Business Problem

The Tanzania Development Trust is a UK charitable organization operating within the country of Tanzania since 1975.

They focus on development in rural Tanzania, aiming to support small projects in the poorest parts of the country where one of their priority areas of funding is clean water. Their stated water project involves boreholing and rope pump installation in areas with limited access to clean water, currently located in the regions of Kagera and Kigoma in the northwest of the country.

A new benefactor wants to expand the project not only geographically to more of the country, but in the scope of repairing existing pumps before they fail. I have been tasked with developing a model to predict the operating condition of a current waterpoint: functional, needs repair, or non-functional.

Research shows that it is much less expensive to repair and rehabilitate a waterpoint, as well as being more protective of the water resources in the country. The primary objective would be identifying these at-risk wells to dispatch resources before they fail. The secondary objective is to identify concentrations of non-functioning water points that may be an eligible location for a new installation.

Imports

In [1]:

```
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import random
random.seed(42)

# suppress warnings if any left at end of project
# import warnings
# warnings.filterwarnings("ignore")

# import training data and target
raw_data = pd.read_csv('data/training_data.csv')
raw_target = pd.read_csv('data/training_target.csv')

# create a raw dataframe combining the two on their shared feature 'id'
raw_df = pd.merge(raw_data, raw_target, on='id')

print(f"Number of datapoints: {raw_df.shape[0]}")
# subtracting 2 from column length to account for id and target columns
print(f"Numer of features: {raw_df.shape[1]-2}")
```

```
Number of datapoints: 59400
Numer of features: 39
```

Lets see the distribution of our target, the functional status of the waterpoint

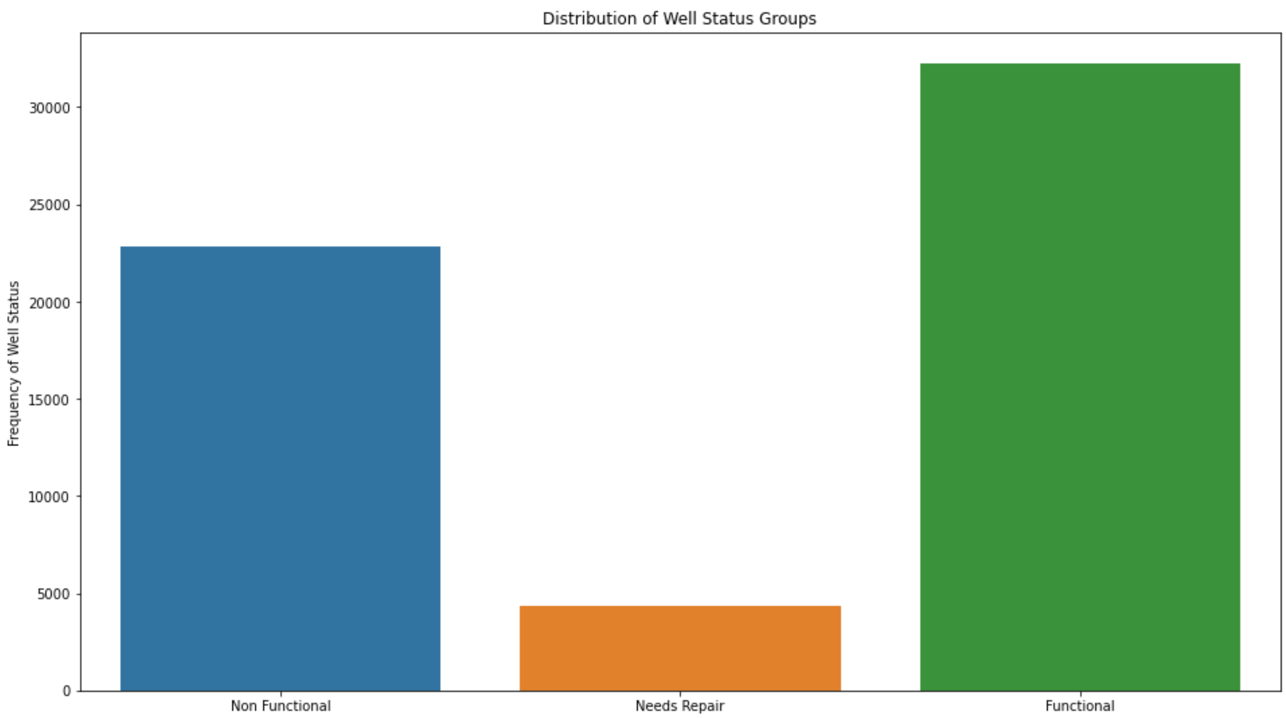
In [2]:

```
# create dataframe for the different well status value counts
status_values = pd.DataFrame(raw_df.status_group.value_counts())
status_values.columns = ['count']
status_values['percent'] = round(raw_df.status_group.value_counts(normalize=True) * 100, 1)
```

```
display(status_values)

# set order for graph
status_order = ['non functional', 'functional needs repair', 'functional']

# countplot of well status group distribution
fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=raw_df, x='status_group', order=status_order)
ax.set(title='Distribution of Well Status Groups',
      ylabel='Frequency of Well Status', xlabel=None)
ax.set_xticklabels(['Non Functional', 'Needs Repair', 'Functional'])

# save image for presentation
# plt.savefig('images/wellstatusdistribution.png')
```

	count	percent
functional	32259	54.3
non functional	22824	38.4
functional needs repair	4317	7.3

Out[2]:
```
[Text(0, 0, 'Non Functional'),
 Text(1, 0, 'Needs Repair'),
 Text(2, 0, 'Functional')]
```



This is a ternary classification problem. The three possible values are:

- functional (F)
- non functional (NF)
- functional needs repair (FR)

Value counts show that our dataset is not balanced with respect to the label values. Only 7.3% of pumps are classified as functional needs repair, while 54.3% are functional and 38.4% are non functional. We will need to keep this imbalance in mind when modeling.

We are going to change our target to numerical values, where:

- 'non function' will equal: 0
- 'functional needs repair' will equal: 1
- 'functional' will equal: 2

In [3]:
```
status_dict = {'non functional': 0,
               'functional needs repair': 1,
               'functional': 2}

raw_df['target'] = raw_df['status_group'].map(lambda x: status_dict[x])
raw_df.drop('status_group', axis=1, inplace=True)
```

Null Checks

In [4]:
```
null_checks = pd.DataFrame(data=raw_df.isna().sum(),
                           columns=['null_count'])
null_checks['percent_of_data'] = round((null_checks.null_count / len(raw_data)) * 100, 1)
null_checks = null_checks[null_checks.percent_of_data > 0.1]
null_checks.sort_values('percent_of_data', ascending=False, inplace=True)
null_checks
```

Out[4]:

	null_count	percent_of_data
scheme_name	28166	47.4
scheme_management	3877	6.5
installer	3655	6.2
funder	3635	6.1
public_meeting	3334	5.6
permit	3056	5.1
subvillage	371	0.6

There are 7 features with null values in our dataset, and we can see what that number of nulls is by percent of total available data.

All of the features that contain null values are object types. We will explore them to determine how best to handle the null values.

subvillage

In [5]:
```
subvillage_nans = raw_df[raw_df.subvillage.isnull()]
round(subvillage_nans.target.value_counts(normalize=True) * 100, 2)
```

Out[5]:
```
2    55.26
0    44.47
1     0.27
Name: target, dtype: float64
```

The null values in subvillage represent 0.6% of our total data. The distribution of the target label is close to the whole dataset

In [6]:
```
subvillage_nans.region.value_counts()
```

```
Dodoma     361
```

Out[6]:
```
Mwanza     10
Name: region, dtype: int64
```

In [7]:
```
raw_df.subvillage.value_counts()
```

Out[7]:
```
Madukani            508
Shuleni             506
Majengo             502
Kati                373
Mtakuja             262
                   ...
Mkandimi B            1
Mkono Wa Mara         1
Usinge Magharibu      1
Unyambaa              1
Nyala                 1
Name: subvillage, Length: 19287, dtype: int64
```

All but 10 of our subvillage nan's come from the region of Dodoma, the rest from Mwanza. More importantly, there are over 19,000 unique values for this feature, making it unlikely to use for modeling anyway as we have other geographical features. We will look at the feature more closely during categorical exploration, but for now we change null values to 'Other'

In [8]:
```
raw_df['subvillage'].fillna(value='Other', inplace=True)
```

permit

In [9]:
```
permit_nans = raw_df[raw_df.permit.isnull()]
permit_nans.reset_index(drop=True, inplace=True)
round(permit_nans.target.value_counts(normalize=True) * 100, 2)
```

Out[9]:
```
2    54.74
0    35.44
1     9.82
Name: target, dtype: float64
```

5% of our dataset have no value for permit. Distribution of the target label is approximately the same as the whole dataset. Per the data documentation, the permit feature is if the water point is permitted or not. We do not want to drop the feature, and the null values represent more than 5% of our data so we need to fix them. The solution we employ is to fill these 3056 missing datapoints randomly with true/false in the same ratio we found in our entire dataset.

In [10]:
```
# get the distribution of permit values we do have
permit_distribution = raw_df.permit.value_counts(normalize=True)

# fill nulls with random choice of true/false in the same distribution
raw_df['permit'] = raw_df['permit'].fillna(pd.Series(np.random.choice([True, False],
                                                       p=list(permit_distribution),
                                                       size=len(raw_df))))
```

public_meeting

In [11]:
```
public_meeting_nans = raw_df[raw_df.public_meeting.isnull()]
public_meeting_nans.reset_index(drop=True, inplace=True)
round(public_meeting_nans.target.value_counts(normalize=True) * 100, 2)
```

Out[11]:
```
2    50.33
0    44.99
```

```
1     4.68
Name: target, dtype: float64
```

5.6% of our dataset has no value for public_meeting. Distribution of the target label is approximately the same as the whole dataset. The feature is a boolean that represents if a public meeting was held. It may or may not be used in modeling, so we will fill the null values in the same ratio we find with the values we do have.

In [12]:

```
meeting_distribution = raw_df.public_meeting.value_counts(normalize=True)

raw_df['public_meeting'] = raw_df['public_meeting'].fillna(
    pd.Series(np.random.choice([True, False],
                               p=list(meeting_distribution),
                               size=len(raw_df))))
```

funder & installer

The features 'funder' and 'installer' have almost the same number of null values; I am curious about the overlap of nulls.

In [13]:

```
# dividing the number of entries with null for both features by the smaller count
len(raw_df[raw_df.funder.isnull() & raw_df.installer.isnull()]) / null_checks.null_count['funder']
```

Out[13]:

```
0.9854195323246218
```

Over 98% of the null values for funder also contain null values for installer.

We need to explore the values of funder to see how best to handle the missing data.

In [14]:

```
funder_df = pd.DataFrame(round(raw_df.funder.value_counts(normalize=True, dropna=False) * 100, 2))
funder_df
```

Out[14]:

	funder
Government Of Tanzania	15.29
NaN	6.12
Danida	5.24
Hesawa	3.71
Rwssp	2.31
...	...
Vgovernment	0.00
Pentekoste	0.00
Petro Patrice	0.00
Njula	0.00
Seleman Rashid	0.00

1898 rows × 1 columns

In [15]:

```
funder_df_top = funder_df[funder_df.funder > 1.0]
print(f"Funders with more than 1% share: {len(funder_df_top)}")
print(f"Percent of total funders represented by above: {funder_df_top.sum()}")
```

```
Funders with more than 1% share: 18
Percent of total funders represented by above: funder    52.69
dtype: float64
```

Including null values, there were 1,898 distinct values for funder. Of that, 18 values (including null) have representative counts more than 1% of total data. Those 18 distinct values represent almost 53% of our total data. We will convert null values to 'Other'. There are still lots of unique values, so something to consider is converting all funders with less than 1% total share as 'Other' to reduce the unique value count, if we even plan to use the feature at all.

Lets look at installer

In [16]:

```
installer_df = pd.DataFrame(round(raw_df.installer.value_counts(normalize=True, dropna=False) * 100

installer_df_top = installer_df[installer_df.installer > 1.0]
print(f"Installers with more than 1% share: {len(installer_df_top)}")
print(f"Percent of total installers represented by above: {installer_df_top.sum()}")
```

```
Installers with more than 1% share: 12
Percent of total installers represented by above: installer    51.6
dtype: float64
```

Similarly to funder, the installer feature is dominated by small share installers. Of the 2,146 distinct values for installer, 12 values (including null) have representative counts more than 1% of total data.Those 12 distinct values represent almost 52% of our total data.

This is similar to the funder feature. We will also convert null values to 'Other', and will consider converting all installers with less than 1% total share of installer as 'Other' to reduce the unique value count.

In [17]:

```
raw_df['funder'].fillna(value='Other', inplace=True)
raw_df['installer'].fillna(value='Other', inplace=True)
```

scheme_management

In [18]:

```
scheme_management_nans = raw_df[raw_df.scheme_management.isnull()]
scheme_management_nans.reset_index(drop=True, inplace=True)
round(scheme_management_nans.target.value_counts(normalize=True) * 100, 2)
```

Out[18]:

```
2    48.31
0    45.94
1     5.75
Name: target, dtype: float64
```

In [19]:

```
round(raw_df.scheme_management.value_counts(normalize=True, dropna=False)*100,2)
```

Out[19]:

```
VWC                 61.94
WUG                  8.76
NaN                  6.53
Water authority      5.31
WUA                  4.85
Water Board          4.63
Parastatal           2.83
Private operator     1.79
Company              1.79
Other                1.29
SWC                  0.16
Trust                0.12
```

```
None                   0.00
Name: scheme_management, dtype: float64
```

6.5% of our data has no value for scheme_management. Distribution of the target data is approximately the same as the whole dataset.

There was only one entry with the value of 'None', we will change that to 'Other'

We will fill null values for scheme_management randomly with other values from the feature in the same ratio as we did in other cases.

In [20]:
```
# set the 'None' to 'Other'
raw_df.at[23603, 'scheme_management'] = 'Other'

# get value counts to preserve ratio of values
scheme_management_list = pd.DataFrame(raw_df.scheme_management.value_counts(normalize=True))

# fill nulls with values in the same ratio as the data we do have
raw_df['scheme_management'] = raw_df['scheme_management'].fillna(
    pd.Series(np.random.choice(list(scheme_management_list.index),
                               p=list(scheme_management_list.scheme_management),
                               size=len(raw_df))))
```

scheme_name

In [21]:
```
raw_df.scheme_name.value_counts(normalize=True, dropna=False)
```

Out[21]:
```
NaN                         0.474175
K                           0.011481
None                        0.010842
Borehole                    0.009192
Chalinze wate               0.006818
                              ...
tove-mtwango                0.000017
Tamp                        0.000017
Tiflo masaki branch line    0.000017
Jodiwaso                    0.000017
Bl Aziz water supply        0.000017
Name: scheme_name, Length: 2697, dtype: float64
```

Almost half (47%) of the scheme_name feature contains no data, and the remaining data contains 2,697 distinct other features, none of which exceed 1% of the dataset. The scheme name, per the documentation, is the individual or group that actually operates the waterpoint. This is compared to the scheme management company, which oversees operation. When the data was collected, it looks like there was little organization with respect to this particular datapoint. Considering the large number of unique values, and that we have the management data, we will likely not use this feature in modeling. We will replace the null values with 'Other'

In [22]:
```
raw_df['scheme_name'].fillna(value='Other', inplace=True)
```

Exploring numerical data

In [23]:
```
num_df = raw_df.select_dtypes(include=np.number).copy()
num_df.describe()
```

Out[23]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	region_code	district_(
count	59400.000000	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.000000	59400.000000	59400.00(

	id	amount_tsh	gps_height	longitude	latitude	num_private	region_code	district_(
mean	37115.131768	317.650385	668.297239	34.077427	-5.706033e+00	0.474141	15.297003	5.62!
std	21453.128371	2997.574558	693.116350	6.567432	2.946019e+00	12.236230	17.587406	9.63.
min	0.000000	0.000000	-90.000000	0.000000	-1.164944e+01	0.000000	1.000000	0.00(
25%	18519.750000	0.000000	0.000000	33.090347	-8.540621e+00	0.000000	5.000000	2.00(
50%	37061.500000	0.000000	369.000000	34.908743	-5.021597e+00	0.000000	12.000000	3.00(
75%	55656.500000	20.000000	1319.250000	37.178387	-3.326156e+00	0.000000	17.000000	5.00(
max	74247.000000	350000.000000	2770.000000	40.345193	-2.000000e-08	1776.000000	99.000000	80.00(

The 'id' feature is a unique identifier, we will leave it in for merge purposes later but will not use it in modeling so no investigation needed.

amount_tsh

The data description states that this is the total amount of water available to the waterpoint.

From the describe report above it looks like at least 50% of our waterpoints do not have any water available, regardless of pump functionality. If we look back, we also see that over 50% of pumps are classified as functional. This is a bit concerning, it's unclear how you can have a functional pump with no water available to pump.

In [24]:

```
len(num_df[num_df.amount_tsh == 0.0]) / len(num_df)
```

Out[24]:

```
0.700993265993266
```

70% of our datapoints list the amount_tsh as equal to 0.0. This can't mean that the waterpoint has no water available. We need to understand more about what total static head means. Research shows that a pump system's static head is the difference between the liquid surface of the reservoir and the discharge end of the pump system. The higher the discharge tube is lifted above the liquid surface, the harder is is for the pump to move the water, and the lower the flow rate will be. I would imagine that the requirements of pump location to discharge would impact the type of pump to be used.

In [25]:

```
tsh_target = pd.DataFrame(round(num_df[num_df.amount_tsh == 0].target.value_counts(normalize=True)*
tsh_target.columns = ['tsh==0']
tsh_target['tsh>0'] = round(num_df[num_df.amount_tsh > 0].target.value_counts(normalize=True)*100,2
tsh_target
```

Out[25]:

	tsh==0	tsh>0
2	47.33	70.68
0	45.35	22.18
1	7.32	7.14

In [26]:

```
num_df[num_df.amount_tsh > 0].amount_tsh.describe()
```

Out[26]:

```
count     17761.000000
mean       1062.351942
std        5409.344940
min           0.200000
25%          50.000000
```

```
50%          250.000000
75%         1000.000000
max       350000.000000
Name: amount_tsh, dtype: float64
```

This feature seems to be a candidate for engineering. Since 70% of our values for total static head are 0, it means most wells feature output at the same level as the water input. Only 30% of wells feature a static head larger than 0, but 70% of those wells are functional versus 47% of those with a static head of 0. We may find success modeling with it staying as a numerical feature, but we'll also engineer it into a binary feature where the value is 1 if the total static head is greater than 0.

In [27]:

```
# helper function to determine output value for population size
def tsh_encode(row):
    tsh = row['amount_tsh']

    if tsh == 0:
        return 0
    else:
        return 1

# create new feature 'age' with the helper function
num_df['positive_tsh'] = num_df.apply(tsh_encode, axis=1)
```

gps_height

The data description states that this is the altitude of the well

---

Research shows that the lowest point in the country is sea level (0), yet we have a minimum of -90, so we will need to investigate that.

In [28]:

```
gps_height_neg = num_df[num_df.gps_height < 0]
print(f"Percent of total data: {round(len(gps_height_neg)/len(num_df)*100,2)}%")
```

```
Percent of total data: 2.52%
```

In [29]:

```
gps_height_neg.describe()
```

Out[29]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	region_code	district_code
count	1496.000000	1496.000000	1496.000000	1496.000000	1496.000000	1496.000000	1496.000000	1496.000000
mean	37297.606952	313.013369	-19.993316	39.352801	-7.727535	0.506684	34.703877	15.531417
std	21119.500129	4017.641868	12.154136	0.458811	1.542230	7.155227	35.259116	21.812220
min	150.000000	0.000000	-90.000000	38.614960	-10.946096	0.000000	4.000000	1.000000
25%	19232.750000	0.000000	-28.000000	38.972421	-8.584131	0.000000	6.000000	1.000000
50%	36699.000000	0.000000	-18.000000	39.281546	-7.415977	0.000000	7.000000	5.000000
75%	55492.750000	50.000000	-11.000000	39.662349	-6.524902	0.000000	60.000000	13.000000
max	74211.000000	138000.000000	-1.000000	40.345193	-5.278598	150.000000	99.000000	67.000000

There are 1,496 data points where the gps_height was less than 0, about 2.5% of our data. Earlier we mentioned that this should not be possible as the listed lowest elevation for Tanzania is 0 ft above sea level (at the Indian Ocean). Research shows that most GPS units are designed to measure height based on the representation of the earth's surface as an 'ellipsoid', and it's perfectly possible to be standing at sea level where the reading should be 0 and have it be a negative number.

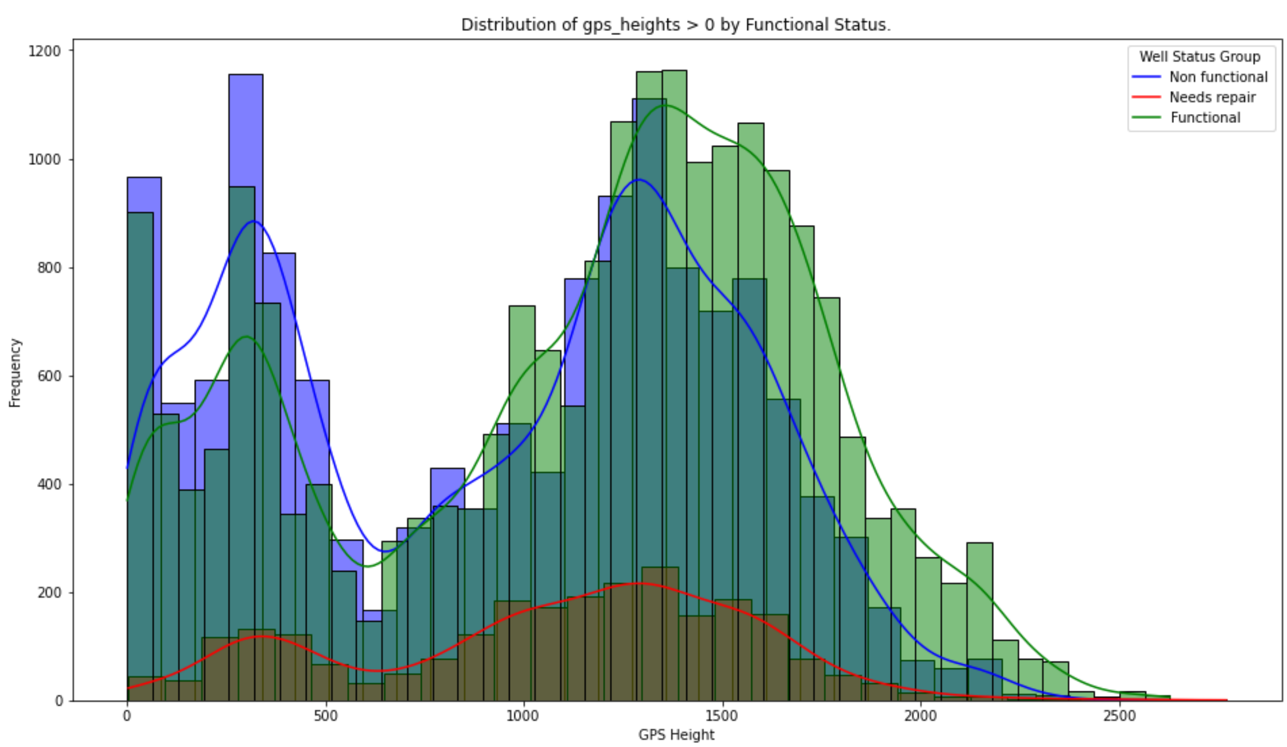
Considering these data are almost all on the southeastern edge of the country (higher longitudes, lower latitudes) closer to the Indian Ocean, it is likely the sites are at or just above sea level and capable of producing negative height readings. Opportunity for further tuning could be to address this inconsistency across all the data, shifting all data points to a more accurate representation of height. I do not think it would be as simple as shifting all values up by the largest negative difference. Because it's such a small percentage of our dataset, we will just set them to 0 rather than worry about adjusting all the values.

In [30]:
```
num_df.gps_height.clip(lower=0.0, inplace=True)
```

In [31]:
```
percent_at_0 = round(len(num_df[num_df.gps_height == 0])/len(num_df)*100,2)
print(f"{percent_at_0}% of our data is at gps_height of 0.")
```

```
36.93% of our data is at gps_height of 0.
```

In [32]:
```
fig, ax = plt.subplots(figsize=(16,9))
sns.histplot(data=num_df[(num_df.target==0) & (num_df.gps_height>0)],
             x='gps_height', color='blue', label='Non functional', kde=True,
             alpha=0.5)
sns.histplot(data=num_df[(num_df.target==1) & (num_df.gps_height>0)],
             x='gps_height', color='red', label='Needs repair', kde=True,
             alpha=0.5)
sns.histplot(data=num_df[(num_df.target==2) & (num_df.gps_height>0)],
             x='gps_height', color='green', label='Functional', kde=True,
             alpha=0.5)
ax.set(title='Distribution of gps_heights > 0 by Functional Status.',
      xlabel='GPS Height', ylabel='Frequency')
ax.legend(title='Well Status Group', labels=['Non functional', 'Needs repair',
                                              'Functional']);
```



We will leave gps_height as a numerical predictor for well status.

longitude/latitude

The data description states that these are the GPS coordinates.

Research shows that Tanzania's most extreme latitudes range from 00°59'S (-0.98333) to 11°45'S (-11.75), while the longitude extremes range from 40°29'E (40.48333) to 29°10'E (29.16667)

The 'latitude' values seem to exceed the northen border of the country (max latitude -2e-08), so we will need to investigate that. The 'longitude' values minimum is 0, so we have some data that is outside the range of the country borders. It's likely from mistakes or errors in data entry, so we need to examine all values below the actual minimum which is 29.16667.

In [33]:
```
longitude_errors = num_df[num_df.longitude < 29.16667]
longitude_errors.describe()
```

Out[33]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	region_code	district_code	pop
count	1812.000000	1812.0	1812.0	1812.0	1.812000e+03	1812.0	1812.000000	1812.000000	
mean	37389.841060	0.0	0.0	0.0	-2.000000e-08	0.0	17.820088	2.497241	
std	21413.129962	0.0	0.0	0.0	3.541310e-22	0.0	1.023562	2.157389	
min	15.000000	0.0	0.0	0.0	-2.000000e-08	0.0	11.000000	1.000000	
25%	18481.750000	0.0	0.0	0.0	-2.000000e-08	0.0	17.000000	1.000000	
50%	37326.000000	0.0	0.0	0.0	-2.000000e-08	0.0	17.000000	1.000000	
75%	55509.750000	0.0	0.0	0.0	-2.000000e-08	0.0	19.000000	6.000000	
max	74193.000000	0.0	0.0	0.0	-2.000000e-08	0.0	19.000000	6.000000	

It looks like we have found that our data includes errors in GPS readings. These errors show up as longitude 0 and latitude -2e-0.8. These entries with GPS errors, however, do not account for all the population point values of 0, or the construction year values of 0, so we will still need to address them.

In [34]:
```
print(f"Percent of data with missing lat/long: {round((len(longitude_errors)/len(num_df))*100, 2)}%
print(f"Total data with population of 0: {len(num_df[num_df.population == 0])}")
print(f"Total data with construction year of 0: {len(num_df[num_df.construction_year == 0])}")
```

```
Percent of data with missing lat/long: 3.05%
Total data with population of 0: 21381
Total data with construction year of 0: 20709
```

In [35]:
```
gps_errors = raw_df[raw_df.longitude == 0.0]
gps_errors.target.value_counts(normalize=True)
```

Out[35]:
```
2    0.480132
0    0.306843
1    0.213024
Name: target, dtype: float64
```

In [36]:
```
gps_errors.region_code.value_counts()
```

Out[36]:
```
17    1057
19     752
11       3
Name: region_code, dtype: int64
```

The missing GPS data comprises about 3% of our dataset, but contains a disproportionate number of the 'functional needs repair' value from the target, which we already have very little data for. Also, all of the missing GPS data comes from three regions: 11, 17, and 19.

What we can do is take the average lat/long from the points we do have for those region_codes and fill our nulls with the average for that region_code with a little randomness added in within a range of + or - one standard deviation from the mean.

In [37]:
```
# get the list of the region codes with errors
error_regions = list(gps_errors.region_code.value_counts().index)

for region in error_regions:
    # split the region based on longitude not being 0.0
    region_no_gps = num_df[(num_df.region_code == region) & (num_df.longitude == 0.0)].copy()
    region_gps_data = num_df[(num_df.region_code == region) & (num_df.longitude != 0.0)].copy()
    # get mean and std for the long/lat of gps data we have
    avg_long = region_gps_data[['longitude', 'latitude']].mean()[0]
    avg_lat = region_gps_data[['longitude', 'latitude']].mean()[1]
    long_std = region_gps_data[['longitude', 'latitude']].std()[0]
    lat_std = region_gps_data[['longitude', 'latitude']].std()[1]
    # initialize empty lists for random data to fill
    fill_long = []
    fill_lat = []
    # append to each list a random value within the standard deviation of the mean
    for x in range(len(region_no_gps)):
        fill_long.append(random.triangular(avg_long+long_std, avg_long-long_std))
        fill_lat.append(random.triangular(avg_lat+lat_std, avg_lat-lat_std))
        x += 1
    # convert the two lists into a dataframe
    fill_df = pd.DataFrame([fill_long, fill_lat]).transpose()
    # sets the column names and indeces to match the ones being replaced
    fill_df.columns = ['longitude', 'latitude']
    fill_df.index = region_no_gps.index
    # replace the missing GPS data with these randomized values
    num_df.loc[region_no_gps.index, ['longitude', 'latitude']] = fill_df
```

num_private

The data description for this feature does not exist.

In [38]:
```
round(num_df.num_private.value_counts(normalize=True)*100, 2)
```

Out[38]:
```
0      98.73
6       0.14
1       0.12
8       0.08
5       0.08
       ...  
42      0.00
136     0.00
35      0.00
131     0.00
94      0.00
Name: num_private, Length: 65, dtype: float64
```

The vast majority (98.73%) of the num_private data has the value 0. There was no descriptor of the feature along with the others for the dataset, so we have no way to reference the value. A guess would be the number of private wells at the waterpoint, or perhaps the number of private users of a waterpoint. Either way, with such a massive value imbalance it's very unlikely that there would be any statistically significant relationship between this feature and the target. We are going to drop it from num_df and consideration in modeling.

In [39]:
```
num_df.drop('num_private', axis=1, inplace=True)
```

region_code

The data description for this is geographic location.

Research shows that what we initially suspected is true: regions are the parent of districts. There are 31 regions, 169 districts, and then further divisions of wards (urban or rural), streets under urban wards, and villages and hamlets under rural wards. We know we have features for subvillage and ward, and will get to them later. For now, since we have codes for region and strings for regions, lets compare them and see what we can discover.

NOTE: we are exploring numerical data for region_code, but cross-referencing the 'region' values from the raw_df

In [40]:
```
print(f"Region numeric unique value count: {len(num_df.region_code.value_counts())}")
print(f"Region string unique value count: {len(raw_df.region.value_counts())}")
print("-----------------------------------")
region_code_vals = list(map(str, list(num_df.region_code.value_counts().sort_index().index)))
print("Region_code values:")
print(", ".join(region_code_vals))
print("-----------------------------------")
high_region_codes = raw_df[(num_df.region_code > 21)].copy()
print(f"Entries with region code > 21: {len(high_region_codes)}")
print(f"Percent of total data: {round(len(high_region_codes)/len(raw_df)*100, 2)}%")
print("-----------------------------------")
gps_data_true = len(raw_df[(raw_df.region_code > 21)]) == len(raw_df[(raw_df.region_code > 21) & (r
print(f"Do all region_codes over 21 have lat/long? {gps_data_true}")
```

```
Region numeric unique value count: 27
Region string unique value count: 21
-----------------------------------
Region_code values:
1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 24, 40, 60, 80, 90, 99
-----------------------------------
Entries with region code > 21: 3930
Percent of total data: 6.62%
-----------------------------------
Do all region_codes over 21 have lat/long? True
```

We can see that the values of region_code go from 1 to 21, and then we have values 24, 40, 60, 80, 90, 99. It's likely that the values 1-21 match up to the 21 string value regions in the feature 'region'.

Entries with region_code values above 21 constitute 6.6% of our dataset, and all of the data categorized in these other region_codes contain correct lat/long data. (note: checked this using the raw_df, not the num_df we modified the missing lat/longs for)

As for the others, they serve some kind of purpose inputting data. We will need to figure out:

- What region_code matches to what region?
- What do the >21 region_code values mean?

---

matching region and region_code

We are going to create a dataframe that goes through the region_codes 1-21 and adds the top reporting region/count from the value_count for that particular region_code. Then we look at any differences between those counts and the raw counts of entries with each region code.

In [41]:
```
region_code_list = []

for x in range(1, 22):
    region = raw_df[raw_df.region_code == x]['region'].value_counts().index[0]
    count = raw_df[raw_df.region_code == x]['region'].value_counts().values[0]
    region_code_list.append((x, region, count))

region_df = pd.DataFrame(region_code_list, columns=['region_code', 'region', 'region_count'])
region_df['region_code_count'] = raw_df.region_code.value_counts().sort_index().values[:21]

region_df['surplus_code_count'] = region_df['region_code_count'] - region_df['region_count']
region_df[region_df.surplus_code_count > 0]
```

Out[41]:

	region_code	region	region_count	region_code_count	surplus_code_count
4	5	Morogoro	4006	4040	34
10	11	Iringa	5294	5300	6
13	14	Tabora	1959	1979	20
16	17	Shinyanga	4956	5011	55
17	18	Kagera	3316	3324	8

Of the 21 regions, 16 of them match up the region with a region_code and both features have the same count of values. There are 5 regions where the region_code value count has a surplus of values compared to the region value count.

For these few number of values, one thought is to update records for these region_codes so that all region_code values match to one region, i.e. we will update all rows where region_code is 5 so that the region 'Morogoro' is reflected. Just to be sure, lets look closer at this example.

In [42]:
```
raw_df[raw_df.region_code == 5].region.value_counts()
```

Out[42]:
```
Morogoro    4006
Tanga         34
Name: region, dtype: int64
```

In [43]:
```
raw_df[(raw_df.region_code == 5) & (raw_df.region == 'Tanga')][['longitude', 'latitude']].mean()
```

Out[43]:
```
longitude    37.180390
latitude     -6.039227
dtype: float64
```

When we looked at the mean lat/longs for the region_code 5 rows that have the region label 'Tanga', it is within the boundary of the region 'Morogoro', near the northrn border with Tanga. We are going to make an assumption that these values of region_code reference the same region string, and assume that is also the case for the remaining surpluses. We will update those region values accordingly so that each region_code corresponds to one and only one region string. **Note: we are modifying the original raw_df here. The 'region' feature is not a part of num_df**

In [44]:
```
fixes = list(zip(list(region_df[region_df.surplus_code_count > 0].region_code.values),
    list(region_df[region_df.surplus_code_count > 0].region.values)))
```

```
for fix in fixes:
    code = fix[0]
    region = fix[1]

    raw_df.loc[raw_df[(raw_df.region_code == code) & (raw_df.region != region)].index, 'region'] =
```

region_codes over 21

Now we need to examine the region_codes whose value is over 21 and figure out what they mean.

In [45]:
```
num_df[num_df.region_code > 21].region_code.value_counts()
```

Out[45]:
```
80    1238
60    1025
90     917
99     423
24     326
40       1
Name: region_code, dtype: int64
```

We have about 6.6% of our data in these incorrectly labeled region_codes. We have just modified our raw_df dataframe and assigned all entries' region values based on the (top) region_code value count. Lets look at our data grouped by region value and see the average for the region_code. If the average is an integer, we know that all entries for that region is the same number as the entries for the region_code (that value being the mean of the region_code feature). If it's not an integer, then it means that the region is represented by different region_codes and we can figure out which codes and reassign them correctly.

In [46]:
```
region_codes = raw_df.groupby('region')[['region_code']].mean().sort_values(by='region_code')
region_codes['is_int'] = region_codes.region_code.apply(lambda x: x.is_integer())
region_codes = region_codes[region_codes.is_int == False]
region_codes
```

Out[46]:

region	region_code	is_int
Arusha	4.140896	False
Pwani	27.018596	False
Lindi	65.955787	False
Mtwara	73.940462	False

We can see that these four regions are the ones without integer value region_code averages. We can deduce that all of the region_code values over 21 are attributed to these 4 regions. Now we will go through each region_code attributed to these regions and look at the lat/long averages. If they are in the same region, the averages should be fairly close in value.

In [47]:
```
# get the list of regions from above
regions = list(region_codes.index)

region_checks = []

# for each region, generate a row of data containing the region
for region in regions:
    codes = list(raw_df[raw_df.region == region].region_code.value_counts().index)
    for code in codes:
        long_avg = raw_df[raw_df.region_code == code][['longitude']].describe().loc[['mean']].longi
        lat_avg = raw_df[raw_df.region_code == code][['latitude']].describe().loc[['mean']].latituc
```

```
        row = [region, code, long_avg, lat_avg]
        region_checks.append(row)

region_check_df = pd.DataFrame(region_checks,
                              columns = ['region','code','long_avg','lat_avg'])
region_check_df
```

Out[47]:

	region	code	long_avg	lat_avg
0	Arusha	2	36.648738	-3.231963
1	Arusha	24	35.661985	-3.380886
2	Pwani	6	38.754707	-6.678934
3	Pwani	60	39.073593	-7.529581
4	Pwani	40	39.217993	-7.001266
5	Lindi	80	39.094711	-9.645071
6	Lindi	8	38.572954	-10.310537
7	Mtwara	90	38.958680	-10.805449
8	Mtwara	99	40.004465	-10.457718
9	Mtwara	9	39.771740	-10.628146

Right away we can see close value counts for these groupings of regions; we cross-referenced these lat/long averages using Google maps to confirm region. Each of these 4 regions had several region codes, and we will consolidate the region_code value to the lowest one. We will reassign them in both the num_df dataframe and the raw_df dataframe.

In [48]:

```
# all Arusha region codes should be 2
num_df.loc[raw_df[raw_df.region_code == 24].index, 'region_code'] = 2
raw_df.loc[raw_df[raw_df.region_code == 24].index, 'region_code'] = 2

# all Pwani region codes should be 6
num_df.loc[raw_df[raw_df.region_code.isin([40, 60])].index, 'region_code'] = 6
raw_df.loc[raw_df[raw_df.region_code.isin([40, 60])].index, 'region_code'] = 6

# all Lindi region codes should be 8
num_df.loc[raw_df[raw_df.region_code == 80].index, 'region_code'] = 8
raw_df.loc[raw_df[raw_df.region_code == 80].index, 'region_code'] = 8

# all Mtwara regions should be code 9
num_df.loc[raw_df[raw_df.region_code.isin([90, 99])].index, 'region_code'] = 9
raw_df.loc[raw_df[raw_df.region_code.isin([90, 99])].index, 'region_code'] = 9
```

district_code

The data description for this is geographic location.

We have established that the regions in our dataset match up with the region_code; there is no 'district' dataset to match with 'district_code'. When researching Tanzanian regions we discovered information on quantity of districts in each region, so we believe that is how our data relates: each region would have multiple districts in it. Lets look at value counts for district_code.

In [49]:

```
num_df.district_code.value_counts().sort_index()
```

Out[49]:
```
0        23
1     12203
2     11173
3      9998
4      8999
5      4356
6      4074
7      3343
8      1043
13      391
23      293
30      995
33      874
43      505
53      745
60       63
62      109
63      195
67        6
80       12
Name: district_code, dtype: int64
```

Some initial observations:

- It seems odd to have districts with a value of 0.
- Research shows that there is one region with 10 districts (Tanga), but we don't have that value.
- 10 is is also the largest value we should have for the feature, as that is the maximum number of districts for regions.

If it is the case that district_code is representative of the actual district within the region, then each region should have at minimum a district_code of 1. The link above will also show that regions at a minimum have 2 districts (the average is about 5.5). Lets go through and see if each region even has the correct number of districts per our research.

In [50]:
```
# create a dataframe of regions matched with their region_code
regions_with_codes = pd.DataFrame(raw_df.groupby('region').mean()['region_code'])
regions_with_codes.reset_index(inplace=True)
regions_with_codes['region_code'] = regions_with_codes.region_code.astype('int')
regions_with_codes.set_index('region_code', inplace=True)
regions_with_codes.sort_index(inplace=True)

district_info = []

for x in range(1, 22):
    # get our region name
    region = regions_with_codes[regions_with_codes.index == x].region.values[0]
    # use the num_df to list all the district codes with that region_code
    districts = sorted(list(num_df[num_df.region_code == x].district_code.value_counts().index))
    # create the row of data
    row = [region, len(districts), districts]
    # append to list
    district_info.append(row)

district_info_df = pd.DataFrame(district_info,
                               columns=['region','district_count', 'district_values'])
district_info_df.sort_values(by='region', inplace=True)
# input expected district count from research (based on alphabetical order of region in our data)
district_info_df['actual_district_count'] = [7, 5, 7, 5, 8, 8, 6, 6, 6, 7, 7, 7, 7, 7, 7, 4, 6, 5,
district_info_df['district_count_discrepancy'] = district_info_df.district_count - district_info_df

district_count_sum = district_info_df.district_count.sum()
```

```
display(f"Total district_code count discrepancy: {district_count_sum}")
print(district_info_df)
```

```
'Total district_code count discrepancy: 129'
           region  district_count                          district_values  \
1          Arusha               7                [1, 2, 3, 5, 6, 7, 30]
6   Dar es Salaam               3                                [1, 2, 3]
0          Dodoma               6                       [0, 1, 3, 4, 5, 6]
10         Iringa               6                       [1, 2, 3, 4, 5, 7]
17         Kagera               8             [1, 2, 3, 4, 6, 7, 8, 30]
15         Kigoma               4                             [1, 2, 3, 4]
2     Kilimanjaro               7                 [1, 2, 3, 4, 5, 6, 7]
7           Lindi               6                [3, 13, 23, 43, 53, 62]
20        Manyara               5                          [1, 2, 3, 4, 5]
19           Mara               5                          [1, 2, 3, 4, 6]
11          Mbeya               7                 [1, 2, 3, 4, 5, 6, 7]
4        Morogoro               6                       [1, 2, 3, 4, 5, 6]
8          Mtwara               5                        [1, 4, 5, 33, 63]
18         Mwanza               8              [1, 2, 3, 4, 5, 6, 7, 8]
5           Pwani              11  [1, 2, 3, 4, 6, 33, 43, 53, 60, 63, 67]
14          Rukwa               4                             [1, 2, 3, 4]
9          Ruvuma               5                          [1, 2, 3, 4, 5]
16      Shinyanga               8             [1, 2, 3, 5, 6, 7, 8, 80]
12        Singida               4                             [1, 2, 3, 4]
13         Tabora               6                       [1, 2, 3, 4, 5, 6]
3           Tanga               8              [1, 2, 3, 4, 5, 6, 7, 8]

    actual_district_count  district_count_discrepancy
1                       7                           0
6                       5                          -2
0                       7                          -1
10                      5                           1
17                      8                           0
15                      8                          -4
2                       6                           1
7                       6                           0
20                      6                          -1
19                      7                          -2
11                      7                           0
4                       7                          -1
8                       7                          -2
18                      7                           1
5                       7                           4
14                      4                           0
9                       6                          -1
16                      5                           3
12                      6                          -2
13                      7                          -1
3                      10                          -2
```

Observations:

- Even the largest count value, district_code of 1, is not represented in all of our regions, which should be the case if each region had a separate count of districts.
- Even if we had the correct number of districts, they were not necessarily numbered in the correct way. Arusha should have 7 districts, and we would expect 1-7 but we have no district_code 4 (instead, we have a 30)
- Some regions have more than the expected number of districts, some have less. If we simply had mislabeled districts, then our sum of discrepancies should be equal, but it is not, we are 9 total districts heavy of what we should have.

It's suspected that there will not be an easy way to reconcile this feature. If we were able to organize this, we would also then need to have unique values for each district among all regions to give it any meaningful impact. It's likely the case that we will not be using district_code in modeling.

In [51]:
```
num_df.drop('district_code', axis=1, inplace=True)
```

population

The data description for this is population around the well.

In [52]:
```
num_df['population'].describe()
```

Out[52]:
```
count    59400.000000
mean       179.909983
std        471.482176
min          0.000000
25%          0.000000
50%         25.000000
75%        215.000000
max      30500.000000
Name: population, dtype: float64
```

In [53]:
```
num_df.population.value_counts(normalize=True)[0]
```

Out[53]:
```
0.35994949494949496
```

In [54]:
```
num_df.population.value_counts(sort=False, bins=15)
```

Out[54]:
```
(-30.501, 2033.333]       58922
(2033.333, 4066.667]        325
(4066.667, 6100.0]           85
(6100.0, 8133.333]           53
(8133.333, 10166.667]        12
(10166.667, 12200.0]          1
(12200.0, 14233.333]          0
(14233.333, 16266.667]        1
(16266.667, 18300.0]          0
(18300.0, 20333.333]          0
(20333.333, 22366.667]        0
(22366.667, 24400.0]          0
(24400.0, 26433.333]          0
(26433.333, 28466.667]        0
(28466.667, 30500.0]          1
Name: population, dtype: int64
```

Just about 36% of our population data is 0, 50% is 25 or under, and 75% is 215 or under. The average population is 180.

When we look at the population auto-binned into 15 bins of equal value width, you can see that the vast majority are under 2000, and also that once we are over about 10,000 people there are only 3 datapoints, with large gaps in between. Lets look at counts with the population at 0, counts where 0 < population <= 180 (our average) and then more than 180.

In [55]:
```
print(f"   [0.0,0.0]    {len(num_df[num_df.population == 0.0])}")
print(f"(0.0, 180.0]    {len(num_df[(num_df.population <= 180) & (num_df.population > 0)])}")
print(f"   (180.0, ]    {len(num_df[num_df.population > 180])}")
```

```
   [0.0,0.0]    21381
(0.0, 180.0]    20633
   (180.0, ]    17386
```

Not quite but almost even separation of these bins. This is one way we may be able to engineer population if necessary.

Lets look at binning the values into 10 bins between 0 and 180 just to get an idea of distribution within that range.

In [56]:
```
num_df[(num_df.population <= 180) & (num_df.population > 0)].population.value_counts(normalize=True
```

Out[56]:
```
(0.82, 18.9]      0.369021
(18.9, 36.8]      0.085882
(36.8, 54.7]      0.102796
(54.7, 72.6]      0.074929
(72.6, 90.5]      0.070033
(90.5, 108.4]     0.074008
(108.4, 126.3]    0.062230
(126.3, 144.2]    0.030340
(144.2, 162.1]    0.110987
(162.1, 180.0]    0.019774
Name: population, dtype: float64
```

Most of these population values are under 19, but that only represents a bit more than a third of the total bin (36.9%). The other bins are between 2 and 11 percent.

Lets explore binning the populations over 180

In [57]:
```
num_df[(num_df.population > 180) & (num_df.population > 0)].population.value_counts(sort=False, bir
```

Out[57]:
```
(150.68, 484.19]        11683
(484.19, 787.38]         3294
(787.38, 1090.57]        1064
(1090.57, 1393.76]        331
(1393.76, 1696.95]        323
                        ...  
(28984.05, 29287.24]        0
(29287.24, 29590.43]        0
(29590.43, 29893.62]        0
(29893.62, 30196.81]        0
(30196.81, 30500.0]         1
Name: population, Length: 100, dtype: int64
```

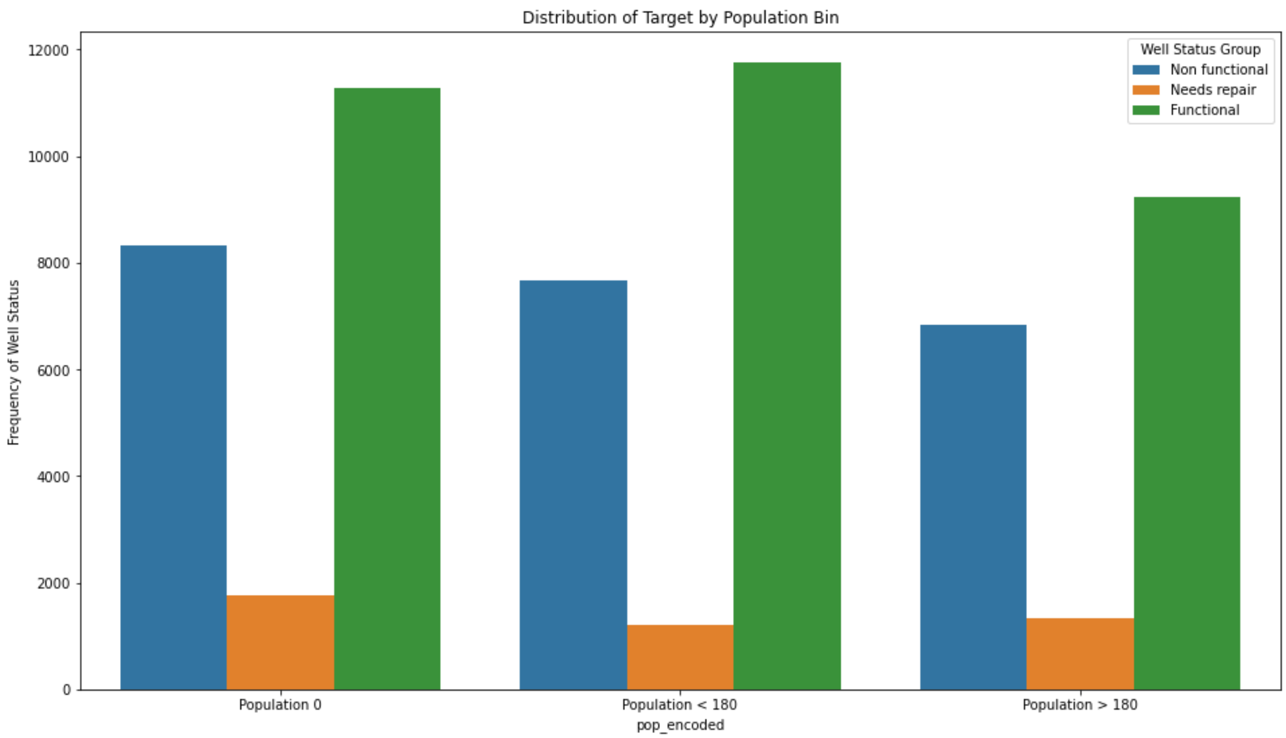
After playing around increasing our bin size all the way up to 100, we could really get a feel that most of these population values were still under 500.

I suspect the best way to include population is not to have it remain numerical, but to convert to a categorical feature. My idea is to bin into these three categories: 0 population, population between 0 and 180, and populations above 180.

In [58]:
```
# helper function to determine output value for population size
def pop_encode(row):
    pop = row['population']

    if pop == 0:
        return 0
    elif (pop > 0) & (pop <= 180):
        return 1
    else:
        return 2

# create new feature 'age' with the helper function
num_df['pop_encoded'] = num_df.apply(pop_encode, axis=1)
```

In [59]:
```
fig, ax = plt.subplots(figsize=(16,9))
```

```
ax = sns.countplot(data=num_df, x='pop_encoded', hue='target')
ax.set_title('Distribution of Target by Population Bin')
ax.set_ylabel('Frequency of Well Status')
ax.set_xticklabels(['Population 0', 'Population < 180', 'Population > 180'])
ax.legend(title='Well Status Group', labels=['Non functional', 'Needs repair',
                                             'Functional']);

# plt.savefig('images/targetdistbypopulationbin.png')
```



construction_year

In [60]:
```
num_df['construction_year'].describe()
```

Out[60]:
```
count    59400.000000
mean      1300.652475
std        951.620547
min          0.000000
25%          0.000000
50%       1986.000000
75%       2004.000000
max       2013.000000
Name: construction_year, dtype: float64
```

In [61]:
```
const_year_0_df = num_df[num_df.construction_year == 0.0].copy()
const_year_df = num_df[num_df.construction_year != 0.0].copy()

print(f"Count of values with construction year of 0: {len(const_year_0_df)}")
print(f"Count of values with a construction year: {len(const_year_df)}")
print("-------------------------------------------")
print(f"Percentage of values with no contruction year: {round(len(const_year_0_df)/len(num_df)*100,
```

```
Count of values with construction year of 0: 20709
Count of values with a construction year: 38691
-------------------------------------------
Percentage of values with no contruction year: 34.86%
```

In [62]:
```
const_year_df.construction_year.describe()
```

Out[62]:
```
count    38691.000000
mean      1996.814686
std         12.472045
min       1960.000000
25%       1987.000000
50%       2000.000000
75%       2008.000000
max       2013.000000
Name: construction_year, dtype: float64
```

In [63]:
```
const_year_df.construction_year.mode()
```

Out[63]:
```
0    2010
dtype: int64
```

A little more than a third (34.9%) of our data contains no construction year. Of the data we do have for construction year, it ranges from 1960 to 2013, with an average year of 1996 and a mode of 2010.

Initial idea was to use the date_recorded feature to calculate an age for the pump. We could then bin that, including a bin for 'unknown'.

In [64]:
```
# add the date_recorded feature to our numerical dataframe
num_df['date_recorded'] = pd.to_datetime(raw_df.date_recorded)

# extract the year from date_recorded into a separate feature
num_df['year'] = num_df['date_recorded'].map(lambda x: x.year)

# helper function to calculate age if we have a construction year
def calc_age(row):
    if row['construction_year'] == 0:
        return 99
    else:
        return int(row['year'] - row['construction_year'])

# create new feature 'age' with the helper function
num_df['age'] = num_df.apply(calc_age, axis=1)
```

In [65]:
```
num_df[num_df.age < 99].age.value_counts(normalize=True)
```

Out[65]:
```
3     0.070818
1     0.059523
2     0.055026
5     0.051175
4     0.048849
13    0.048306
7     0.036288
6     0.035693
11    0.034944
14    0.029981
8     0.029981
33    0.028947
15    0.025665
23    0.023390
10    0.022434
16    0.021349
9     0.021038
19    0.019798
27    0.019695
18    0.019488
28    0.018325
31    0.018325
35    0.016722
```

```
17    0.016438
39    0.015533
37    0.015507
26    0.015223
0     0.015197
25    0.015068
21    0.014939
29    0.014577
12    0.014448
20    0.013983
41    0.012613
30    0.009279
43    0.009201
38    0.009072
36    0.008400
22    0.008348
24    0.006746
40    0.006022
34    0.004756
32    0.004497
53    0.002352
42    0.002326
50    0.002171
45    0.001706
46    0.001241
44    0.001215
48    0.001060
51    0.000801
49    0.000646
47    0.000362
52    0.000284
-5    0.000078
-4    0.000052
-7    0.000026
-3    0.000026
-2    0.000026
-1    0.000026
Name: age, dtype: float64
```

Initial observations:

- The most frequent age is 3 years, at 7%. 7 of the 10 most frequent values for age are under 10.
- We have some negative values, which should not be possible as you can't sample a waterpoint that hasn't been constructed yet. Need to check on this.

In [66]:

```
num_df.year.value_counts()
```

Out[66]:

```
2011    28674
2013    24271
2012     6424
2004       30
2002        1
Name: year, dtype: int64
```

In [67]:

```
num_df[num_df.year > 2005].date_recorded.mean()
```

Out[67]:

```
Timestamp('2012-03-30 20:23:54.688136960')
```

It looks like our date_recorded feature has some errors in it. We have one entry with a year of 2002, and 30 in 2004. The majority of our data was collected in 2011, 2012, and 2013. The average date for the data (not including these 31 date_recorded outliers) is the end of March 2012. If we look at the distribution of the years this looks accurate. Lets look a little closer to see how we can fix these datapoints from years before they were constructed.

In [68]:
```
num_df[num_df.age < 0]
```

Out[68]:

	id	amount_tsh	gps_height	longitude	latitude	region_code	population	construction_year	target	pc
8729	20198	0.0	86.0	38.959776	-5.247278	4	120	2008	0	
10441	55069	20.0	307.0	38.768656	-7.298419	6	1	2006	0	
13366	48759	100.0	1331.0	34.290885	-1.699609	20	80	2011	2	
23373	20534	50.0	239.0	39.272736	-11.019000	9	317	2009	2	
27501	53086	500.0	1611.0	34.900561	-8.873813	11	65	2009	2	
32619	9195	0.0	1856.0	31.539761	-7.983106	15	900	2005	0	
33942	5971	0.0	0.0	39.283105	-7.422852	6	200	2007	0	
39559	15921	0.0	301.0	38.558421	-5.140405	4	713	2009	0	
48555	1251	0.0	284.0	38.929212	-7.111349	6	185	2008	2	

We can see that all the errors come from datapoints reported as 'collected' in 2004. If the one 'collected' in 2002 doesn't report a negative age, then it was constructed prior to that year. Since it's only 31 datapoints, we are going to change all the years of 2004 and 2002 to 2012, the median year of observations. We then need to repeat the creation of the 'age' feature, then drop the year column from num_df

In [69]:
```
num_df.loc[num_df[num_df.year == 2002].index, 'year'] = 2012
num_df.loc[num_df[num_df.year == 2004].index, 'year'] = 2012

num_df['age'] = num_df.apply(calc_age, axis=1)

num_df.drop(['year'], axis=1, inplace=True)
```

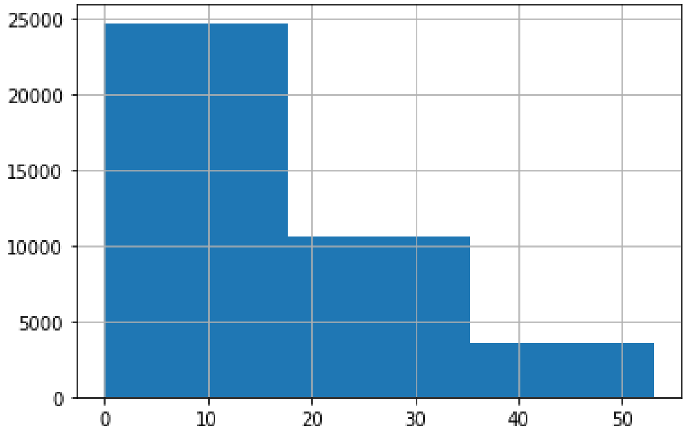
In [70]:
```
num_df[num_df.age < 99].age.describe()
```

Out[70]:
```
count    38691.000000
mean        15.359257
std         12.491646
min          0.000000
25%          5.000000
50%         13.000000
75%         25.000000
max         53.000000
Name: age, dtype: float64
```

In [71]:
```
num_df[num_df.age < 99].age.value_counts(bins=4)
```

Out[71]:
```
(-0.054, 13.25]    21043
(13.25, 26.5]       8915
(26.5, 39.75]       7106
(39.75, 53.0]       1627
Name: age, dtype: int64
```

In [72]:
```
num_df[num_df.age < 99].age.hist(bins=3);
```



The idea at this point was to bin this into an encoded categorical at the quartiles, so 0-5, 5-13, 13-25, and 25-53 and then the 'dropped' category is the ones with no age.

That process was more elaborate and may be difficult to pipeline for production. A second idea is to not calculate age, but bin the construction year by decade while including a categorical value for no construction year. Lets implement that to to see how it looks.

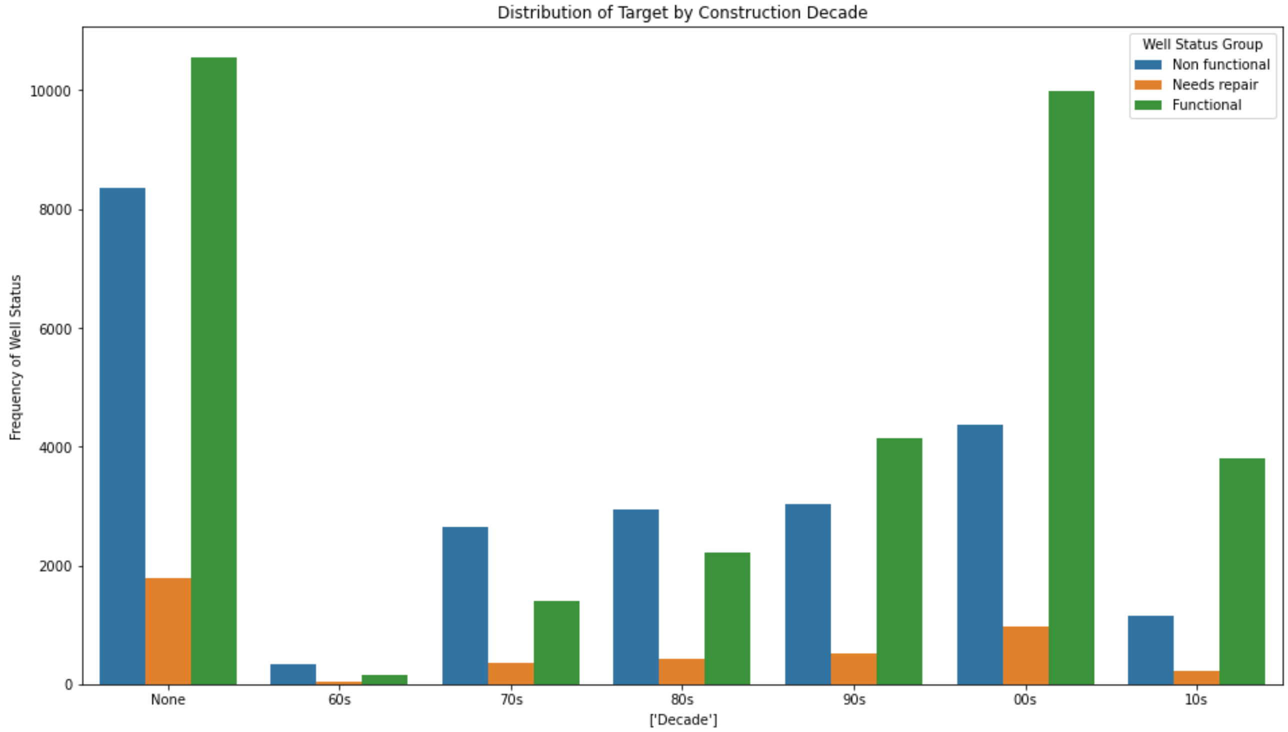
In [73]:

```
# helper function to determine output value for construction year
def const_encode(row):

    # meta-helper function to get the 2nd digit from the right to determine decade
    def get_decade(number):
        return number // 10 % 10

    if row.construction_year == 0:
        return 'None'
    else:
        return f'{get_decade(row.construction_year)}0s'

# create new feature 'age' with the helper function
num_df['const_year_encoded'] = num_df.apply(const_encode, axis=1)
```

After exploring the categorical data we will have to encode what features we are using, and at that time we can also encode these feature.

In [74]:

```
decade_order = ['None', '60s', '70s', '80s', '90s', '00s', '10s']

fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=num_df, x='const_year_encoded', hue='target',
                  order=decade_order)
ax.set_title('Distribution of Target by Construction Decade')
ax.set_ylabel('Frequency of Well Status')
ax.set_xlabel(['Decade'])
ax.legend(title='Well Status Group', labels=['Non functional', 'Needs repair',
                                             'Functional']);

# plt.savefig('images/targetdistbydecadeconst.png')
```



Exploring categorical data

We still need the ID and target columns (for merging and investigation respectively), so we can't just wholesale select object columns from our raw_data. So we make a list of features to drop to make a dataframe of all our categorical data with those 2 numerical features.

In [75]:
```
num_features = ['amount_tsh', 'gps_height', 'longitude', 'latitude',
                'num_private', 'region_code', 'district_code', 'population',
                'construction_year']

cat_df = raw_df.drop(num_features, axis=1).copy()
list(cat_df.columns)
```

Out[75]:
```
['id',
 'date_recorded',
 'funder',
 'installer',
 'wpt_name',
 'basin',
 'subvillage',
 'region',
 'lga',
 'ward',
 'public_meeting',
 'recorded_by',
 'scheme_management',
 'scheme_name',
 'permit',
 'extraction_type',
 'extraction_type_group',
 'extraction_type_class',
 'management',
 'management_group',
 'payment',
 'payment_type',
 'water_quality',
 'quality_group',
```

```
 'quantity',
 'quantity_group',
 'source',
 'source_type',
 'source_class',
 'waterpoint_type',
 'waterpoint_type_group',
 'target']
```

We already know that the 'id' feature is a unique numerical identifier. This will allow us to merge our cat_df with our num_df after investigative all the categorical variables. We already know that there are some features we will likely not use in modeling, such as 'date_recorded' and 'subvillage', so we will start a running drop list that will all be dropped before merging with numerical data.

In [76]:

```
drop_list = []
```

Helper functions

In [77]:

```
def value_count_report(feature):
    """
    This is a helper function to report value counts for categeorical features
    of the dataset and return a dataframe of the feature value counts for
    further investigation.

    Input(s):
    - 'feature' (required): string of feature to investigate

    Output(s):
    - 'feature_df': a DataFrame of the unique values and counts for the feature
    """
    # set up dataframe for unique values and counts. We have already dealt with
    # null values so no need to worry about including them here.
    feature_df = pd.DataFrame(cat_df[feature].value_counts())
    feature_df['percentage'] = round(cat_df[feature].value_counts(normalize=True)*100,2)

    # a second dataframe subset of the first where the value count is 1
    feature_df_singles = feature_df[feature_df[feature] == 1]

    # quick report on total unique values, how many are single, and what percent that is
    print(f"Unique values for '{feature}': {len(feature_df)}")
    print("--------------------------")
    print(f"Unique values with a single representative: {len(feature_df_singles)}")
    print(f"Percent of values that are single: {round((len(feature_df_singles)/len(feature_df)*100)

    return feature_df
```

Inspiration for rendering DataFrames side-by-side with a CSS override.

In [78]:

```
from IPython.display import display, HTML

css = """
.output {
    flex-direction: row;
}
"""

HTML('<style>{}</style>'.format(css))
```

Out[78]:

date_recorded

The 'date_recorded' feature is likely not going to mean anything for analysis, and we have already used it to calculate ages of waterpoints. We will add this feature to our running drop list.

In [79]:
```
drop_list.append('date_recorded')
```

funder / installer

The data description states that the funder is who funded the well and the installer is who installed it.

During null checks we noticed that both of these features have a large number of unique values and weren't likely to be used for modeling, we'll look at them a bit closer just to be sure.

In [80]:
```
funder_df = value_count_report('funder')
print("-------------------------------------------------")
installer_df = value_count_report('installer')
```

```
Unique values for 'funder': 1898
-------------------------
Unique values with a single representative: 974
Percent of values that are single: 51.32%
-------------------------------------------------
Unique values for 'installer': 2146
-------------------------
Unique values with a single representative: 1098
Percent of values that are single: 51.16%
```

In [81]:
```
display(funder_df)
display(installer_df)
```

	funder	percentage
Government Of Tanzania	9084	15.29
Other	3635	6.12
Danida	3114	5.24
Hesawa	2202	3.71
Rwssp	1374	2.31
...	...	...
Mbwana Omari	1	0.00
Makundya	1	0.00
Village Res	1	0.00
Drwssp	1	0.00
Seleman Rashid	1	0.00

1898 rows × 2 columns

	installer	percentage
DWE	17402	29.30
Other	3655	6.15

	installer	percentage
Government	1825	3.07
RWE	1206	2.03
Commu	1060	1.78
...	...	...
Private person	1	0.00
COEW	1	0.00
Lions club kilimanjaro	1	0.00
Jackson Makore	1	0.00
LOMOLOKI	1	0.00

2146 rows × 2 columns

We have almost 1900 unique funders, just over half of which are represented just once, and a similar situation with installers.

It doesn't appear that either feature is suitable for modeling, even with engineering. There are just too many unique values to be able to consolidate. The values that do have larger representation are pretty much government or government organizations, but they still only represent a small portion of the values.

In [82]:
```
drop_list.extend(['funder', 'installer'])
```

wpt_name

The data description states that this feature is the name of the waterpoint, if there is one

In [83]:
```
wptname_df = value_count_report('wpt_name')
```

```
Unique values for 'wpt_name': 37400
--------------------------
Unique values with a single representative: 32928
Percent of values that are single: 88.04%
```

88% of our waterpoint names are represented by a single entry. Out of curiosity, lets look at our top 20 values.

In [84]:
```
wptname_top20 = wptname_df[:20]
wptname_top20.reset_index(inplace=True)
wptname_top20.columns = ['wpt_name', 'count', 'percentage']
wptname_top20
```

Out[84]:

	wpt_name	count	percentage
0	none	3563	6.00
1	Shuleni	1748	2.94
2	Zahanati	830	1.40
3	Msikitini	535	0.90
4	Kanisani	323	0.54
5	Bombani	271	0.46
6	Sokoni	260	0.44

	wpt_name	count	percentage
7	Ofisini	254	0.43
8	School	208	0.35
9	Shule Ya Msingi	199	0.34
10	Shule	152	0.26
11	Sekondari	146	0.25
12	Muungano	133	0.22
13	Mkombozi	111	0.19
14	Madukani	104	0.18
15	Mbugani	94	0.16
16	Hospital	94	0.16
17	Upendo	93	0.16
18	Kituo Cha Afya	90	0.15
19	Mkuyuni	88	0.15

Swahili is the national language of Tanzania. We are going to translate some of these names to see what they mean.

In [85]:

```
translations = ['none','at school','clinics','in the mosque','church','none',
                'none','office','school','primary school','school',
                'secondary','in the congregation','savior', 'shops',
                'in the park', 'hospital','love','health center', 'none']
wptname_top20.assign(translated = translations)
```

Out[85]:

	wpt_name	count	percentage	translated
0	none	3563	6.00	none
1	Shuleni	1748	2.94	at school
2	Zahanati	830	1.40	clinics
3	Msikitini	535	0.90	in the mosque
4	Kanisani	323	0.54	church
5	Bombani	271	0.46	none
6	Sokoni	260	0.44	none
7	Ofisini	254	0.43	office
8	School	208	0.35	school
9	Shule Ya Msingi	199	0.34	primary school
10	Shule	152	0.26	school
11	Sekondari	146	0.25	secondary
12	Muungano	133	0.22	in the congregation
13	Mkombozi	111	0.19	savior
14	Madukani	104	0.18	shops
15	Mbugani	94	0.16	in the park
16	Hospital	94	0.16	hospital

	wpt_name	count	percentage	translated
17	Upendo	93	0.16	love
18	Kituo Cha Afya	90	0.15	health center
19	Mkuyuni	88	0.15	none

Here would be an opportunity to expand if we could pull in translation and fuzzy logic for word types. Waterpoints are named after the place they are located and most of the ones with multiple value counts are at places like schools, houses of worship, offices, and shops. It will be too difficult at this point to find a way to convert this feature, so we will add it to the drop list. But if we could convert, it may be insightful if you could categorize the location type

In [86]:
```
drop_list.append('wpt_name')
```

basin

The data description states that this feature is a geographic water basin

In [87]:
```
basin_df = value_count_report('basin')
```

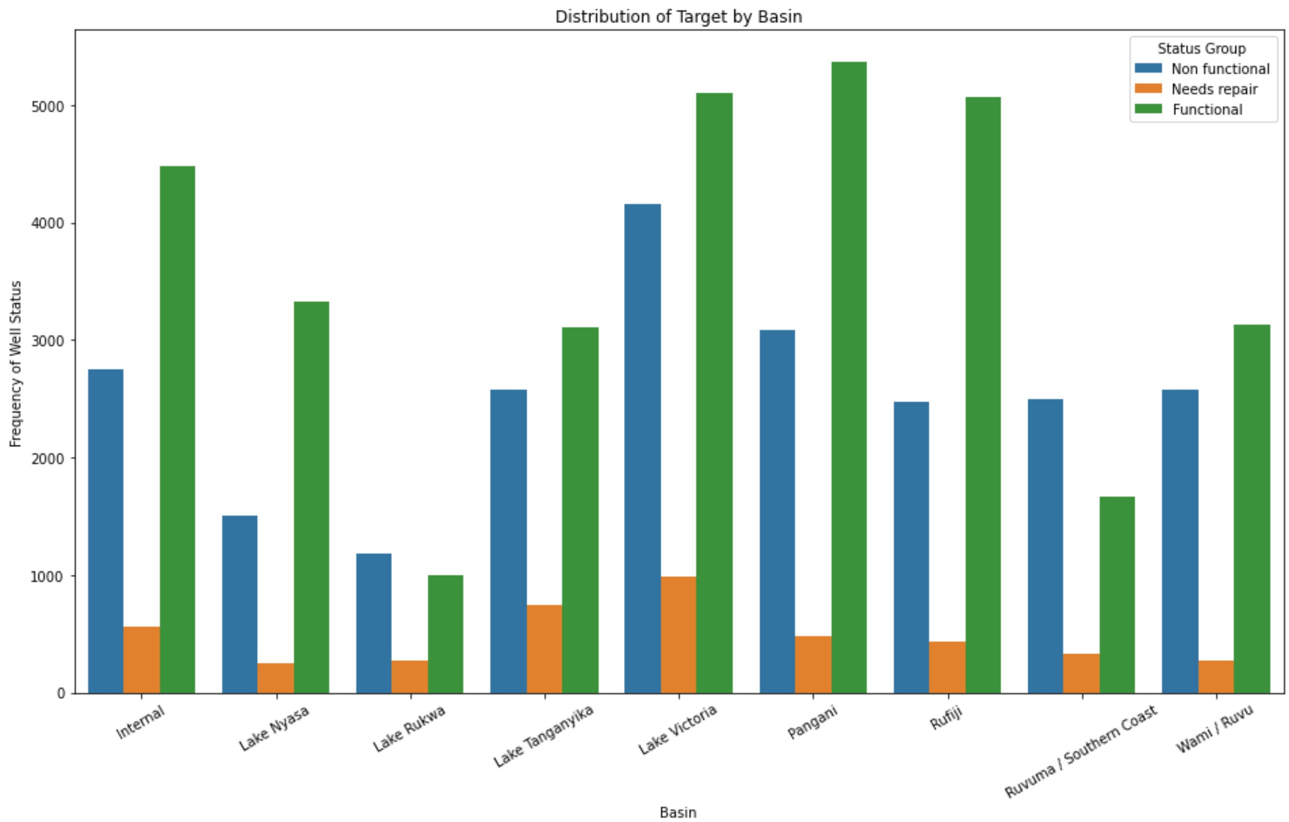
```
Unique values for 'basin': 9
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
```

In [88]:
```
basin_df
```

Out[88]:

	basin	percentage
Lake Victoria	10248	17.25
Pangani	8940	15.05
Rufiji	7976	13.43
Internal	7785	13.11
Lake Tanganyika	6432	10.83
Wami / Ruvu	5987	10.08
Lake Nyasa	5085	8.56
Ruvuma / Southern Coast	4493	7.56
Lake Rukwa	2454	4.13

In [89]:
```
# set up order for regions
basin_abc = sorted(list(cat_df.basin.value_counts().index))

fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='basin', hue='target', order=basin_abc)
ax.set_title('Distribution of Target by Basin')
ax.set_ylabel('Frequency of Well Status')
ax.set_xlabel('Basin')
ax.set_xticklabels(ax.get_xticklabels(),rotation = 30)
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                       'Functional']);

# plt.savefig('images/targetdistbybasin.png')
```



Nothing crazy looking here, we will need to encode this for modeling but we'll get to that after analysis of all categoricals

subvillage

The data description states that this feature is a geographic location.

In [90]:
```
subvillage_df = value_count_report('subvillage')
```

```
Unique values for 'subvillage': 19288
--------------------------
Unique values with a single representative: 9424
Percent of values that are single: 48.86%
```

As we saw earlier when accounting for nulls we have a lot of subvillages, over 19 thousand, about half of which are represented by a single instance. We will not model with this, add it to the drop list.

In [91]:
```
drop_list.append('subvillage')
```

region/lga/ward

The data description states that these features are all geographic locations.

During research%20is%20an,are%20composed%20of%20several%20villages.) we discovered the administrative separation in Tanzania goes region > district > division > ward > village. We already sorted out the region feature and will likely use that by one hot encoding, but lets look at them all side by side to be sure.

In [92]:
```
region_df = value_count_report('region')
print("----------------------------------------------")
```

```
lga_df = value_count_report('lga')
print("----------------------------------------------")
ward_df = value_count_report('ward')
print("----------------------------------------------")
```

```
Unique values for 'region': 21
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
----------------------------------------------
Unique values for 'lga': 125
--------------------------
Unique values with a single representative: 1
Percent of values that are single: 0.8%
----------------------------------------------
Unique values for 'ward': 2092
--------------------------
Unique values with a single representative: 30
Percent of values that are single: 1.43%
----------------------------------------------
```

In [93]:

```
display(region_df)
display(lga_df)
display(ward_df)
```

	region	percentage
Iringa	5300	8.92
Shinyanga	5011	8.44
Mbeya	4639	7.81
Kilimanjaro	4379	7.37
Morogoro	4040	6.80
Arusha	3350	5.64
Kagera	3324	5.60
Mwanza	3047	5.13
Kigoma	2816	4.74
Ruvuma	2640	4.44
Pwani	2635	4.44
Tanga	2513	4.23
Dodoma	2201	3.71
Singida	2093	3.52
Tabora	1979	3.33
Mara	1969	3.31
Rukwa	1808	3.04
Mtwara	1730	2.91
Manyara	1583	2.66
Lindi	1538	2.59
Dar es Salaam	805	1.36

	lga	percentage

	lga	percentage
Njombe	2503	4.21
Arusha Rural	1252	2.11
Moshi Rural	1251	2.11
Bariadi	1177	1.98
Rungwe	1106	1.86
...	...	...
Moshi Urban	79	0.13
Kigoma Urban	71	0.12
Arusha Urban	63	0.11
Lindi Urban	21	0.04
Nyamagana	1	0.00

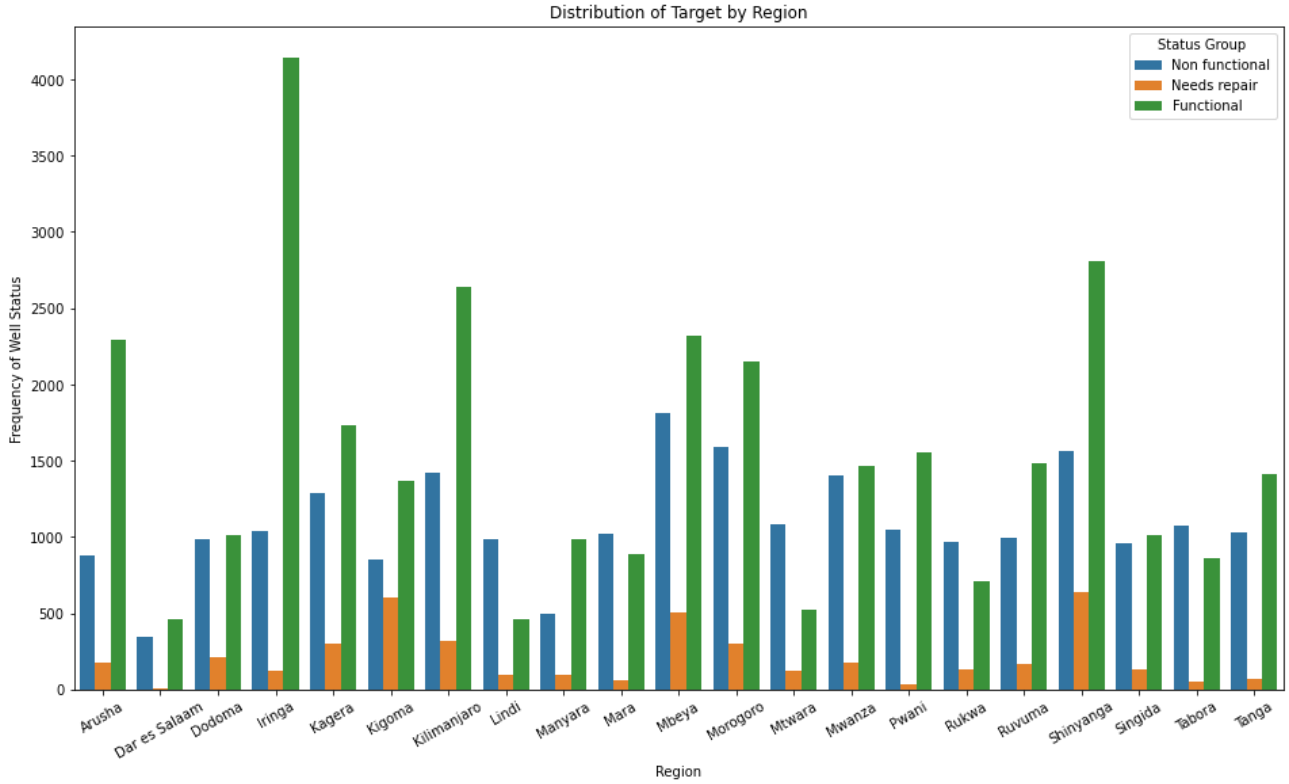
125 rows × 2 columns

	ward	percentage
Igosi	307	0.52
Imalinyi	252	0.42
Siha Kati	232	0.39
Mdandu	231	0.39
Nduruma	217	0.37
...	...	...
Uchindile	1	0.00
Kitete	1	0.00
Mitole	1	0.00
Mlimani	1	0.00
Mwanga Kaskazini	1	0.00

2092 rows × 2 columns

In [94]:

```
# set up order for regions
regions_abc = sorted(list(cat_df.region.value_counts().index))

fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='region', hue='target', order=regions_abc)
ax.set_title('Distribution of Target by Region')
ax.set_ylabel('Frequency of Well Status')
ax.set_xlabel('Region')
ax.set_xticklabels(ax.get_xticklabels(),rotation = 30)
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                       'Functional']);

# plt.savefig('images/targetdistbyregion.png')
```



In [95]:

```
region_target_df = cat_df.groupby(['region', 'target']).size().reset_index(name='target_count')
a = cat_df.region.value_counts()
region_target_df['target_perc'] = region_target_df['target_count'].div(region_target_df['region'].m
display(region_target_df[region_target_df.target == 0].sort_values(by='target_perc', ascending=Fals
display(region_target_df[region_target_df.target == 1].sort_values(by='target_perc', ascending=Fals
display(region_target_df[region_target_df.target == 2].sort_values(by='target_perc', ascending=Fals
```

	region	target	target_count	target_perc
21	Lindi	0	987	0.641743
36	Mtwara	0	1080	0.624277
57	Tabora	0	1070	0.540677
45	Rukwa	0	966	0.534292
27	Mara	0	1023	0.519553
39	Mwanza	0	1401	0.459797
54	Singida	0	954	0.455805
6	Dodoma	0	983	0.446615
3	Dar es Salaam	0	341	0.423602
60	Tanga	0	1032	0.410665
42	Pwani	0	1043	0.395825
33	Morogoro	0	1593	0.394307
30	Mbeya	0	1816	0.391464
12	Kagera	0	1291	0.388387
48	Ruvuma	0	996	0.377273
18	Kilimanjaro	0	1417	0.323590

	region	target	target_count	target_perc
24	Manyara	0	500	0.315856
51	Shinyanga	0	1566	0.312512
15	Kigoma	0	850	0.301847
0	Arusha	0	881	0.262985
9	Iringa	0	1034	0.195094

	region	target	target_count	target_perc
16	Kigoma	1	603	0.214134
52	Shinyanga	1	638	0.127320
31	Mbeya	1	504	0.108644
7	Dodoma	1	209	0.094957
13	Kagera	1	304	0.091456
46	Rukwa	1	135	0.074668
34	Morogoro	1	300	0.074257
19	Kilimanjaro	1	322	0.073533
37	Mtwara	1	126	0.072832
49	Ruvuma	1	164	0.062121
55	Singida	1	128	0.061156
25	Manyara	1	96	0.060644
22	Lindi	1	93	0.060468
40	Mwanza	1	178	0.058418
1	Arusha	1	175	0.052239
28	Mara	1	60	0.030472
61	Tanga	1	73	0.029049
58	Tabora	1	47	0.023749
10	Iringa	1	123	0.023208
43	Pwani	1	36	0.013662
4	Dar es Salaam	1	3	0.003727

	region	target	target_count	target_perc
11	Iringa	2	4143	0.781698
2	Arusha	2	2294	0.684776
26	Manyara	2	987	0.623500
20	Kilimanjaro	2	2640	0.602877
44	Pwani	2	1556	0.590512
5	Dar es Salaam	2	461	0.572671
50	Ruvuma	2	1480	0.560606
62	Tanga	2	1408	0.560287

	region	target	target_count	target_perc
53	Shinyanga	2	2807	0.560168
35	Morogoro	2	2147	0.531436
14	Kagera	2	1729	0.520156
32	Mbeya	2	2319	0.499892
17	Kigoma	2	1363	0.484020
56	Singida	2	1011	0.483039
41	Mwanza	2	1468	0.481785
8	Dodoma	2	1009	0.458428
29	Mara	2	886	0.449975
59	Tabora	2	862	0.435574
47	Rukwa	2	707	0.391040
38	Mtwara	2	524	0.302890
23	Lindi	2	458	0.297789

Initial insights by region are:

- The regions with highest percent non-functional points were in the southeast regions and the Serengeti Plain to the east and south of Lake Victoria
- The regions with the highest percent functional waterpoints were in the Masai Steppe (northeast region) and along the east coast.
- The regions with the highest percent waterpoints needing repair were in the northwest (on the Serengeti Plain) and the southwest (Great Rift Valley)

Our intuition looks to be correct in choosing the region over other geographic features to use in modeling. This also means we will not need the region_code that we spent all that time fixing in numerical data. We will add 'lga' and 'ward' to the drop list.

In [96]:
```
drop_list.extend(['lga', 'ward'])
```

public_meeting

The data description states that this feature is a true/false if there was a public meeting

In [97]:
```
public_meeting_df = value_count_report('public_meeting')
```

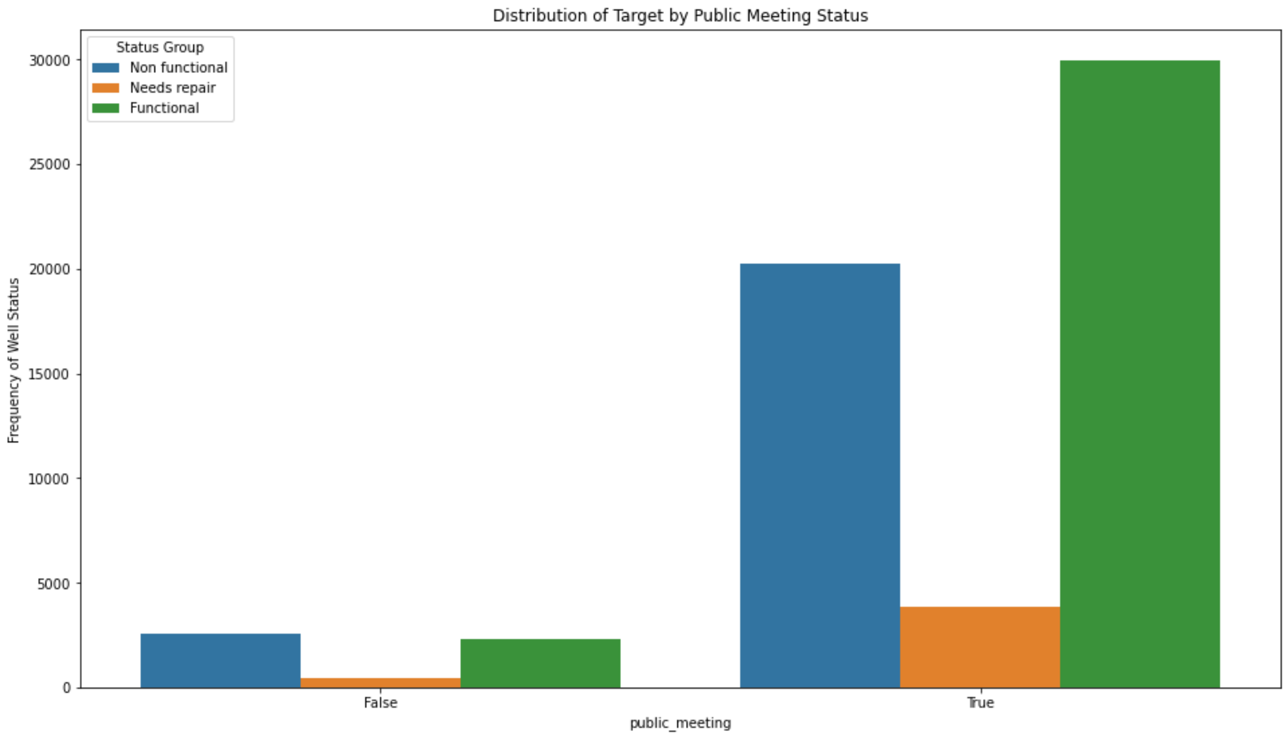
```
Unique values for 'public_meeting': 2
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
```

In [98]:
```
public_meeting_df
```

Out[98]:

	public_meeting	percentage
True	54058	91.01
False	5342	8.99

In [99]:
```
fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='public_meeting', hue='target')
ax.set_title('Distribution of Target by Public Meeting Status')
ax.set_ylabel('Frequency of Well Status')
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                        'Functional']);

# plt.savefig('images/targetdistbypublicmeeting.png')
```



I'm not sure if this will impact modeling, but it's a simple boolean so we will leave it in for now (will encode at the end of categorical analysis).

recorded_by

The data description states that this feature is who entered the data

In [100…
```
recorded_by_df = value_count_report('recorded_by')
```

```
Unique values for 'recorded_by': 1
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
```

In [101…
```
recorded_by_df
```

Out[101…

	recorded_by	percentage
GeoData Consultants Ltd	59400	100.0

All of the data was recorded by one organization, so nothing will be gained using this feature. We will add it to the drop list.

In [102…
```
drop_list.append('recorded_by')
```

scheme_management / scheme_name

The data description states that these features represent who operates the waterpoint

In [103…

```
scheme_management_df = value_count_report('scheme_management')
print("---------------------------------------------")
scheme_name_df = value_count_report('scheme_name')
```

```
Unique values for 'scheme_management': 11
-------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
---------------------------------------------
Unique values for 'scheme_name': 2697
-------------------------
Unique values with a single representative: 712
Percent of values that are single: 26.4%
```

In [104…

```
display(scheme_management_df)
display(scheme_name_df)
```

	scheme_management	percentage
VWC	39347	66.24
WUG	5606	9.44
Water authority	3380	5.69
WUA	3076	5.18
Water Board	2937	4.94
Parastatal	1789	3.01
Company	1132	1.91
Private operator	1126	1.90
Other	826	1.39
SWC	105	0.18
Trust	76	0.13

	scheme_name	percentage
Other	28166	47.42
K	682	1.15
None	644	1.08
Borehole	546	0.92
Chalinze wate	405	0.68
...	...	...
Mwambashima piped scheme	1	0.00
Mradi wa maji wa Wino	1	0.00
Borehole drilling project	1	0.00
Bukonyo Water Supply	1	0.00
Iton	1	0.00

2697 rows × 2 columns

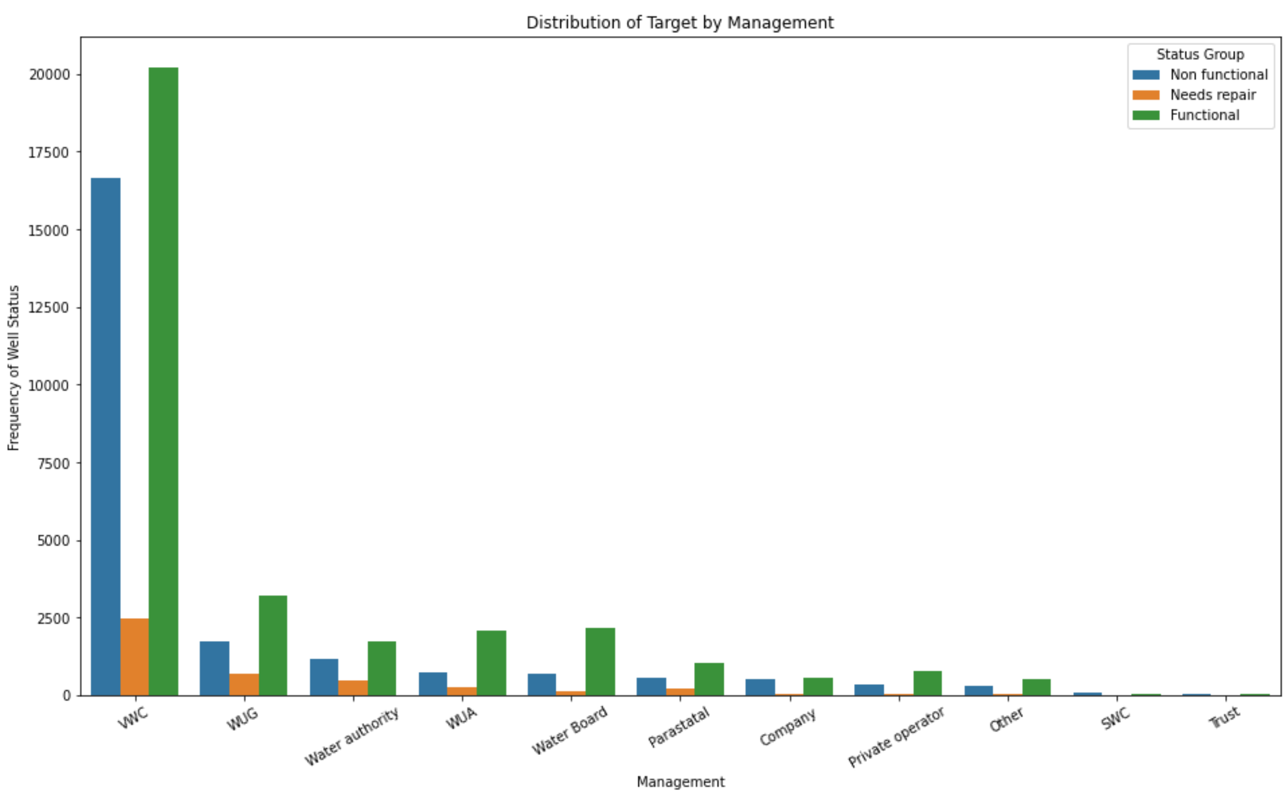
Of the two features regarding who operates the waterpoint, it's clear that we should use scheme_management. Almost half (47.42%) of our scheme_name data is 'Other'. The remaining values are very sparse, the next most frequent being 'K' at 1.15%. I don't suspect there is a way to use this data. Adding to the drop list.

In [105…

```
drop_list.append('scheme_name')
```

In [106…

```
# set up order for management
mgmt_order = list(scheme_management_df.index)

fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='scheme_management', hue='target',
                   order=mgmt_order)
ax.set_title('Distribution of Target by Management')
ax.set_ylabel('Frequency of Well Status')
ax.set_xlabel('Management')
ax.set_xticklabels(ax.get_xticklabels(),rotation = 30)
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                        'Functional']);

# plt.savefig('images/targetdistbymanagement.png')
```



permit

The data description states that this feature indicates if the waterpoint is permitted.

In [107…

```
permit_df = value_count_report('permit')
```

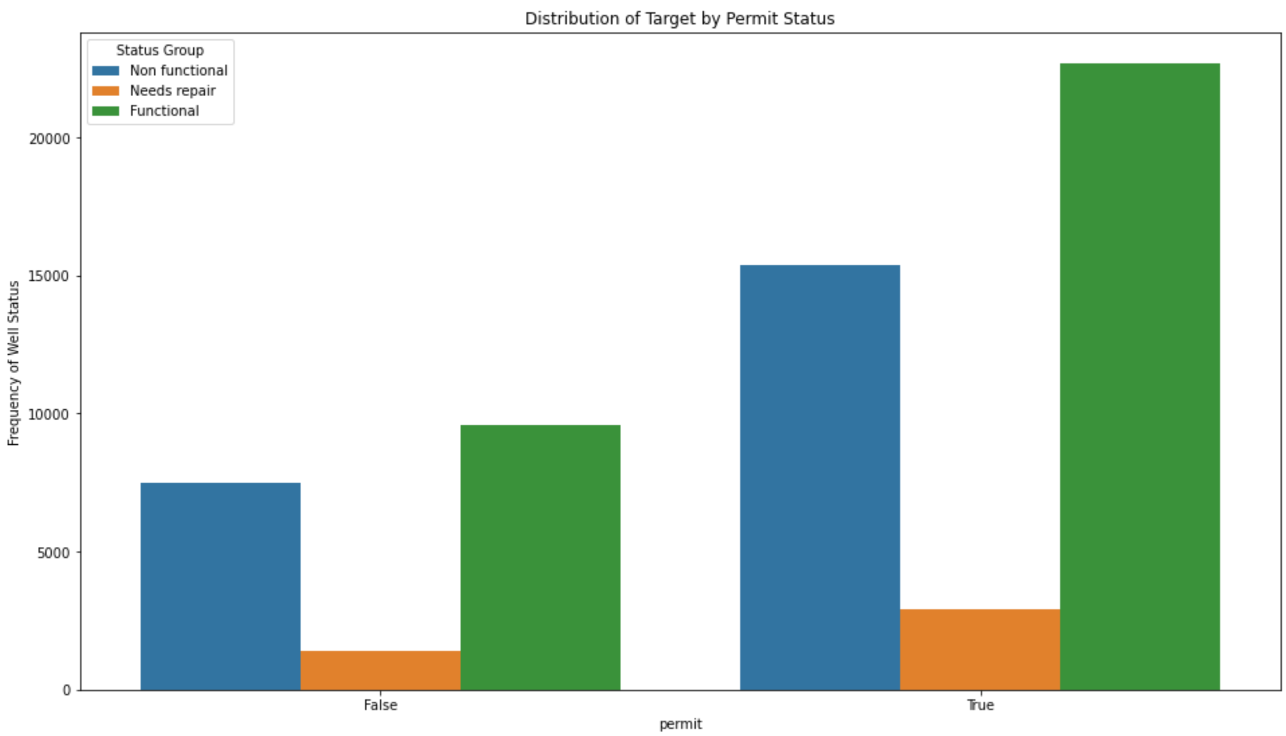
```
Unique values for 'permit': 2
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
```

In [108…
```
permit_df
```

Out[108…

	permit	percentage
True	40971	68.97
False	18429	31.03

In [109…
```
fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='permit', hue='target')
ax.set_title('Distribution of Target by Permit Status')
ax.set_ylabel('Frequency of Well Status')
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                        'Functional']);

# plt.savefig('images/targetdistbypermitstatus.png')
```



extraction_type / _group / _class

The data description states that these features are the kind of extraction the waterpoint uses.

In [110…
```
extraction_type_df = value_count_report('extraction_type')
print("---------------------------------------------")
extraction_type_group_df = value_count_report('extraction_type_group')
print("---------------------------------------------")
extraction_type_class_df = value_count_report('extraction_type_class')
print("---------------------------------------------")
```

```
Unique values for 'extraction_type': 18
-------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
---------------------------------------------
Unique values for 'extraction_type_group': 13
-------------------------
Unique values with a single representative: 0
```

```
Percent of values that are single: 0.0%
---------------------------------------------
Unique values for 'extraction_type_class': 7
-------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
---------------------------------------------
```

In [111…

```
display(extraction_type_df)
display(extraction_type_group_df)
display(extraction_type_class_df)
```

	extraction_type	percentage
gravity	26780	45.08
nira/tanira	8154	13.73
other	6430	10.82
submersible	4764	8.02
swn 80	3670	6.18
mono	2865	4.82
india mark ii	2400	4.04
afridev	1770	2.98
ksb	1415	2.38
other - rope pump	451	0.76
other - swn 81	229	0.39
windmill	117	0.20
india mark iii	98	0.16
cemo	90	0.15
other - play pump	85	0.14
walimi	48	0.08
climax	32	0.05
other - mkulima/shinyanga	2	0.00

	extraction_type_group	percentage
gravity	26780	45.08
nira/tanira	8154	13.73
other	6430	10.82
submersible	6179	10.40
swn 80	3670	6.18
mono	2865	4.82
india mark ii	2400	4.04
afridev	1770	2.98
rope pump	451	0.76
other handpump	364	0.61
other motorpump	122	0.21

	extraction_type_group	percentage
wind-powered	117	0.20
india mark iii	98	0.16

	extraction_type_class	percentage
gravity	26780	45.08
handpump	16456	27.70
other	6430	10.82
submersible	6179	10.40
motorpump	2987	5.03
rope pump	451	0.76
wind-powered	117	0.20

We see the same pattern of repeated values, but consolidation of groups into more general classifications as we progress through the three features. It looks like instead of some branding we saw in values of extraction_type and extraction_type_group, we see more general class distinctions in extraction_type_class

I would reason that our model might perform better with the simpler of the three extraction_type categories. With too many distinctions by extraction_type we may make a model that overfits, and it also may not accounts for new branded pumps in the future that our model hasn't seen. If we use the class, we can still get some distinction with the type of waterpoint, but account for new pumps simply by using the class.

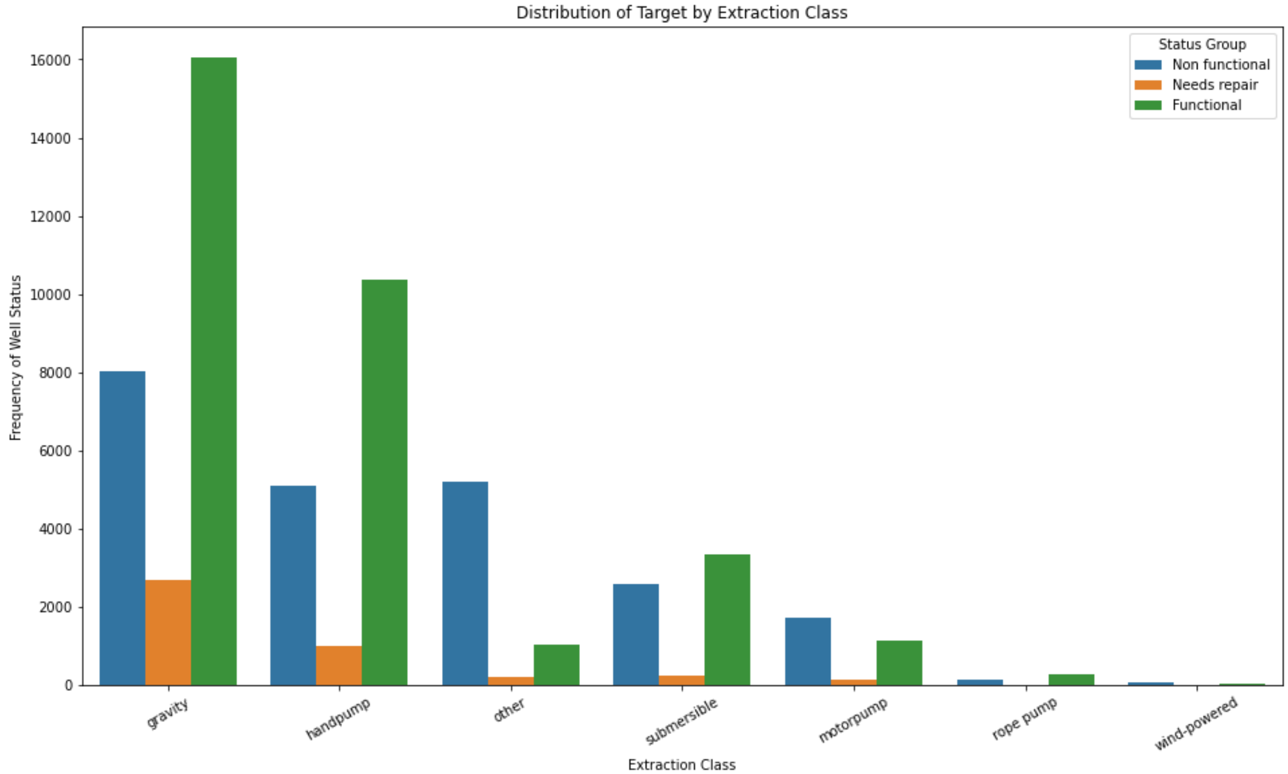
We will add extraction_type and extraction_type_group to the drop list.

In [112…

```
drop_list.extend(['extraction_type', 'extraction_type_group'])
```

In [113…

```
# set up order for extraction type
extract_order = list(extraction_type_class_df.index)

fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='extraction_type_class', hue='target',
                   order=extract_order)
ax.set_title('Distribution of Target by Extraction Class')
ax.set_ylabel('Frequency of Well Status')
ax.set_xlabel('Extraction Class')
ax.set_xticklabels(ax.get_xticklabels(),rotation = 30)
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                        'Functional']);

# plt.savefig('images/targetdistbyextractclass.png')
```



management / management_group

The data description states that these features are how the waterpoint is managed

In [114…

```
management_df = value_count_report('management')
print("----------------------------------------------")
management_group_df = value_count_report('management_group')
print("----------------------------------------------")
```

```
Unique values for 'management': 12
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
----------------------------------------------
Unique values for 'management_group': 5
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
----------------------------------------------
```

In [115…

```
display(management_df)
display(management_group_df)
```

	management	percentage
vwc	40507	68.19
wug	6515	10.97
water board	2933	4.94
wua	2535	4.27
private operator	1971	3.32
parastatal	1768	2.98

	management	percentage
water authority	904	1.52
other	844	1.42
company	685	1.15
unknown	561	0.94
other - school	99	0.17
trust	78	0.13

	management_group	percentage
user-group	52490	88.37
commercial	3638	6.12
parastatal	1768	2.98
other	943	1.59
unknown	561	0.94

'management' looks remarkably similar to the value counts we had for 'scheme_management', lets look at that again

In [116…

```
scheme_management_df
```

Out[116…

	scheme_management	percentage
VWC	39347	66.24
WUG	5606	9.44
Water authority	3380	5.69
WUA	3076	5.18
Water Board	2937	4.94
Parastatal	1789	3.01
Company	1132	1.91
Private operator	1126	1.90
Other	826	1.39
SWC	105	0.18
Trust	76	0.13

'management_goup' seems to be a kind of classification of management types. A vast majority (88.37%) are 'user-group' managed, and we have a value for unknown and other. It looks like of the management features we have available, the one we will use is scheme_management. We will add management and management_group to the drop list.

In [117…

```
drop_list.extend(['management', 'management_group'])
```

payment / payment_type

The data description states that these features are what the water costs.

In [118…

```
payment_df = value_count_report('payment')
print("----------------------------------------------")
payment_type_df = value_count_report('payment_type')
print("----------------------------------------------")
```

```
Unique values for 'payment': 7
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
----------------------------------------------
Unique values for 'payment_type': 7
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
----------------------------------------------
```

In [119…

```
display(payment_df)
display(payment_type_df)
```

	payment	percentage
never pay	25348	42.67
pay per bucket	8985	15.13
pay monthly	8300	13.97
unknown	8157	13.73
pay when scheme fails	3914	6.59
pay annually	3642	6.13
other	1054	1.77

	payment_type	percentage
never pay	25348	42.67
per bucket	8985	15.13
monthly	8300	13.97
unknown	8157	13.73
on failure	3914	6.59
annually	3642	6.13
other	1054	1.77

We definitely don't need two of the same feature. We will add payment_type to the drop list. We will also combine the 'unknown' and 'other' categories into one: 'other'.

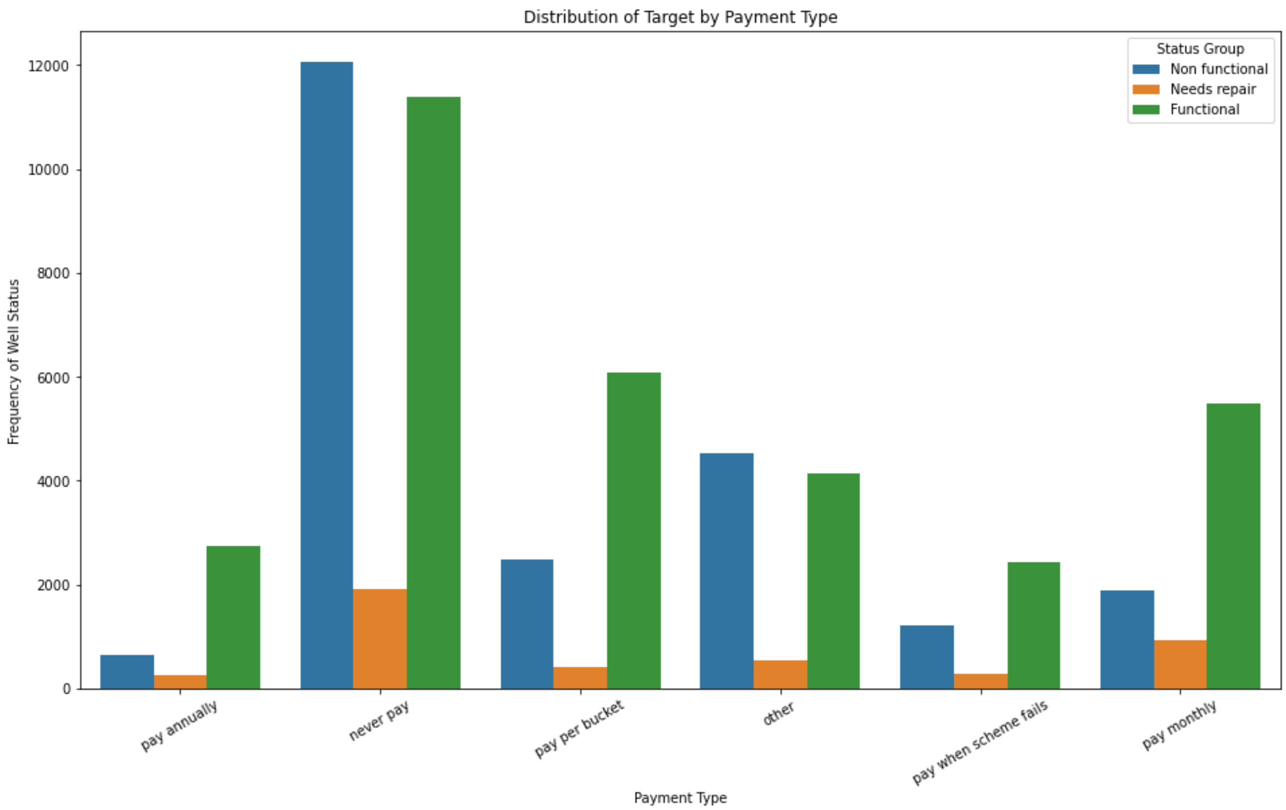
In [120…

```
drop_list.append('payment_type')

cat_df.loc[cat_df[cat_df.payment == 'unknown'].index, 'payment'] = 'other'
```

In [121…

```
# set up order for payment
payment_order = list(payment_df.index).remove('unknown')

fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='payment', hue='target',
                   order=payment_order)
ax.set_title('Distribution of Target by Payment Type')
```

```
ax.set_ylabel('Frequency of Well Status')
ax.set_xlabel('Payment Type')
ax.set_xticklabels(ax.get_xticklabels(),rotation = 30)
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                        'Functional']);

# plt.savefig('images/targetdistbypayment.png')
```



water_quality / quality_group

The data description states that these features are the the quality of the water.

In [122…

```
water_quality_df = value_count_report('water_quality')
print("---------------------------------------------")
quality_group_df = value_count_report('quality_group')
print("---------------------------------------------")
```

```
Unique values for 'water_quality': 8
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
---------------------------------------------
Unique values for 'quality_group': 6
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
---------------------------------------------
```

In [123…

```
display(water_quality_df)
display(quality_group_df)
```

	water_quality	percentage
soft	50818	85.55

	water_quality	percentage
salty	4856	8.18
unknown	1876	3.16
milky	804	1.35
coloured	490	0.82
salty abandoned	339	0.57
fluoride	200	0.34
fluoride abandoned	17	0.03

	quality_group	percentage
good	50818	85.55
salty	5195	8.75
unknown	1876	3.16
milky	804	1.35
colored	490	0.82
fluoride	217	0.37

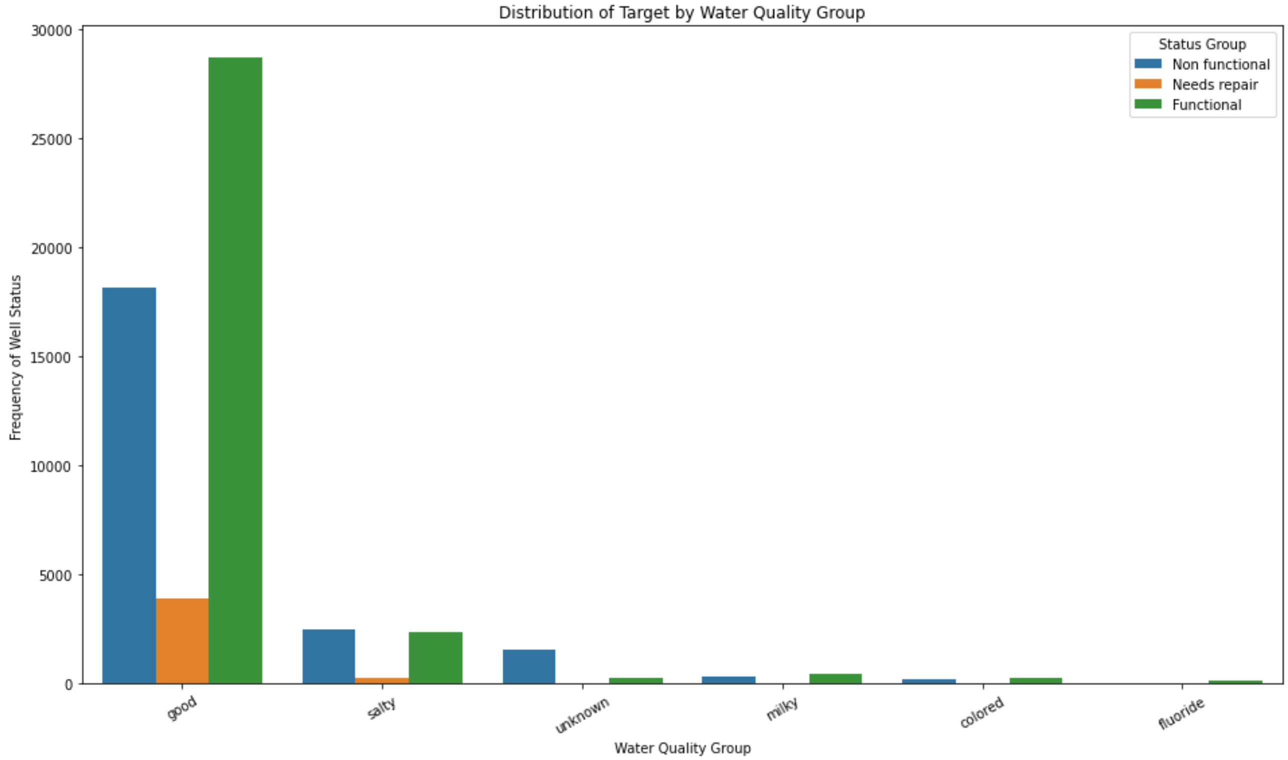
Seems like these are both pretty straightforward categorical, the vast majority of which is 'soft' in quality or 'good' in quality_group (85.55%). Quality_group seems to consolidate the two salty categories and the two fluoride categories. We will use the quality_group in modeling, after encoding, and will add 'water_quality' to the drop list.

In [124…

```
drop_list.append('water_quality')
```

In [125…

```
# set up order for quality group
quality_order = list(quality_group_df.index)

fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='quality_group', hue='target',
                   order=quality_order)
ax.set_title('Distribution of Target by Water Quality Group')
ax.set_ylabel('Frequency of Well Status')
ax.set_xlabel('Water Quality Group')
ax.set_xticklabels(ax.get_xticklabels(),rotation = 30)
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                       'Functional']);

# plt.savefig('images/targetdistbywaterquality.png')
```



quantity / quantity_group

The data description states that these features are the quantity of the water.

In [126…

```
quantity_df = value_count_report('quantity')
print("---------------------------------------------")
quantity_group_df = value_count_report('quantity_group')
print("---------------------------------------------")
```

```
Unique values for 'quantity': 5
-------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
---------------------------------------------
Unique values for 'quantity_group': 5
-------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
---------------------------------------------
```

In [127…

```
display(quantity_df)
display(quantity_group_df)
```

	quantity	percentage
enough	33186	55.87
insufficient	15129	25.47
dry	6246	10.52
seasonal	4050	6.82
unknown	789	1.33

	quantity_group	percentage

	quantity_group	percentage
enough	33186	55.87
insufficient	15129	25.47
dry	6246	10.52
seasonal	4050	6.82
unknown	789	1.33

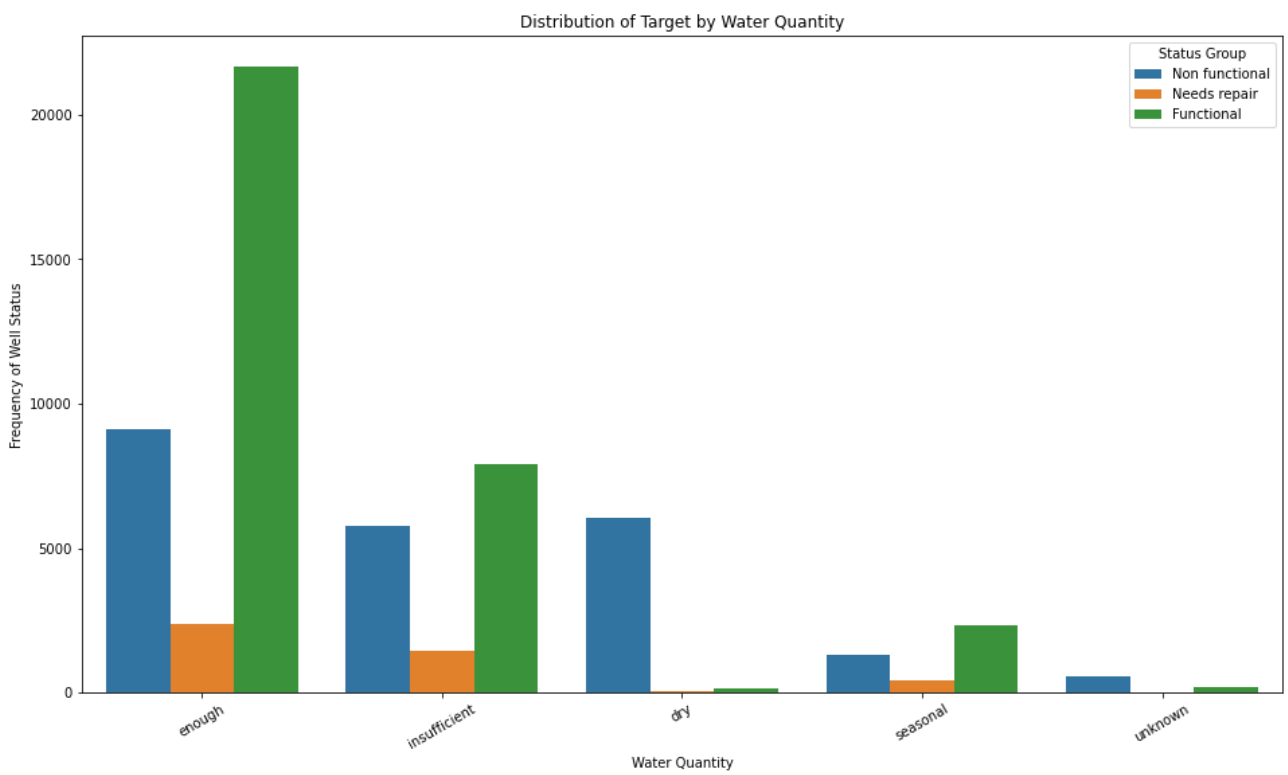
These features are both exactly the same. We will add quantity_group the drop list.

In [128…

```
drop_list.append('quantity_group')
```

In [129…

```
# set up order for quantity
quantity_order = list(quantity_df.index)

fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='quantity', hue='target',
                   order=quantity_order)
ax.set_title('Distribution of Target by Water Quantity')
ax.set_ylabel('Frequency of Well Status')
ax.set_xlabel('Water Quantity')
ax.set_xticklabels(ax.get_xticklabels(),rotation = 30)
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                        'Functional']);

# plt.savefig('images/targetdistbywaterquantity.png')
```



source / _type / _class

The data description states that these are the source of the water.

In [130…

```
source_df = value_count_report('source')
print("----------------------------------------------")
source_type_df = value_count_report('source_type')
print("----------------------------------------------")
source_class_df = value_count_report('source_class')
print("----------------------------------------------")
```

```
Unique values for 'source': 10
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
----------------------------------------------
Unique values for 'source_type': 7
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
----------------------------------------------
Unique values for 'source_class': 3
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
----------------------------------------------
```

In [131…

```
display(source_df)
display(source_type_df)
display(source_class_df)
```

	source	percentage
spring	17021	28.65
shallow well	16824	28.32
machine dbh	11075	18.64
river	9612	16.18
rainwater harvesting	2295	3.86
hand dtw	874	1.47
lake	765	1.29
dam	656	1.10
other	212	0.36
unknown	66	0.11

	source_type	percentage
spring	17021	28.65
shallow well	16824	28.32
borehole	11949	20.12
river/lake	10377	17.47
rainwater harvesting	2295	3.86
dam	656	1.10
other	278	0.47

	source_class	percentage
groundwater	45794	77.09

	source_class	percentage
surface	13328	22.44
unknown	278	0.47

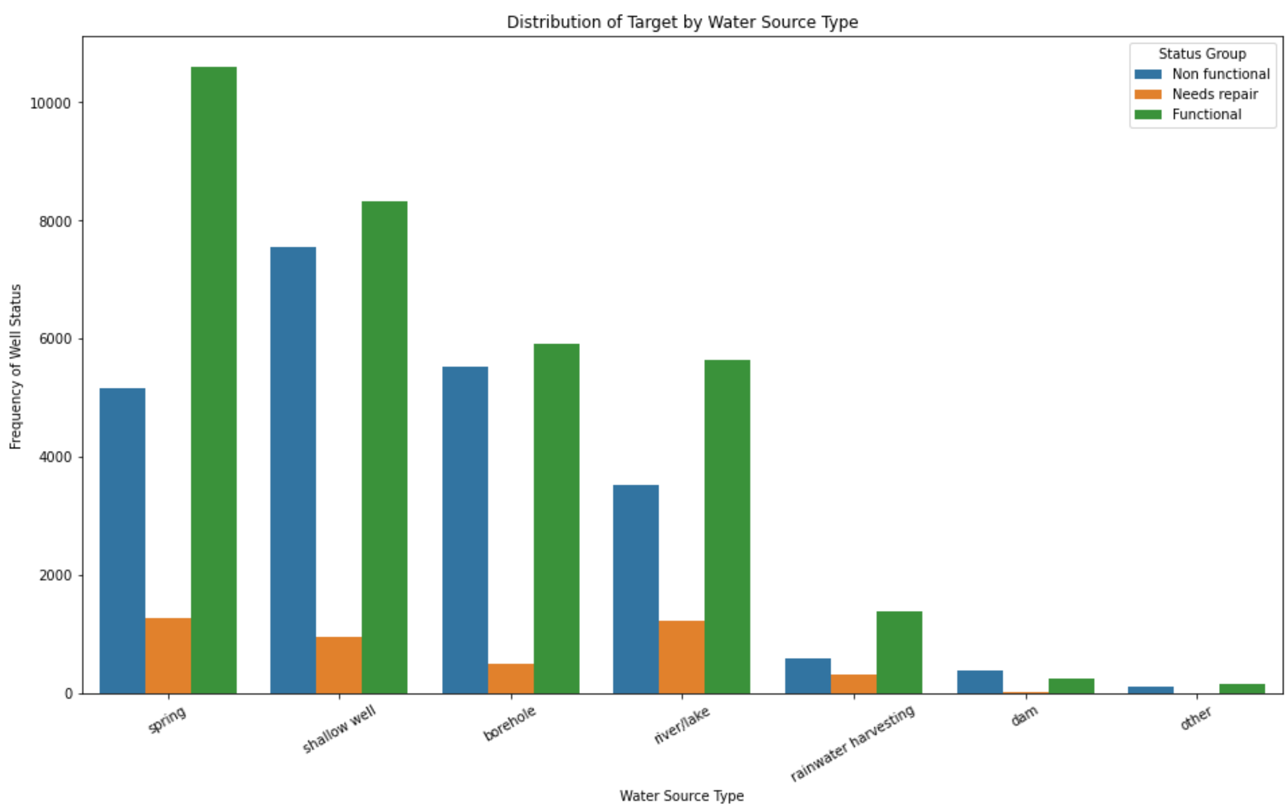
As with the extraction type features, we have increasing organization and consolidation of categories. I think that source_class contains too few value types, while source_type consolidates river and lake together, and unknown into other, and the two borehole categories into one. We will add source and source_class to the drop list.

In [132…

```
drop_list.extend(['source', 'source_class'])
```

In [133…

```
# set up order for source type
source_order = list(source_type_df.index)

fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='source_type', hue='target',
                   order=source_order)
ax.set_title('Distribution of Target by Water Source Type')
ax.set_ylabel('Frequency of Well Status')
ax.set_xlabel('Water Source Type')
ax.set_xticklabels(ax.get_xticklabels(),rotation = 30)
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                        'Functional']);

# plt.savefig('images/targetdistbywatersource.png')
```



waterpoint_type / _group

The data description states that these are the kind of waterpoint.

In [134…

```
waterpoint_type_df = value_count_report('waterpoint_type')
print("---------------------------------------------")
```

```
waterpoint_type_group_df = value_count_report('waterpoint_type_group')
print("---------------------------------------------")
```

```
Unique values for 'waterpoint_type': 7
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
---------------------------------------------
Unique values for 'waterpoint_type_group': 6
--------------------------
Unique values with a single representative: 0
Percent of values that are single: 0.0%
---------------------------------------------
```

In [135…

```
display(waterpoint_type_df)
display(waterpoint_type_group_df)
```

	waterpoint_type	percentage
communal standpipe	28522	48.02
hand pump	17488	29.44
other	6380	10.74
communal standpipe multiple	6103	10.27
improved spring	784	1.32
cattle trough	116	0.20
dam	7	0.01

	waterpoint_type_group	percentage
communal standpipe	34625	58.29
hand pump	17488	29.44
other	6380	10.74
improved spring	784	1.32
cattle trough	116	0.20
dam	7	0.01

waterpoint_type_group consolidated the standpipes together. I would say we keep them separate, use waterpoint_type and add waterpoint_type_group to the drop list.

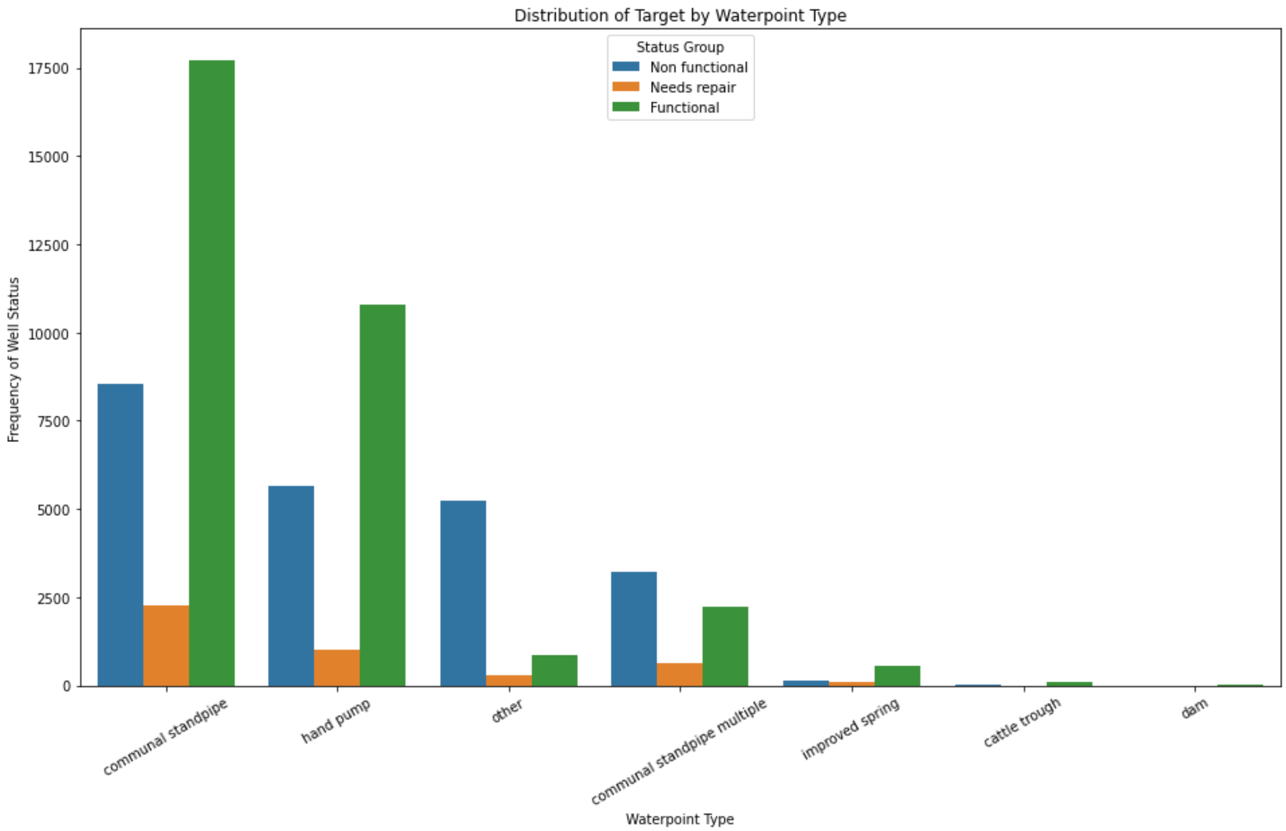
In [136…

```
drop_list.append('waterpoint_type_group')
```

In [137…

```
# set up order for waterpoint type
waterpoint_order = list(waterpoint_type_df.index)

fig, ax = plt.subplots(figsize=(16,9))
ax = sns.countplot(data=cat_df, x='waterpoint_type', hue='target',
                   order=waterpoint_order)
ax.set_title('Distribution of Target by Waterpoint Type')
ax.set_ylabel('Frequency of Well Status')
ax.set_xlabel('Waterpoint Type')
ax.set_xticklabels(ax.get_xticklabels(),rotation = 30)
ax.legend(title='Status Group', labels=['Non functional', 'Needs repair',
                                        'Functional']);
```

```
# plt.savefig('images/targetdistbywaterpointtype.png')
```



In [138…

```
drop_list
```

Out[138…

```
['date_recorded',
 'funder',
 'installer',
 'wpt_name',
 'subvillage',
 'lga',
 'ward',
 'recorded_by',
 'scheme_name',
 'extraction_type',
 'extraction_type_group',
 'management',
 'management_group',
 'payment_type',
 'water_quality',
 'quantity_group',
 'source',
 'source_class',
 'waterpoint_type_group']
```

Preparing final dataframe

In [139…

```
# drop the features from our drop list
final_cat = cat_df.drop(drop_list, axis=1)
# also dropping the id column and the target, because we have that in numerical
final_cat.drop(['id', 'target'], axis=1, inplace=True)

# we do not need id, region_code, or date_recorded from numerical data
num_drop_list = ['id', 'region_code', 'date_recorded']
```

```
final_num = num_df.drop(num_drop_list, axis=1)

# combine the numerical and categorical data
final_df = pd.concat([final_cat, final_num], axis=1)
final_df.shape
```

Out[139…

```
(59400, 22)
```

We will save the encoded dataframe (with target) to a new .csv file, which we will open in our modeling notebook to reduce clutter.

In [140…

```
final_df.to_csv('data/modeling_data.csv')
```

In [ ]: