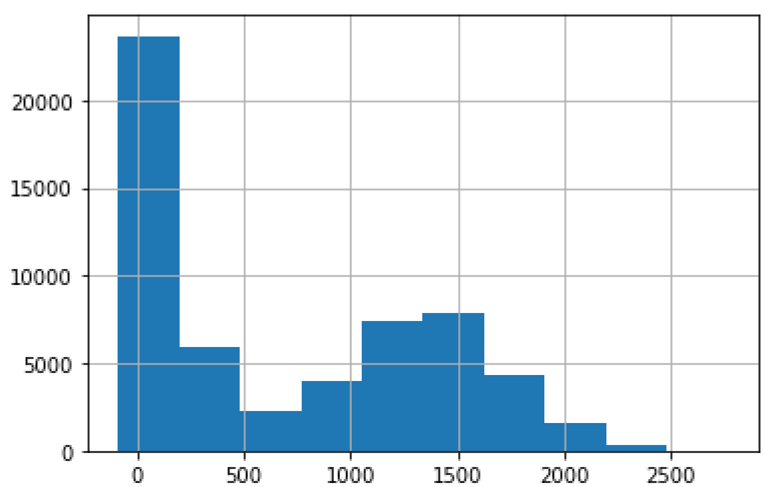
Out[24]:

	amount_tsh	date_recorded	gps_height	longitude	latitude	num_private	regior
count	57350.000000	57350.000000	57350.00000	57350.000000	57350.000000	57350.000000	57350
mean	220.729431	734587.341883	687.53299	35.145596	-5.883289	0.484882	15
std	770.155360	335.843580	693.40072	2.608792	2.810017	12.430483	17
min	0.000000	731137.000000	-90.00000	29.607122	-11.649440	0.000000	1
25%	0.000000	734226.000000	0.00000	33.280201	-8.640322	0.000000	5
50%	0.000000	734784.000000	421.00000	35.000347	-5.168022	0.000000	12
75%	25.000000	734908.000000	1331.00000	37.231554	-3.373151	0.000000	17
max	9000.000000	735205.000000	2770.00000	40.345193	-0.998464	1776.000000	99

gps_height

In [25]:
```
df.gps_height.hist()
```

Out[25]: <AxesSubplot:>



In [26]:
```
df.gps_height.describe()
```

Out[26]:
```
count    57350.00000
mean       687.53299
std        693.40072
min        -90.00000
25%          0.00000
50%        421.00000
75%       1331.00000
max       2770.00000
Name: gps_height, dtype: float64
```

In [27]:
```
gps_height_std = df.gps_height.mean() + df.gps_height.std()*3
gps_height_std
# Showing how many we are removing for reference
print("Outliers:", df.gps_height[df['gps_height'] > gps_height_std].count())
# Remove outliers from the data
df = df[df['gps_height'] < gps_height_std]
```

```
Outliers: 1
```

num_private

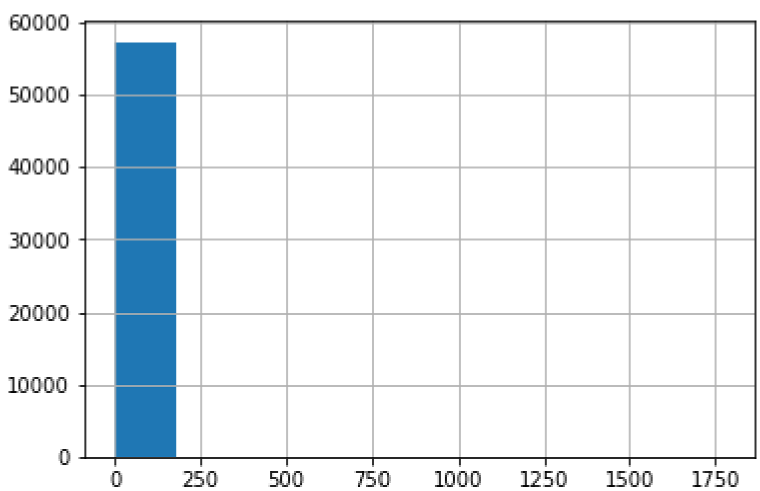
There is no description for this column.

In [28]:
```
#Drop this because it is  almost constant
df.num_private.value_counts(normalize=True)
```

Out[28]:
```
0      0.986922
6      0.001412
1      0.001255
5      0.000802
8      0.000802
         ...
180    0.000017
213    0.000017
23     0.000017
55     0.000017
94     0.000017
Name: num_private, Length: 65, dtype: float64
```

In [29]:
```
df.num_private.hist()
```

Out[29]: <AxesSubplot:>



In [30]:
```
df = df.drop('num_private', axis=1)
```

In [ ]:

region_code, district_code both are prob cat

In [31]:
```
df.region_code.describe()
```

Out[31]:
```
count    57349.000000
mean        15.242341
std         17.877940
min          1.000000
25%          5.000000
50%         12.000000
75%         17.000000
max         99.000000
Name: region_code, dtype: float64
```

Population

population around the well

In [32]:
```
df.population.value_counts(normalize=True)
```

Out[32]:
```
0       0.340651
1       0.122060
200     0.033741
150     0.032485
250     0.029259
          ...
363     0.000017
491     0.000017
2570    0.000017
587     0.000017
1439    0.000017
Name: population, Length: 1042, dtype: float64
```

A lot of 0 values. Abandoned? Surely not.

In [33]:
```
df.population.describe()
```

Out[33]:
```
count    57349.000000
mean       185.269630
std        478.157306
min          0.000000
25%          0.000000
50%         35.000000
75%        230.000000
max      30500.000000
Name: population, dtype: float64
```

In [34]:
```
df.population.median()
```
Out[34]:
```
35.0
```

I think I'll replace the 0 values with the median. Will do this after split

In [35]:
```
df.population.replace(0,df.population.median(axis=0),inplace=True)
```

In [36]:
```
df.population.describe()
```
Out[36]:
```
count    57349.000000
mean       197.192418
std        473.805467
min          1.000000
25%         35.000000
50%         35.000000
75%        230.000000
max      30500.000000
Name: population, dtype: float64
```

In [35]:
```
population_std = df.population.mean() + df.population.std()*3
population_std
# Showing how many we are removing for reference
print("Outliers:", df.population[df['population'] > population_std].count())
# Remove outliers from the data
df = df[df['population'] < population_std]
```
```
Outliers: 702
```

construction_year

In [36]:
```
df.construction_year.value_counts(normalize=True)
```

Out[36]:
```
0       0.332921
2010    0.045104
2008    0.045033
2009    0.043639
2000    0.036154
2007    0.027574
2006    0.025156
2003    0.022243
2011    0.021572
2004    0.019471
2012    0.018783
1978    0.018130
2002    0.017883
2005    0.017494
1995    0.016929
1999    0.016929
1998    0.016629
1990    0.016629
1985    0.016312
1980    0.014158
1996    0.013787
1984    0.013416
1982    0.012869
1994    0.012587
1972    0.012357
1974    0.011580
1997    0.011210
1992    0.011033
1993    0.010451
2001    0.009356
1988    0.009091
1983    0.008438
1975    0.007573
1986    0.007538
1976    0.007220
1970    0.007167
1991    0.005649
1989    0.005490
1987    0.005190
1981    0.004148
1977    0.003548
1979    0.003354
1973    0.003195
2013    0.003107
1971    0.002507
1960    0.001801
1967    0.001553
1963    0.001465
1968    0.001324
1969    0.001024
1964    0.000706
1962    0.000530
1961    0.000371
1965    0.000335
```

```
1966    0.000282
Name: construction_year, dtype: float64
```

Once agiain a lot of 0's here

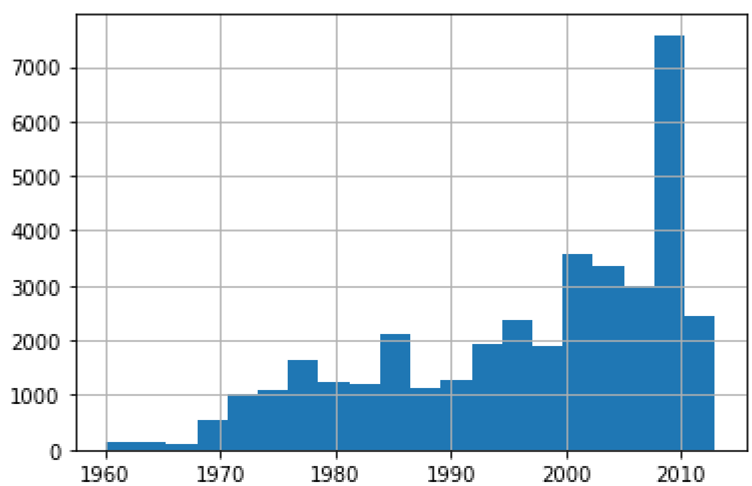
In [37]:
```
year = df[df['construction_year'] != 0]
```

In [38]:
```
year.construction_year.describe()
```

Out[38]:
```
count    37788.000000
mean      1996.768233
std         12.500440
min       1960.000000
25%       1987.000000
50%       2000.000000
75%       2008.000000
max       2013.000000
Name: construction_year, dtype: float64
```

In [39]:
```
year.construction_year.hist(bins=20)
```

Out[39]:
```
<AxesSubplot:>
```



Categorical Cleaning

In [40]:
```
df.isna().sum()
```

Out[40]:
```
amount_tsh                  0
date_recorded               0
funder                   3588
gps_height                  0
installer                3602
longitude                   0
latitude                    0
wpt_name                    0
basin                       0
subvillage                371
region                      0
region_code                 0
district_code               0
lga                         0
ward                        0
population                  0
public_meeting           2929
recorded_by                 0
scheme_management        3679
permit                   2997
construction_year           0
extraction_type             0
extraction_type_group       0
extraction_type_class       0
management                  0
management_group            0
payment                     0
payment_type                0
water_quality               0
quality_group               0
quantity                    0
quantity_group              0
source                      0
source_type                 0
source_class                0
waterpoint_type             0
waterpoint_type_group       0
status_group                0
dtype: int64
```

funder

In [41]:
```
df.funder.describe()
```

Out[41]:
```
count                       53059
unique                       1823
top       Government Of Tanzania
freq                         8784
Name: funder, dtype: object
```

In [42]:
```
#tons of unique/missing values. Dropping and focusing on others
df =df.drop('funder', axis=1)
```

In [43]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 56647 entries, 0 to 59399
Data columns (total 37 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   amount_tsh             56647 non-null  float64
 1   date_recorded          56647 non-null  int64  
 2   gps_height             56647 non-null  int64  
 3   installer              53045 non-null  object 
 4   longitude              56647 non-null  float64
 5   latitude               56647 non-null  float64
 6   wpt_name               56647 non-null  object 
 7   basin                  56647 non-null  object 
 8   subvillage             56276 non-null  object 
 9   region                 56647 non-null  object 
 10  region_code            56647 non-null  int64  
 11  district_code          56647 non-null  int64  
 12  lga                    56647 non-null  object 
 13  ward                   56647 non-null  object 
 14  population             56647 non-null  int64  
 15  public_meeting         53718 non-null  object 
 16  recorded_by            56647 non-null  object 
 17  scheme_management      52968 non-null  object 
 18  permit                 53650 non-null  object 
 19  construction_year      56647 non-null  int64  
 20  extraction_type        56647 non-null  object 
 21  extraction_type_group  56647 non-null  object 
 22  extraction_type_class  56647 non-null  object 
 23  management             56647 non-null  object 
 24  management_group       56647 non-null  object 
 25  payment                56647 non-null  object 
 26  payment_type           56647 non-null  object 
 27  water_quality          56647 non-null  object 
 28  quality_group          56647 non-null  object 
 29  quantity               56647 non-null  object 
 30  quantity_group         56647 non-null  object 
 31  source                 56647 non-null  object 
 32  source_type            56647 non-null  object 
 33  source_class           56647 non-null  object 
 34  waterpoint_type        56647 non-null  object 
 35  waterpoint_type_group  56647 non-null  object 
 36  status_group           56647 non-null  object 
dtypes: float64(3), int64(6), object(28)
memory usage: 16.4+ MB
```

Installer

In [44]:
```
df.installer.describe()
```

Out[44]:
```
count     53045
unique     2069
top         DWE
freq      16051
Name: installer, dtype: object
```

In [45]:
```
#Dropping for same reeason.
df = df.drop('installer', axis=1)
```

wpt_name

This is just the name of the waterpoint. Dropping because should be irrelevant

In [46]:
```
df = df.drop('wpt_name', axis=1)
```

Basin

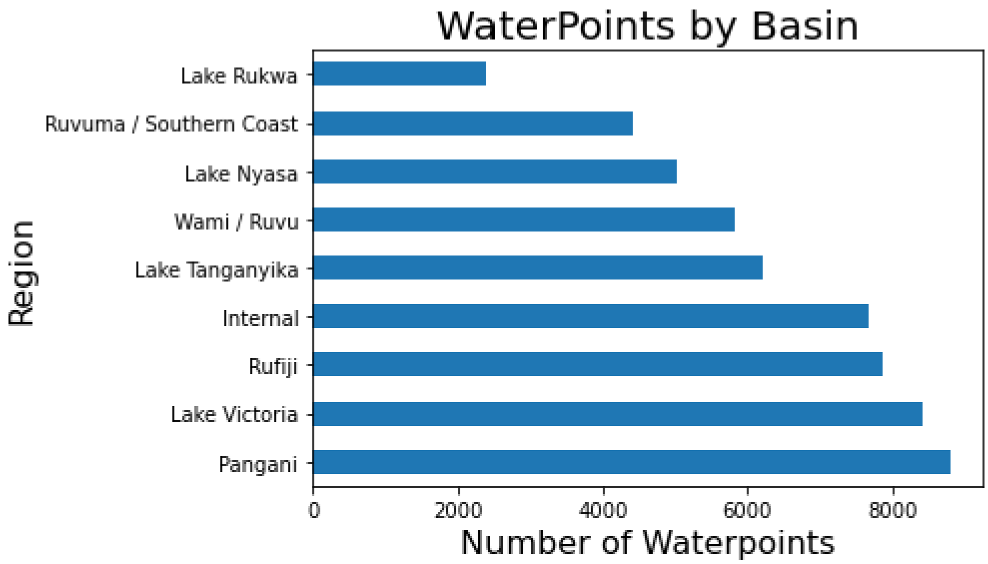
In [47]:
```
df.basin.describe()
```

Out[47]:
```
count       56647
unique          9
top       Pangani
freq         8805
Name: basin, dtype: object
```

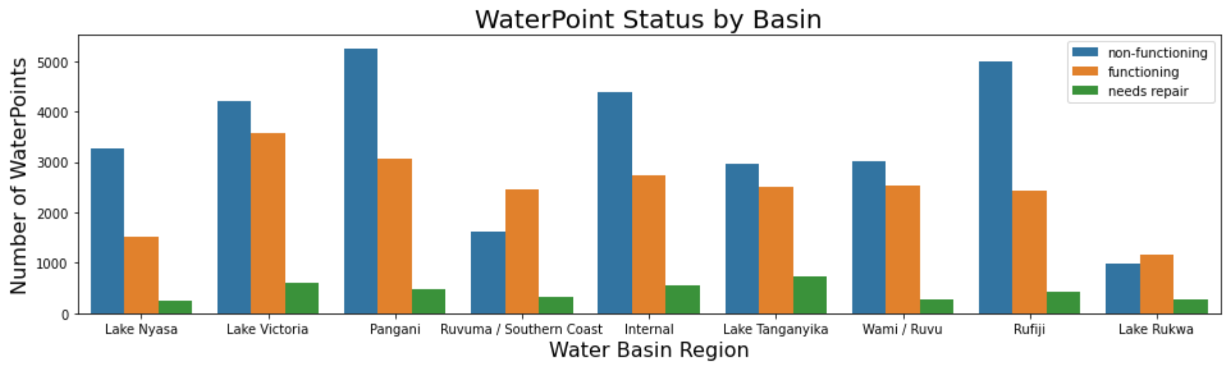
In [48]:
```
df.basin.value_counts(normalize=True)
```

Out[48]:
```
Pangani                    0.155436
Lake Victoria              0.148393
Rufiji                     0.139054
Internal                   0.135541
Lake Tanganyika            0.109732
Wami / Ruvu                0.102742
Lake Nyasa                 0.088760
Ruvuma / Southern Coast    0.077798
Lake Rukwa                 0.042544
Name: basin, dtype: float64
```

In [49]:
```
df.basin.value_counts().plot(kind='barh')
plt.xlabel('Number of Waterpoints', fontsize=16)
plt.ylabel('Region', fontsize=16)
plt.title("WaterPoints by Basin", fontsize=20)
plt.show()
```



In [50]:
```
plt.figure(figsize=(16,4))
ax = sns.countplot(x="basin", hue='status_group', data=df)
plt.xlabel('Water Basin Region', fontsize=16)
plt.ylabel('Number of WaterPoints', fontsize=16)
plt.title("WaterPoint Status by Basin", fontsize=20)
labels = ['non-functioning', 'functioning', 'needs repair']
plt.legend(labels)
plt.show()
```



subvillage

In [51]:
```
df.subvillage.describe()
```

Out[51]:
```
count       56276
unique      18348
top       Shuleni
freq          482
Name: subvillage, dtype: object
```

In [52]:
```
df = df.drop('subvillage', axis=1)
```

Region

In [53]:
```
df.region.describe()
```

Out[53]:
```
count      56647
unique        21
top       Iringa
freq        5249
Name: region, dtype: object
```

In [54]:
```
#already have region code which is the same thing. Dropping
df =df.drop('region', axis=1)
```

Looking at the data a bit, I'm going to drop lga and ward as well for similar reasons. Too many geograghic features

In [55]:
```
df = df.drop(columns='lga', axis=1)
df = df.drop(columns='ward', axis=1)
```

public_meeting

Whether the waterpoint is open to the public

some missing values

In [56]:
```
df.public_meeting.describe()
```

Out[56]:
```
count     53718
unique        2
top        True
freq      48953
Name: public_meeting, dtype: object
```

In [57]:
```
df.public_meeting.value_counts(normalize=True)
```

Out[57]:
```
True     0.911296
False    0.088704
Name: public_meeting, dtype: float64
```

Almost all are open to public. Going to fill missing values with true

In [58]:
```
df['public_meeting'].fillna(True, inplace=True)
```

recorded_by

In [59]:
```
df.recorded_by.describe()
```

Out[59]:
```
count                         56647
unique                            1
top       GeoData Consultants Ltd
freq                          56647
Name: recorded_by, dtype: object
```

All recorded by the same group. Removing since this won't be useful

In [60]:
```
df = df.drop('recorded_by', axis=1)
```

Scheme_management

In [61]:
```
df.scheme_management.describe()
```

Out[61]:
```
count      52968
unique        12
top          VWC
freq       35613
Name: scheme_management, dtype: object
```

In [62]:
```
df.scheme_management.value_counts()
```

Out[62]:
```
VWC                    35613
WUG                     4205
Water authority         3081
WUA                     2847
Water Board             2717
Parastatal              1579
Private operator        1034
Company                 1034
Other                    691
SWC                       96
Trust                     70
None                       1
Name: scheme_management, dtype: int64
```

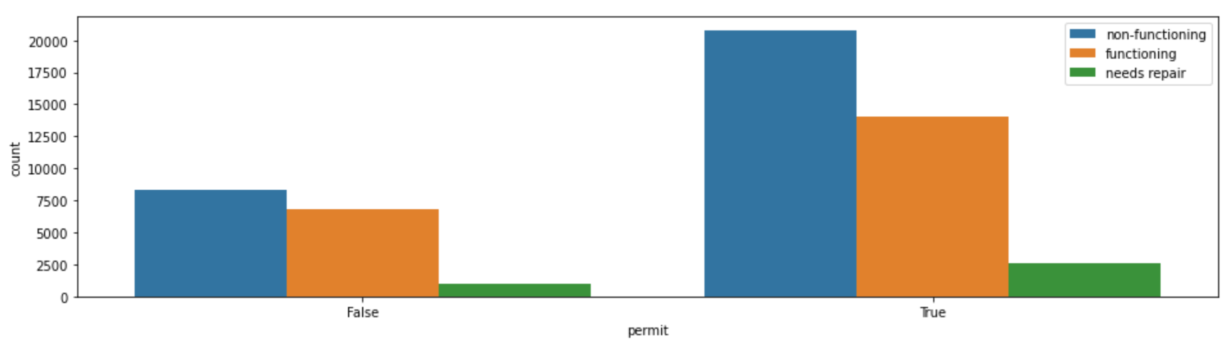
In [63]:
```
#Dropping for same reason as many above
df = df.drop('scheme_management', axis=1)
```

permit

In [64]:
```
df.permit.value_counts()
```

Out[64]:
```
True     37526
False    16124
Name: permit, dtype: int64
```

In [65]:
```

plt.figure(figsize=(16,4))
ax = sns.countplot(x="permit", hue='status_group', data=df)
labels = ['non-functioning', 'functioning', 'needs repair']
plt.legend(labels)
plt.show()
```



Weird. I expected those with permits to be more regulated than those without

There are some missing values here. Filling them with false.

In [66]:
```
df['permit'].fillna(False, inplace=True)
```

extraction

These 3 seem to have similar data.

In [67]:
```
df.extraction_type.value_counts()
```

Out[67]:
```
gravity                      26389
nira/tanira                   7269
other                         6050
submersible                   4535
swn 80                        3404
mono                          2767
india mark ii                 2206
afridev                       1609
ksb                           1331
other - rope pump              444
other - swn 81                 224
windmill                       107
cemo                            90
india mark iii                  87
other - play pump               81
climax                          32
walimi                          20
other - mkulima/shinyanga        2
Name: extraction_type, dtype: int64
```

In [68]:
```
df.extraction_type_group.value_counts()
```

Out[68]:
```
gravity            26389
nira/tanira         7269
other               6050
submersible         5866
swn 80              3404
mono                2767
india mark ii       2206
afridev             1609
rope pump            444
other handpump       327
other motorpump      122
wind-powered         107
india mark iii        87
Name: extraction_type_group, dtype: int64
```

In [69]:
```
df.extraction_type_class.value_counts()
```

Out[69]:
```
gravity          26389
handpump         14902
other             6050
submersible       5866
motorpump         2889
rope pump          444
wind-powered       107
Name: extraction_type_class, dtype: int64
```

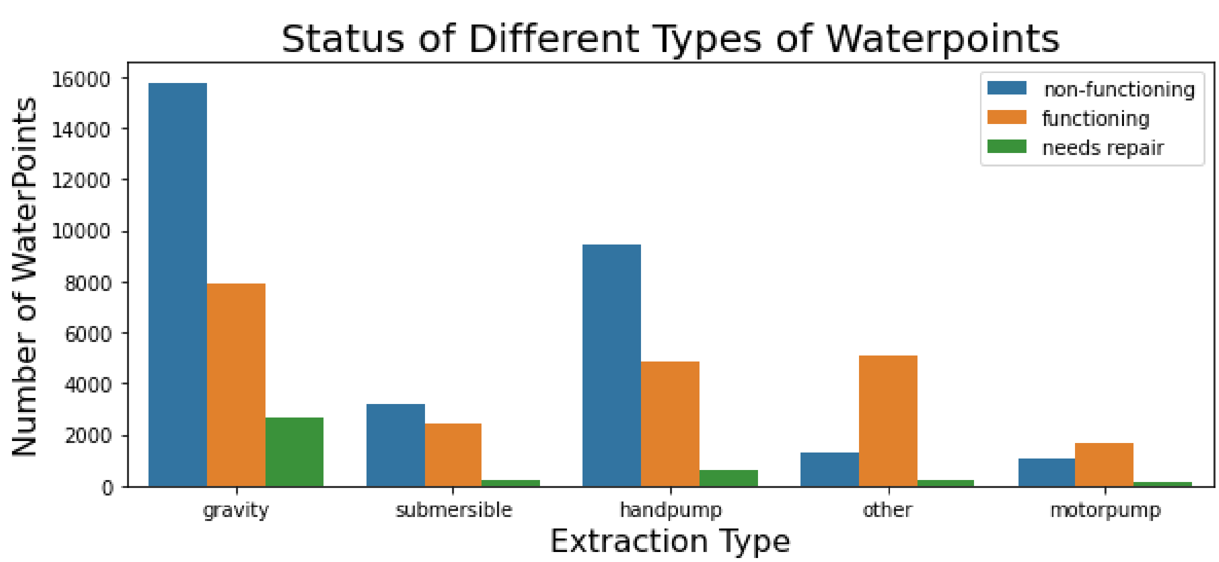
Going to keep class and drop the other two.

In [70]:
```
df = df.drop(columns=['extraction_type', 'extraction_type_group'], axis=1)
```

In [71]:
```
#putting low cardinality into other group
df.extraction_type_class = df.extraction_type_class.replace(to_replace =
                                                            ['rope pump',
                                                             'wind-powered'],
                                                            value = 'other')
df.extraction_type_class.value_counts()
```

Out[71]:
```
gravity         26389
handpump        14902
other            6601
submersible      5866
motorpump        2889
Name: extraction_type_class, dtype: int64
```

In [72]:
```
plt.figure(figsize=(10,4))
ax = sns.countplot(x="extraction_type_class", hue='status_group', data=df)
plt.xlabel('Extraction Type', fontsize=16)
plt.ylabel('Number of WaterPoints', fontsize=16)
plt.title("Status of Different Types of Waterpoints", fontsize=20)
labels = ['non-functioning', 'functioning', 'needs repair']
plt.legend(labels)
plt.show()
```



management

In [73]:
```
df.management.value_counts()
```

Out[73]:
```
vwc                 39119
wug                  5498
water board          2888
wua                  2509
private operator     1923
parastatal           1660
water authority       881
other                 791
company               663
unknown               541
other - school         98
trust                  76
Name: management, dtype: int64
```

In [74]:
```
df.management_group.value_counts()
```

Out[74]:
```
user-group    50014
commercial     3543
parastatal     1660
other           889
unknown         541
Name: management_group, dtype: int64
```

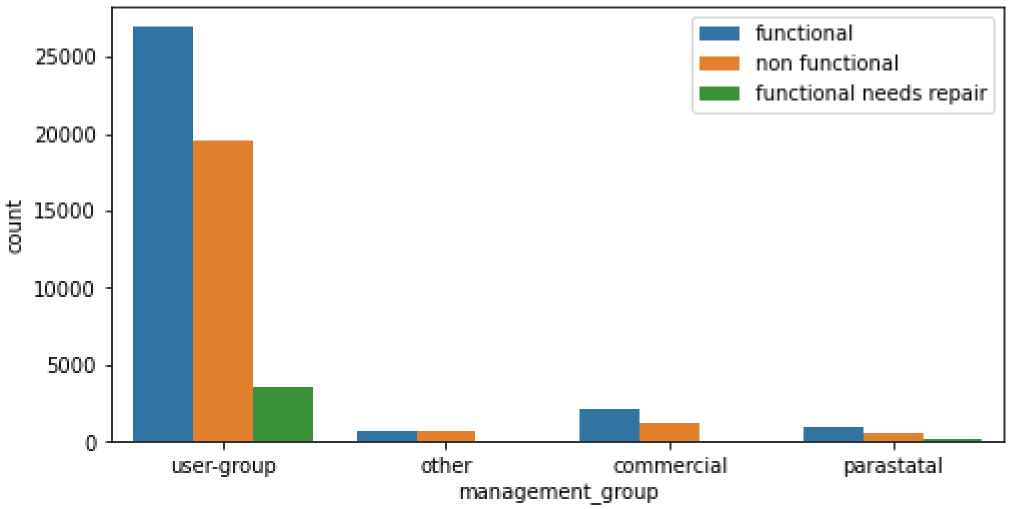
In [75]:
```
df = df.drop('management', axis=1)
```

In [76]:
```
df.management_group = df.management_group.replace(to_replace = ['unknown'],
                                                  value = 'other')
df.management_group.value_counts()
```

Out[76]:
```
user-group    50014
commercial     3543
parastatal     1660
other          1430
Name: management_group, dtype: int64
```

In [77]:
```
plt.figure(figsize=(8,4))
ax = sns.countplot(x="management_group", hue='status_group', data=df)
plt.legend()
```

Out[77]:
```
<matplotlib.legend.Legend at 0x237bf68b760>
```



Payment

In [78]:
```
df.payment.value_counts()
```

Out[78]:
```
never pay                24097
pay per bucket            8707
pay monthly               8059
unknown                   7582
pay when scheme fails     3804
pay annually              3506
other                      892
Name: payment, dtype: int64
```

In [79]:
```
df.payment_type.value_counts()
```

Out[79]:
```
never pay      24097
per bucket      8707
monthly         8059
unknown         7582
on failure      3804
annually        3506
other            892
Name: payment_type, dtype: int64
```

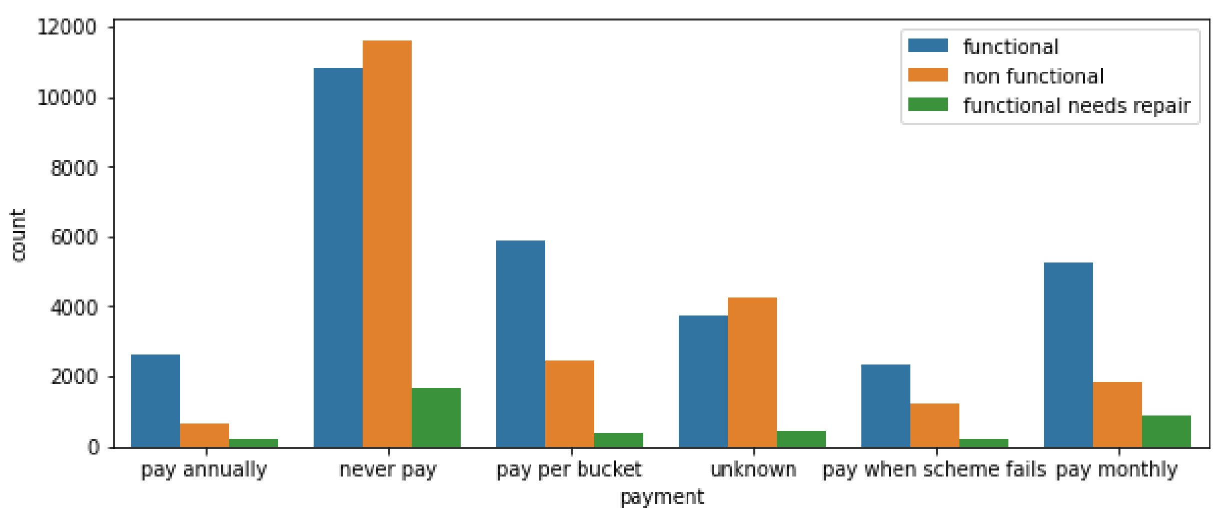
In [80]:
```
#Looks liek a duplicate column. Removing extra
df = df.drop('payment_type', axis=1)
```

In [81]:
```
# group 'unknowns' and 'other' together to reduce bins
df.payment = df.payment.replace(to_replace = ['other'],
                                              value = 'unknown')
df.payment.value_counts()
```

Out[81]:
```
never pay                24097
pay per bucket            8707
unknown                   8474
pay monthly               8059
pay when scheme fails     3804
pay annually              3506
Name: payment, dtype: int64
```

In [82]:
```

plt.figure(figsize=(10,4))
ax = sns.countplot(x="payment", hue='status_group', data=df)
plt.legend()
```

Out[82]: <matplotlib.legend.Legend at 0x237bf404820>



Water Quality

In [83]:
```
df.quality_group.value_counts()
```

Out[83]:
```
good        48664
salty        4862
unknown      1646
milky         798
colored       473
fluoride      204
Name: quality_group, dtype: int64
```

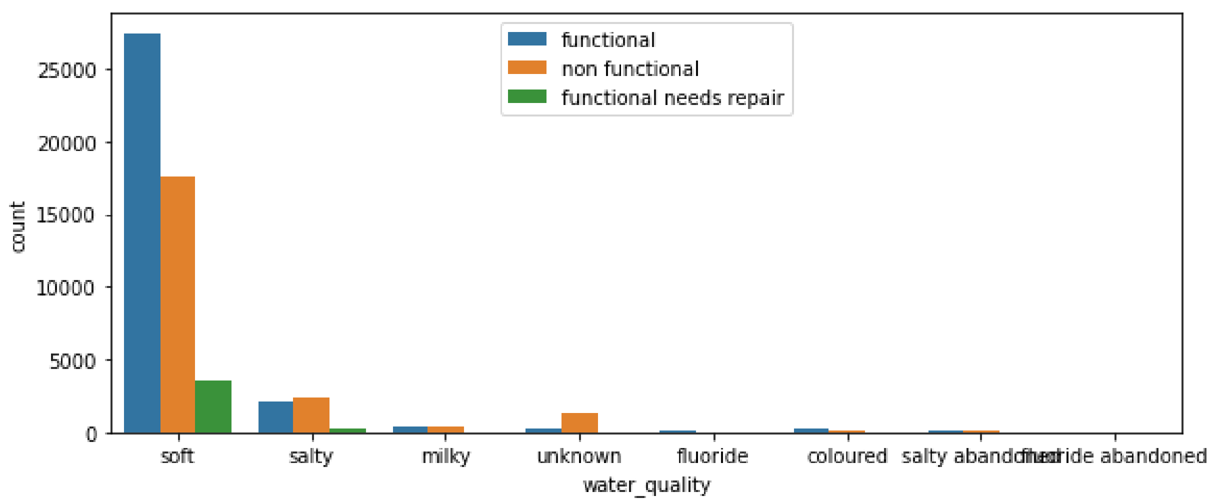
In [ ]:
```
```

These are almost identical. Just notes the abandoned. Dropping former

In [84]:
```
df = df.drop('quality_group', axis=1)
```

In [85]:
```
plt.figure(figsize=(10,4))
ax = sns.countplot(x="water_quality", hue='status_group', data=df)
plt.legend()
```

Out[85]:
```
<matplotlib.legend.Legend at 0x237bf785e80>
```

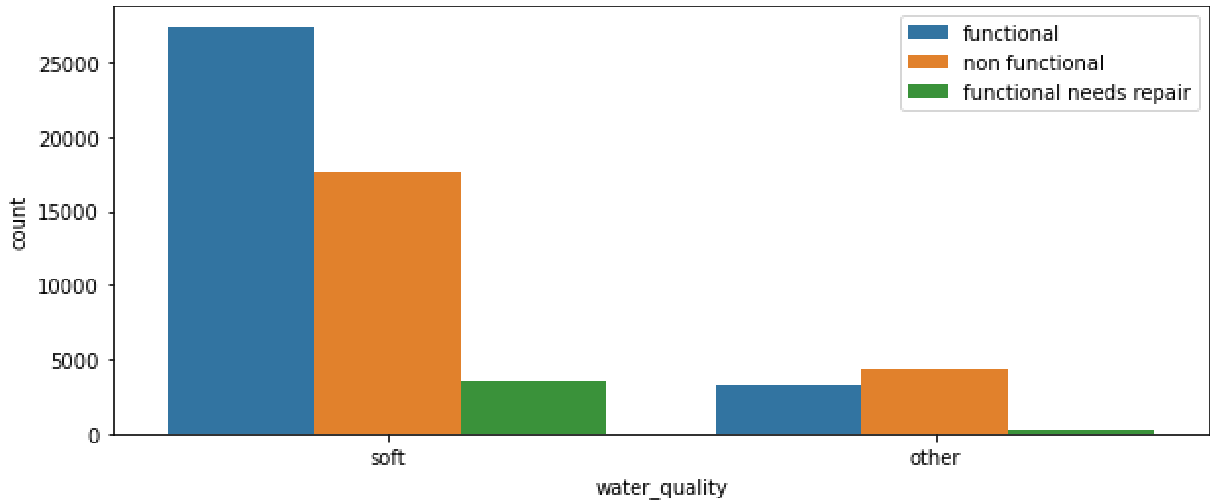


In [86]:
```
# Group all to make it wither good or bad water
df.water_quality = df.water_quality.replace(to_replace = ['salty', 'milky', 'unkn
                                            'fluoride', 'coloured','salty abandon
                                            'fluoride abandoned'],
                                                value = 'other')
df.water_quality.value_counts()
```

Out[86]:
```
soft     48664
other     7983
Name: water_quality, dtype: int64
```

In [87]:
```
plt.figure(figsize=(10,4))
ax = sns.countplot(x="water_quality", hue='status_group', data=df)
plt.legend()
```

Out[87]: <matplotlib.legend.Legend at 0x237c0667dc0>



Quantity

In [88]:
```
df.quantity.value_counts()
```

Out[88]:
```
enough          31684
insufficient    14302
dry              5934
seasonal         3965
unknown           762
Name: quantity, dtype: int64
```

In [89]:
```
df.quantity_group.value_counts()
```

Out[89]:
```
enough          31684
insufficient    14302
dry              5934
seasonal         3965
unknown           762
Name: quantity_group, dtype: int64
```

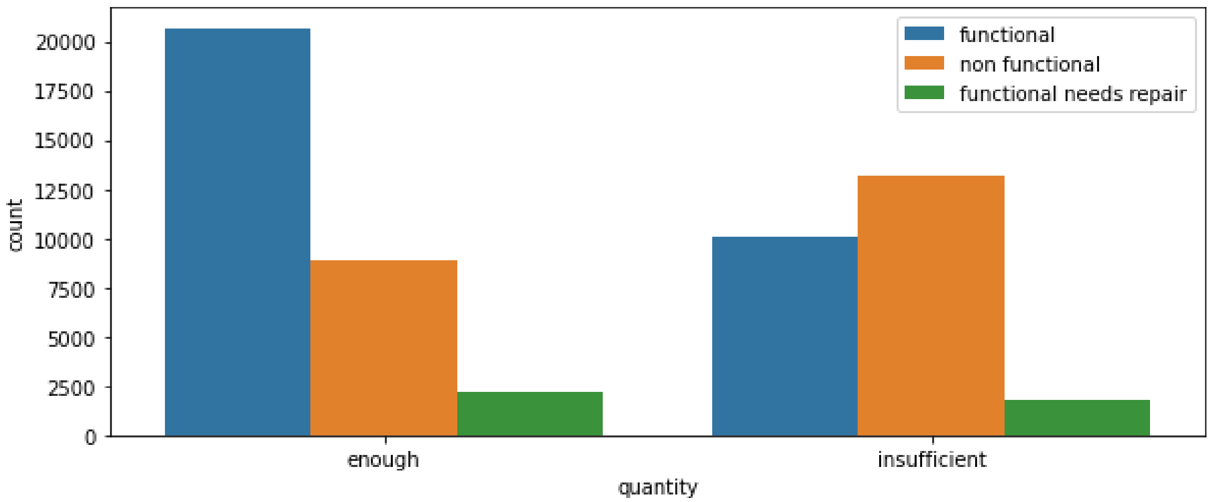
In [90]:
```
#duplicated columns
df = df.drop('quantity_group', axis=1)
```

In [91]:
```
# changing groups to either sufficient or not
df.quantity = df.quantity.replace(to_replace = ['unknown', 'dry',
                                                'seasonal'],
                                               value = 'insufficient')
df.quantity.value_counts()
```

Out[91]:
```
enough          31684
insufficient    24963
Name: quantity, dtype: int64
```

In [92]:
```
plt.figure(figsize=(10,4))
ax = sns.countplot(x="quantity", hue='status_group', data=df)
plt.legend()
```

Out[92]: <matplotlib.legend.Legend at 0x237c06c0d30>



Source

In [93]:
```
df.source.value_counts()
```

Out[93]:
```
spring                  16833
shallow well            15288
machine dbh             10555
river                    9409
rainwater harvesting     2194
hand dtw                  864
dam                       621
lake                      620
other                     202
unknown                    61
Name: source, dtype: int64
```

In [94]:
```
df.source_class.value_counts()
```

Out[94]:
```
groundwater    43540
surface        12844
unknown          263
Name: source_class, dtype: int64
```

In [95]:
```
df.source_type.value_counts()
```

Out[95]:
```
spring                  16833
shallow well            15288
borehole                11419
river/lake              10029
rainwater harvesting     2194
dam                       621
other                     263
Name: source_type, dtype: int64
```

Looks like these three are redundant info dropping two

In [96]:
```
df = df.drop(columns=['source', 'source_type'], axis=1)
```

Most of the sources are from groundwater. Very little data in unknown cat

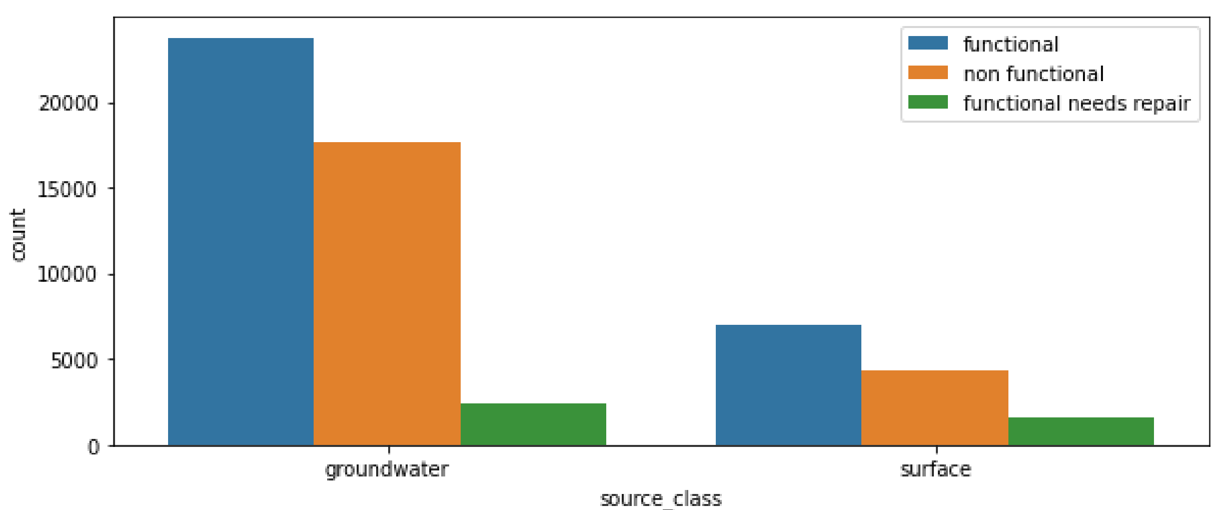
Putting those values under groundwater to reduce bins

In [97]:
```
df.source_class = df.source_class.replace(to_replace = 'unknown',
                                                value = 'groundwater')
df.source_class.value_counts()
```

Out[97]:
```
groundwater    43803
surface        12844
Name: source_class, dtype: int64
```

In [98]:
```
plt.figure(figsize=(10,4))
ax = sns.countplot(x="source_class", hue='status_group', data=df)
plt.legend()
```

Out[98]:
```
<matplotlib.legend.Legend at 0x237c0855ca0>
```



Waterpoint Type

In [99]:
```
df.waterpoint_type_group.value_counts()
```

Out[99]:
```
communal standpipe    33811
hand pump             15882
other                  6076
improved spring         767
cattle trough           105
dam                       6
Name: waterpoint_type_group, dtype: int64
```

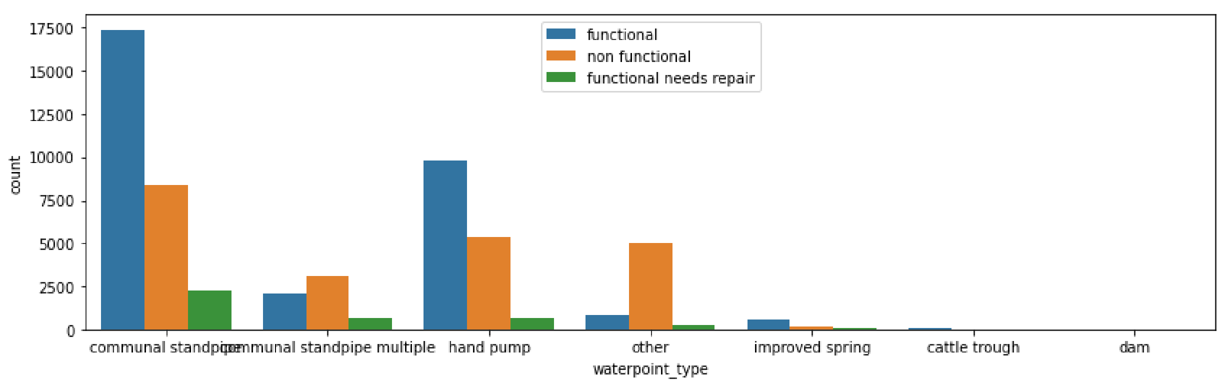
In [100]:
```
df.waterpoint_type.value_counts()
```

Out[100]:
```
communal standpipe             28012
hand pump                      15882
other                           6076
communal standpipe multiple     5799
improved spring                  767
cattle trough                    105
dam                                6
Name: waterpoint_type, dtype: int64
```

In [101]:
```
#dropping similar columns
df = df.drop('waterpoint_type_group', axis=1)
```

In [102]:
```
plt.figure(figsize=(14,4))
ax = sns.countplot(x="waterpoint_type", hue='status_group', data=df)
plt.legend()
```

Out[102]: <matplotlib.legend.Legend at 0x237c1450070>



I'm going to group some of these together

In [103]:
```
# all standpipes will be in a group
df.waterpoint_type = df.waterpoint_type.replace(to_replace = 'communal standpipe
                                                 value = 'communal standpipe')
df.waterpoint_type.value_counts()
```

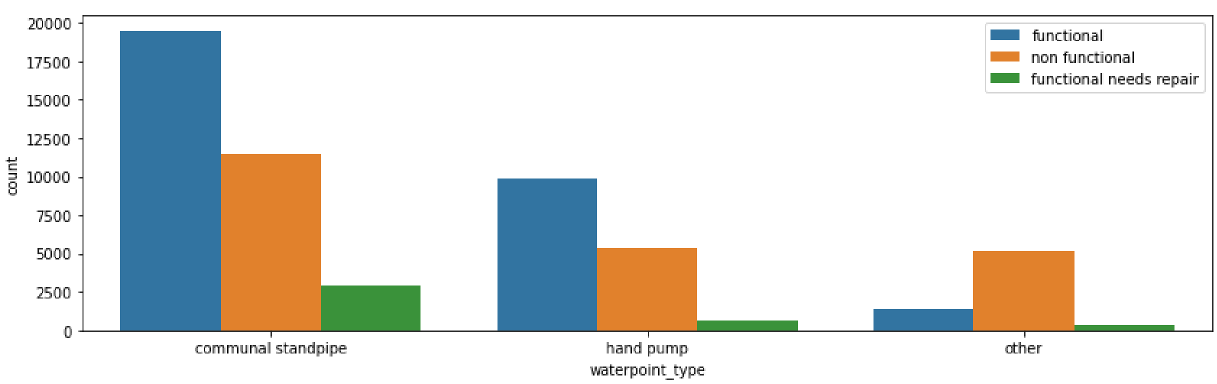
Out[103]:
```
communal standpipe    33811
hand pump             15882
other                  6076
improved spring         767
cattle trough           105
dam                       6
Name: waterpoint_type, dtype: int64
```

In [104]:
```
# Putting all the lower cardinality into the other group leaving only 3 columns
df.waterpoint_type = df.waterpoint_type.replace(to_replace = ['improved spring',
                                                    'cattle trough', 'dam'],
                                                     value = 'other')
df.waterpoint_type.value_counts()
```

Out[104]:
```
communal standpipe    33811
hand pump             15882
other                  6954
Name: waterpoint_type, dtype: int64
```

In [105]:
```
plt.figure(figsize=(14,4))
ax = sns.countplot(x="waterpoint_type", hue='status_group', data=df)
plt.legend()
```

Out[105]: <matplotlib.legend.Legend at 0x237c14502b0>



In [106]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 56647 entries, 0 to 59399
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   amount_tsh            56647 non-null  float64
 1   date_recorded         56647 non-null  int64  
 2   gps_height            56647 non-null  int64  
 3   longitude             56647 non-null  float64
 4   latitude              56647 non-null  float64
 5   basin                 56647 non-null  object 
 6   region_code           56647 non-null  int64  
 7   district_code         56647 non-null  int64  
 8   population            56647 non-null  int64  
 9   public_meeting        56647 non-null  bool   
 10  permit                56647 non-null  bool   
 11  construction_year     56647 non-null  int64  
 12  extraction_type_class  56647 non-null  object 
 13  management_group      56647 non-null  object 
 14  payment               56647 non-null  object 
 15  water_quality         56647 non-null  object 
 16  quantity              56647 non-null  object 
 17  source_class          56647 non-null  object 
 18  waterpoint_type       56647 non-null  object 
 19  status_group          56647 non-null  object 
dtypes: bool(2), float64(3), int64(6), object(9)
memory usage: 10.8+ MB
```

Cleaned Data

One Hot Encoding Categoricals

In [107]:
```
cat_dummies = ['basin', 'public_meeting', 'permit',
       'extraction_type_class', 'management_group', 'payment', 'water_quality',
       'quantity', 'source_class', 'waterpoint_type']
```

In [108]:
```
enc = OneHotEncoder(handle_unknown='ignore')
# passing bridge-types-cat column (label encoded values of bridge_types)
enc_df = pd.DataFrame(enc.fit_transform(df[['basin', 'public_meeting', 'permit',
       'extraction_type_class', 'management_group', 'payment', 'water_quality',
       'quantity', 'source_class', 'waterpoint_type']]).toarray())
# merge with main df bridge_df on key values
#bridge_df = bridge_df.join(enc_df)
#bridge_df
```

In [109]:
```
enc.get_feature_names()
enc_df.columns = enc.get_feature_names()
```

In [110]:
```
enc_df.head()
```

Out[110]:

	x0_Internal	x0_Lake Nyasa	x0_Lake Rukwa	x0_Lake Tanganyika	x0_Lake Victoria	x0_Pangani	x0_Rufiji	x0_Ruvuma / Southern Coast	x0_Wa / Ru
0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	(
1	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	(
2	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	(
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	(
4	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	(

5 rows × 37 columns

In [111]:
```
enc_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56647 entries, 0 to 56646
Data columns (total 37 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   x0_Internal                   56647 non-null  float64
 1   x0_Lake Nyasa                 56647 non-null  float64
 2   x0_Lake Rukwa                 56647 non-null  float64
 3   x0_Lake Tanganyika            56647 non-null  float64
 4   x0_Lake Victoria              56647 non-null  float64
 5   x0_Pangani                    56647 non-null  float64
 6   x0_Rufiji                     56647 non-null  float64
 7   x0_Ruvuma / Southern Coast    56647 non-null  float64
 8   x0_Wami / Ruvu                56647 non-null  float64
 9   x1_False                      56647 non-null  float64
 10  x1_True                       56647 non-null  float64
 11  x2_False                      56647 non-null  float64
 12  x2_True                       56647 non-null  float64
 13  x3_gravity                    56647 non-null  float64
 14  x3_handpump                   56647 non-null  float64
 15  x3_motorpump                  56647 non-null  float64
 16  x3_other                      56647 non-null  float64
 17  x3_submersible                56647 non-null  float64
 18  x4_commercial                 56647 non-null  float64
 19  x4_other                      56647 non-null  float64
 20  x4_parastatal                 56647 non-null  float64
 21  x4_user-group                 56647 non-null  float64
 22  x5_never pay                  56647 non-null  float64
 23  x5_pay annually               56647 non-null  float64
 24  x5_pay monthly                56647 non-null  float64
 25  x5_pay per bucket             56647 non-null  float64
 26  x5_pay when scheme fails      56647 non-null  float64
 27  x5_unknown                    56647 non-null  float64
 28  x6_other                      56647 non-null  float64
 29  x6_soft                       56647 non-null  float64
 30  x7_enough                     56647 non-null  float64
 31  x7_insufficient               56647 non-null  float64
 32  x8_groundwater                56647 non-null  float64
 33  x8_surface                    56647 non-null  float64
 34  x9_communal standpipe         56647 non-null  float64
 35  x9_hand pump                  56647 non-null  float64
 36  x9_other                      56647 non-null  float64
dtypes: float64(37)
memory usage: 16.0 MB
```

In [112]:
```
df2 = df.drop(columns=['basin', 'public_meeting', 'permit',
       'extraction_type_class', 'management_group', 'payment', 'water_quality',
       'quantity', 'source_class', 'waterpoint_type'], axis=1)
```

In [113]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 56647 entries, 0 to 59399
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   amount_tsh         56647 non-null  float64
 1   date_recorded      56647 non-null  int64  
 2   gps_height         56647 non-null  int64  
 3   longitude          56647 non-null  float64
 4   latitude           56647 non-null  float64
 5   region_code        56647 non-null  int64  
 6   district_code      56647 non-null  int64  
 7   population         56647 non-null  int64  
 8   construction_year  56647 non-null  int64  
 9   status_group       56647 non-null  object 
dtypes: float64(3), int64(6), object(1)
memory usage: 7.3+ MB
```

In [114]:
```
df3 = df2.join(enc_df, how='left')
```

In [115]:
```
df3.columns
```

Out[115]:
```
Index(['amount_tsh', 'date_recorded', 'gps_height', 'longitude', 'latitude',
       'region_code', 'district_code', 'population', 'construction_year',
       'status_group', 'x0_Internal', 'x0_Lake Nyasa', 'x0_Lake Rukwa',
       'x0_Lake Tanganyika', 'x0_Lake Victoria', 'x0_Pangani', 'x0_Rufiji',
       'x0_Ruvuma / Southern Coast', 'x0_Wami / Ruvu', 'x1_False', 'x1_True',
       'x2_False', 'x2_True', 'x3_gravity', 'x3_handpump', 'x3_motorpump',
       'x3_other', 'x3_submersible', 'x4_commercial', 'x4_other',
       'x4_parastatal', 'x4_user-group', 'x5_never pay', 'x5_pay annually',
       'x5_pay monthly', 'x5_pay per bucket', 'x5_pay when scheme fails',
       'x5_unknown', 'x6_other', 'x6_soft', 'x7_enough', 'x7_insufficient',
       'x8_groundwater', 'x8_surface', 'x9_communal standpipe', 'x9_hand pump',
       'x9_other'],
      dtype='object')
```

In [116]:
```
df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 56647 entries, 0 to 59399
Data columns (total 47 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   amount_tsh                   56647 non-null  float64
 1   date_recorded                56647 non-null  int64  
 2   gps_height                   56647 non-null  int64  
 3   longitude                    56647 non-null  float64
 4   latitude                     56647 non-null  float64
 5   region_code                  56647 non-null  int64  
 6   district_code                56647 non-null  int64  
 7   population                   56647 non-null  int64  
 8   construction_year            56647 non-null  int64  
 9   status_group                 56647 non-null  object 
 10  x0_Internal                  54030 non-null  float64
 11  x0_Lake Nyasa                54030 non-null  float64
 12  x0_Lake Rukwa                54030 non-null  float64
 13  x0_Lake Tanganyika           54030 non-null  float64
 14  x0_Lake Victoria             54030 non-null  float64
 15  x0_Pangani                   54030 non-null  float64
 16  x0_Rufiji                    54030 non-null  float64
 17  x0_Ruvuma / Southern Coast   54030 non-null  float64
 18  x0_Wami / Ruvu               54030 non-null  float64
 19  x1_False                     54030 non-null  float64
 20  x1_True                      54030 non-null  float64
 21  x2_False                     54030 non-null  float64
 22  x2_True                      54030 non-null  float64
 23  x3_gravity                   54030 non-null  float64
 24  x3_handpump                  54030 non-null  float64
 25  x3_motorpump                 54030 non-null  float64
 26  x3_other                     54030 non-null  float64
 27  x3_submersible               54030 non-null  float64
 28  x4_commercial                54030 non-null  float64
 29  x4_other                     54030 non-null  float64
 30  x4_parastatal                54030 non-null  float64
 31  x4_user-group                54030 non-null  float64
 32  x5_never pay                 54030 non-null  float64
 33  x5_pay annually              54030 non-null  float64
 34  x5_pay monthly               54030 non-null  float64
 35  x5_pay per bucket            54030 non-null  float64
 36  x5_pay when scheme fails     54030 non-null  float64
 37  x5_unknown                   54030 non-null  float64
 38  x6_other                     54030 non-null  float64
 39  x6_soft                      54030 non-null  float64
 40  x7_enough                    54030 non-null  float64
 41  x7_insufficient              54030 non-null  float64
 42  x8_groundwater               54030 non-null  float64
 43  x8_surface                   54030 non-null  float64
 44  x9_communal standpipe        54030 non-null  float64
 45  x9_hand pump                 54030 non-null  float64
 46  x9_other                     54030 non-null  float64
dtypes: float64(40), int64(6), object(1)
memory usage: 23.2+ MB
```

In [117]:
```
df3 = df3.fillna(0.0)
```

In [155]:
```
df4 = df3[df3.status_group != 'functional needs repair']
#decided to drop the needs repair status. There are far less of these, and these
```

In [119]:
```
df4.status_group.value_counts()
```

Out[119]:
```
functional        30752
non functional    22002
Name: status_group, dtype: int64
```

Split data into test and train

In [120]:
```
y = df4.status_group
X = df4.drop('status_group', axis=1)
```

In [121]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[121]:
```
((39565, 46), (13189, 46), (39565,), (13189,))
```

Models

Random Forest

After tinking with this model quite a bit, these are the hyperparameter we ended up using.

In [202]:
```
forest_clf = RandomForestClassifier(random_state=42, max_depth=15,n_estimators=50
                                    min_samples_leaf=2,
                                   min_samples_split=2)
forest_model = forest_clf.fit(X_train, y_train)

forest_training_preds = forest_clf.predict(X_train)
forest_training_accuracy = accuracy_score(y_train, forest_training_preds)

forest_val_preds = forest_clf.predict(X_test)
forest_val_accuracy = accuracy_score(y_test, forest_val_preds)
```

```
Forest Training Accuracy:
Forest Validation accuracy:
```

In [207]:
```
print(classification_report(y_test, forest_val_preds))
#test report
```

```
                precision    recall  f1-score   support

    functional       0.72      0.88      0.79      7754
non functional       0.75      0.52      0.61      5603

      accuracy                           0.73     13357
     macro avg       0.73      0.70      0.70     13357
  weighted avg       0.73      0.73      0.72     13357
```

In [208]:
```
print(classification_report(y_train, forest_training_preds))
#training report
```

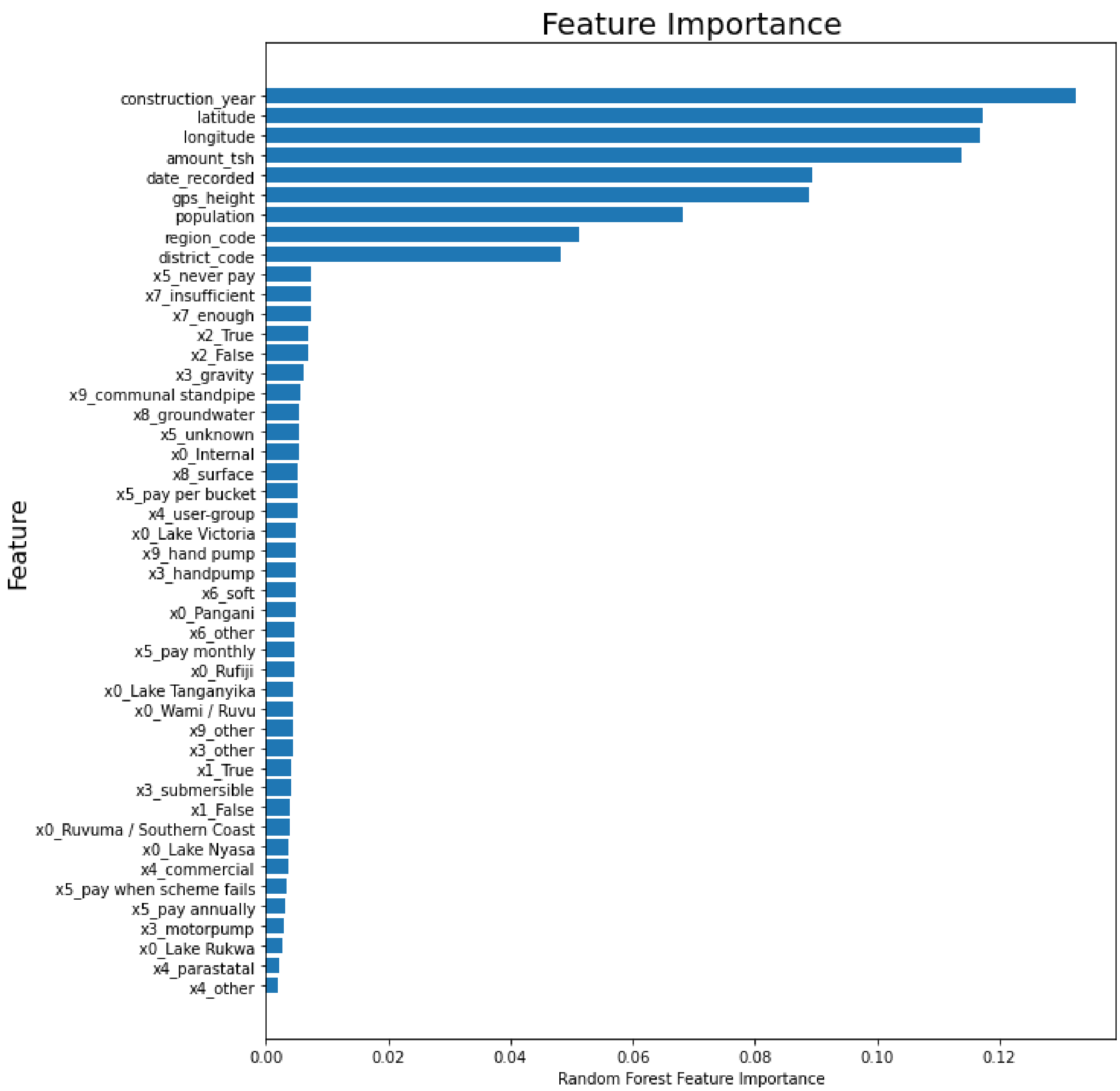
```
                precision    recall  f1-score   support

    functional       0.81      0.95      0.87     23428
non functional       0.90      0.69      0.78     16642

      accuracy                           0.84     40070
     macro avg       0.86      0.82      0.83     40070
  weighted avg       0.85      0.84      0.84     40070
```

It does look like our model is overfitting a bit, but not too much. Accuracy is 73% vs the 85% from the training

In [205]:
```
print(confusion_matrix(y_test, forest_val_preds))
```

```
[[6797  957]
 [2693 2910]]
```

In [206]:
```
sorted_idx = forest_clf.feature_importances_.argsort()
plt.figure(figsize=(10,12))
plt.barh(X.columns[sorted_idx], forest_clf.feature_importances_[sorted_idx])
plt.ylabel('Feature', fontsize=16)
plt.title("Feature Importance", fontsize=20)
plt.xlabel("Random Forest Feature Importance")
plt.savefig('Feature Importance')
```



In [ ]:

In [179]:
```
# Forst Model with GridSearch parameters
param_grid_2 = {
    'max_depth': [5, 10, 30, None],
    'min_samples_split': [2, 3],
    'min_samples_leaf': [1, 2, 5],
    'n_estimators': [10, 25, 100],
}
```

In [198]:
```
# GridSearch Classifier
# This time I'm going to try criterion='entropy'
forest_clf = RandomForestClassifier(random_state=42)
grid_clf = GridSearchCV(forest_clf, param_grid_2, scoring='accuracy', cv=3, n_jok
grid_clf.fit(X_train, y_train)

best_parameters = grid_clf.best_params_

print("Grid Search found the following optimal parameters: ")
for param_name in sorted(best_parameters.keys()):
    print("%s: %r" % (param_name, best_parameters[param_name]))

training_preds_forest = grid_clf.predict(X_train)
training_accuracy_forest = accuracy_score(y_train, training_preds_forest)

val_preds_forest = grid_clf.predict(X_test)
val_accuracy_forest = accuracy_score(y_test, val_preds_forest)

print("")
print("Training Accuracy: {:.4}%".format(training_accuracy_forest * 100))
print("Validation accuracy: {:.4}%".format(val_accuracy_forest * 100))
```

```
Grid Search found the following optimal parameters:
max_depth: None
min_samples_leaf: 2
min_samples_split: 2
n_estimators: 100

Training Accuracy: 96.94%
Validation accuracy: 72.97%
```

In [182]:
```
# Classification report
print(classification_report(y_test, val_preds_forest))
```

```
                precision    recall  f1-score   support

    functional       0.73      0.84      0.78      7754
non functional       0.73      0.57      0.64      5603

      accuracy                           0.73     13357
     macro avg       0.73      0.71      0.71     13357
  weighted avg       0.73      0.73      0.72     13357
```

In [183]:
```
print(classification_report(y_train, training_preds_forest))
```

```
                precision    recall  f1-score   support

    functional       0.96      0.99      0.97     23428
non functional       0.98      0.94      0.96     16642

      accuracy                           0.97     40070
     macro avg       0.97      0.97      0.97     40070
  weighted avg       0.97      0.97      0.97     40070
```

After running several different grid searches, I still was having trouble with overfitting. I decided to go with the previous hyperparameters instead.

XGBoost

In [122]:
```
# XGB classifier
xgb_clf = xgb.XGBClassifier()
xgb_clf.fit(X_train, y_train)

xgb_training_preds = xgb_clf.predict(X_train)
xgb_training_accuracy = accuracy_score(y_train, xgb_training_preds)

xgb_val_preds = xgb_clf.predict(X_test)
xgb_val_accuracy = accuracy_score(y_test, xgb_val_preds)

print("XGB Training Accuracy: {:.4}%".format(xgb_training_accuracy * 100))
print("XGB Validation accuracy: {:.4}%".format(xgb_val_accuracy * 100))
```

```
XGB Training Accuracy: 81.52%
XGB Validation accuracy: 74.65%
```

In [123]:
```
print(classification_report(y_test, xgb_val_preds))
```

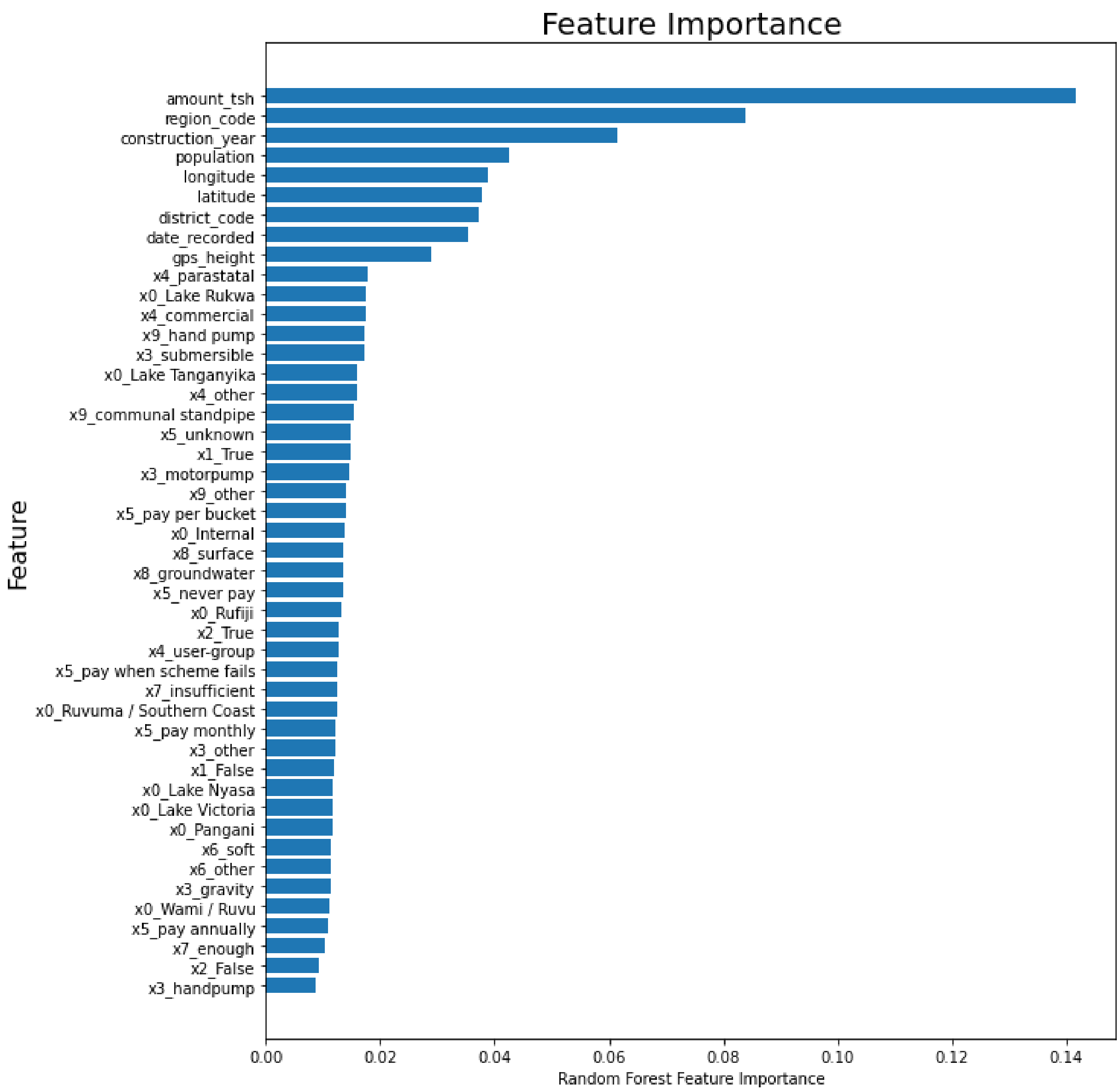
```
                precision    recall  f1-score   support

    functional       0.76      0.83      0.79      7694
non functional       0.73      0.63      0.67      5495

      accuracy                           0.75     13189
     macro avg       0.74      0.73      0.73     13189
  weighted avg       0.74      0.75      0.74     13189
```

In [124]:
```
print(classification_report(y_train, xgb_training_preds))
```

```
                precision    recall  f1-score   support

    functional       0.81      0.89      0.85     23058
non functional       0.82      0.71      0.76     16507

      accuracy                           0.82     39565
     macro avg       0.82      0.80      0.81     39565
  weighted avg       0.82      0.82      0.81     39565
```

Our model here is a bit better overall. It's a little more accurate, and overfits less

In [153]:
```
sorted_idx2 = xgb_clf.feature_importances_.argsort()
plt.figure(figsize=(10,12))
plt.barh(X.columns[sorted_idx2], xgb_clf.feature_importances_[sorted_idx2])
plt.ylabel('Feature', fontsize=16)
plt.title("Feature Importance", fontsize=20)
plt.xlabel("Random Forest Feature Importance")
plt.savefig('Feature Importance2')
```



Decision Tree

In [150]:
```
tree = DecisionTreeClassifier(random_state=42)
DTclf = tree.fit(X_train, y_train)

tree_training_pred = tree.predict(X_train)
tree_training_accuracy = accuracy_score(y_train, tree_training_pred)

tree_val_preds = tree.predict(X_test)
tree_val_accuracy = accuracy_score(y_test, tree_val_preds)
```

In [152]:
```
print(classification_report(y_test, tree_val_preds))
```

```
                precision    recall  f1-score   support

    functional       0.75      0.75      0.75      7694
non functional       0.65      0.66      0.65      5495

      accuracy                           0.71     13189
     macro avg       0.70      0.70      0.70     13189
  weighted avg       0.71      0.71      0.71     13189
```

In [151]:
```
print(classification_report(y_train, tree_training_pred))
```

```
                precision    recall  f1-score   support

    functional       1.00      1.00      1.00     23058
non functional       1.00      1.00      1.00     16507

      accuracy                           1.00     39565
     macro avg       1.00      1.00      1.00     39565
  weighted avg       1.00      1.00      1.00     39565
```

Conclusions

Our best model was the XGBoost. It was abe to correctly guess the waterpoint status 74% of the time.

The best most important feature for identifying the state of the wells were the amount of water available to the waterpoint.

Construction year and location was also important factors.

Recommendations

Look into these water points with low amounts of access to water. Why are these not getting the water they need? If we can give these wells better access to water, we should be able to solve a large portion of the problems.

There is definitely a pattern with location and the status of the wells. We saw this in the visualizations and in our models. Try to find why this is. Is it a problem with the local regulations or something larger?

The population surrounding the wells also seems to be important. A lower population probably means that there are less regulations and maintenance. These wells are still needed though. The government needs to focus on getting these wells back online.

Future Work

We focused solely on the functioning and non functioning wells, since it was the more pressing issue. In the future we need to also better recognize which wells need maintenance, so the gap does not increase.

This data only go up to 2013. Update the data with more recent well information.

In [ ]: