Tanzania Machine Learning Water Pump Classification

Data Exploration Notebook

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This project it available on github here: Github Project Link (https://github.com/ddey117/Tanzanian_Water_Pump_Classification)

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Overview

The website 'DrivenData' (https://www.drivendata.org/about/) finds partners to collaborate with in order to aggregate data to make available in an open competition of Data Scientists from around the globe to come together to solve large social issues. For this project, DrivenData partnered with Taarifa and the Tanzanian Ministry of Water in order to predict the functionality of water pumps in the country of Tanzania. Machine learning classifiers from the 'scikit-learn ' (https://scikit-learn.org/stable/) library were used to create a model for predictive maintenance of the water pumps.

Business Problem

Please feel free to check out my blog **here** for a more detailed dive into the problem.

Tanzania Water Scarcity

Several water points are established in Tanzania which currently supply the population with water, although this system is quite inefficient. Poor infrastructure and spotty maintenance plague the system with broken taps, broken pipes, and damaged supply sources. In addition, water pumps and plumbing make attractive targets for thieves. These factors and others block access to clean water from the established system.

The most common form of maintenance for these points is to repair them once they are no longer functional. This is not very efficient and is somewhat expensive, but it is magnitudes cheaper than establishing a new water point through drilling and installing of large equipment.

A better approach would be to prevent repairs from becoming necessary in the first place. Predictive maintenance constantly monitors the status of pumps in order to more efficiently maintain them. This is the goal of this project. Timely verification of the status of water pumps in the region can prevent further compounding of issues and can reduce maintenance costs significantly. Most importantly, it can bring fresh water to those who need it in a more efficient manner than before it was implemented.

For the past two decades, the Ministry of Water has been implementing sector reforms that aim at improving resource management and improving water supply in both rural and urban environments. An attempt to determine if predictive maintenance could help the Ministry of Water in the overall success of their mission statement.

Because the first goal is to predict if an unknown water pump is either functional or nonfunctional before ever sending anyone to physically check the pump I decided to simplify things for this project and only predict two labels instead of the three described by DrivenData in their competition. Future work could prove valuable to treat the issues as a tertiary classification problem, with focus on creating a more sophisticated model with proper class imbalance techniques. Focusing for now on creating a strong predictive model for a binary classification problem can be very beneficial for the immediate needs of the Ministry of Water.

A team will need different equipment, training, and other resources in order to do simple maintenance on a functional pump versus fully repairing a non-functional pump. It is critical to improve the efficiency of pump maintenance and repair to ensure more people can get what they need to survive as quickly as possible.

Without any model to make predictions, the Ministry of Water would have to physically check all of the pumps. The teams sent could bring just what they would need to maintain clean pumps, and only have what they need for a little over half of the pumps. Then they could record which pumps were maintained and which pumps still need to be repaired, go back to base, gather the proper supplies, and deploy again with the proper resources.

The ‘date recorded’ column in the dataset available from the DrivenData competition reveals that in 2011 nearly 28k water pumps were physically checked for their status. This seems to be the current capacity for just the exploratory part of maintenance before ever sending the proper equipment or supplies to fix what needs fixed. We could imagine how resource intensive this could be through a

little bit of speculation. If one team could check 3 pumps a day, worked five days a week with no holidays, and never took any additional time off, it would still take around 40 teams even under these unrealistic, intense conditions. This doesn't even consider the few months a year that Tanzania has heavy rains that could prove to slow progress even further. These 40 teams would need the proper equipment to navigate long distances. Tanzania has some of the most diverse geography in the world, with from some of the world's tallest mountain ranges and volcanoes, dense jungle, arid grassland with no shade from the intensity of the African sun, treacherous valleys, and seasonal flooding as just some features of Tanzania geography that can impede this first round of physical exploration before the second round in which resources can finally be directed to where they need to be. This burden can significantly lower whatever money and resources would even be left to buy and send the equipment that is needed after funding all of this exploration.

Thus, being able to reliably predict the status of a pump without physically checking the water pump could be extremely important. Reducing the amount of resources necessary for this crucial step can free up resources to return functionality to important water points to the communities that desperately need them, increasing the amount of people with access to fresh water. Furthermore, these communities will get access to fresh water on a much shorter timeline.

In [1]:
```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import pandas_profiling
from collections import Counter
from sklearn.preprocessing import OneHotEncoder

sns.set_theme(style="darkgrid")
```

Data Understanding

Target: status_group

There is a clear class imbalance when looking at the distrubtion of the three target labels. There are a lot fewer pumps that are functional but need repair than either the function or non functional pumps. This could create a bias in my models towards the heavier weighted samples unless I attempt to balance the data. For my project, I decided to simplify things and create a binary classifcation model that identifies pumps as either being functional or non-functional. All functional-needs-repair pumps will be binned with non-functional pumps. Future work will focus on more sophisticated methods to handle the class imbalance and build a model to solve a tertiary problem instead.

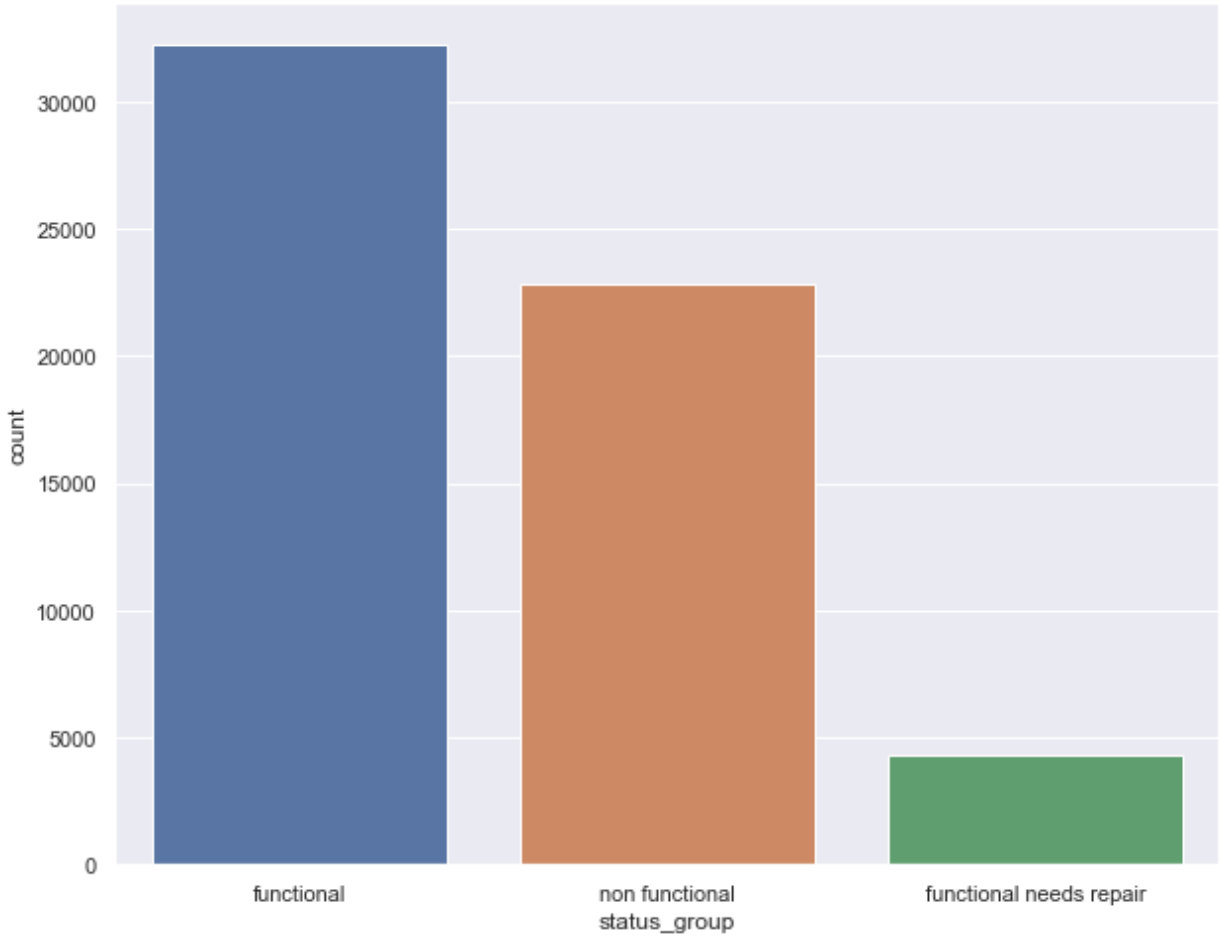
Data Understanding

In [2]:
```
train_labels = pd.read_csv('data/0bf8bc6e-30d0-4c50-956a-603fc693d966.c
display(train_labels.head())
train_labels.status_group.value_counts(normalize=True)
```

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

Out[2]:
```
functional                  0.543081
non functional              0.384242
functional needs repair     0.072677
Name: status_group, dtype: float64
```

In [3]:
```
fig = plt.figure(figsize=(10,8))
sns.countplot(x='status_group', data=train_labels)
plt.show();
```



In [4]:
```
train_features = pd.read_csv('data/4910797b-ee55-40a7-8668-10efd5c1b960
train_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 40 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object 
 3   funder                 55765 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              55745 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59400 non-null  object 
 9   num_private            59400 non-null  int64  
 10  basin                  59400 non-null  object 
 11  subvillage             59029 non-null  object 
 12  region                 59400 non-null  object 
 13  region_code            59400 non-null  int64  
 14  district_code          59400 non-null  int64  
 15  lga                    59400 non-null  object 
 16  ward                   59400 non-null  object 
 17  population             59400 non-null  int64  
 18  public_meeting         56066 non-null  object 
 19  recorded_by            59400 non-null  object 
 20  scheme_management      55523 non-null  object 
 21  scheme_name            31234 non-null  object 
 22  permit                 56344 non-null  object 
 23  construction_year      59400 non-null  int64  
 24  extraction_type        59400 non-null  object 
 25  extraction_type_group  59400 non-null  object 
 26  extraction_type_class  59400 non-null  object 
 27  management             59400 non-null  object 
 28  management_group       59400 non-null  object 
 29  payment                59400 non-null  object 
 30  payment_type           59400 non-null  object 
 31  water_quality          59400 non-null  object 
 32  quality_group          59400 non-null  object 
 33  quantity               59400 non-null  object 
 34  quantity_group         59400 non-null  object 
 35  source                 59400 non-null  object 
 36  source_type            59400 non-null  object 
 37  source_class           59400 non-null  object 
 38  waterpoint_type        59400 non-null  object 
 39  waterpoint_type_group  59400 non-null  object 
dtypes: float64(3), int64(7), object(30)
memory usage: 18.1+ MB
```

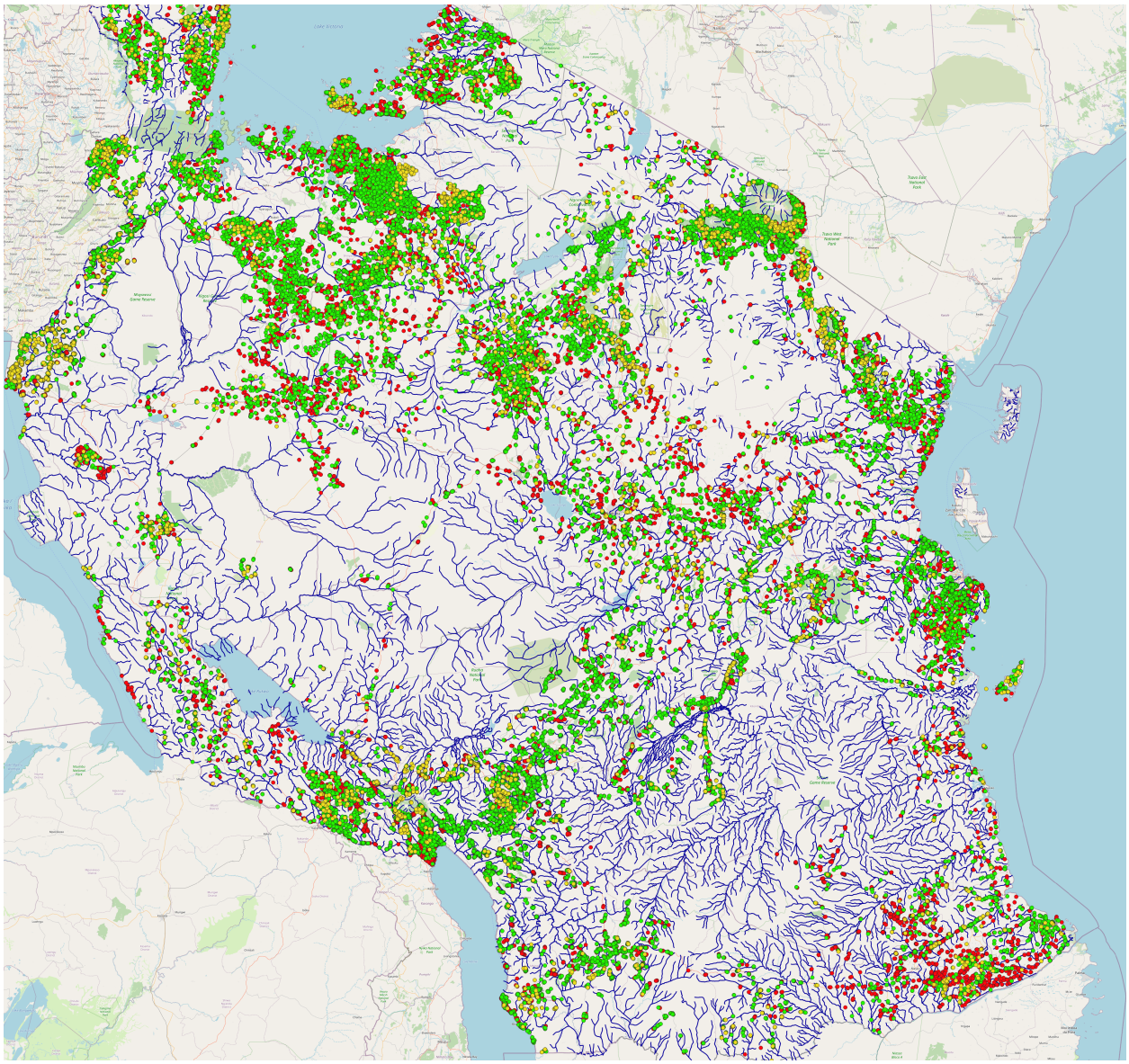
In [5]:
```
#merge training features and training labels in order
#to explore the data
df = train_features.merge(train_labels, on='id').copy()
```

Geodata Exploration

River Distance using QGIS

In [6]:
```
#create a subset of data that just contains
#coordinates of the pumps
#in order to analyze using free open source
#QGIS software and open GIS data
latlong = df[['latitude', 'longitude', 'status_group']]
latlong.to_csv('data/latlong2.csv')
```

The map below was created using QGIS software. Green doots represent fully functional pumps. Yellow dots refer to pumps that are functional but in need of repair. The red dots are the pumps that are non-functional. A quick glance will reveal that there are some clusters that represent different distrubtions of functional to non functional pumps. However, it doesn't look like latitude or longitude alone would be very predictive variables to consider. Will drop latitude and longitude for modeling and keep other more broad geological predictors.



click below for a pdf version of map with zoom functionality.

water_pump_pdf (images/map_image.png.pdf)

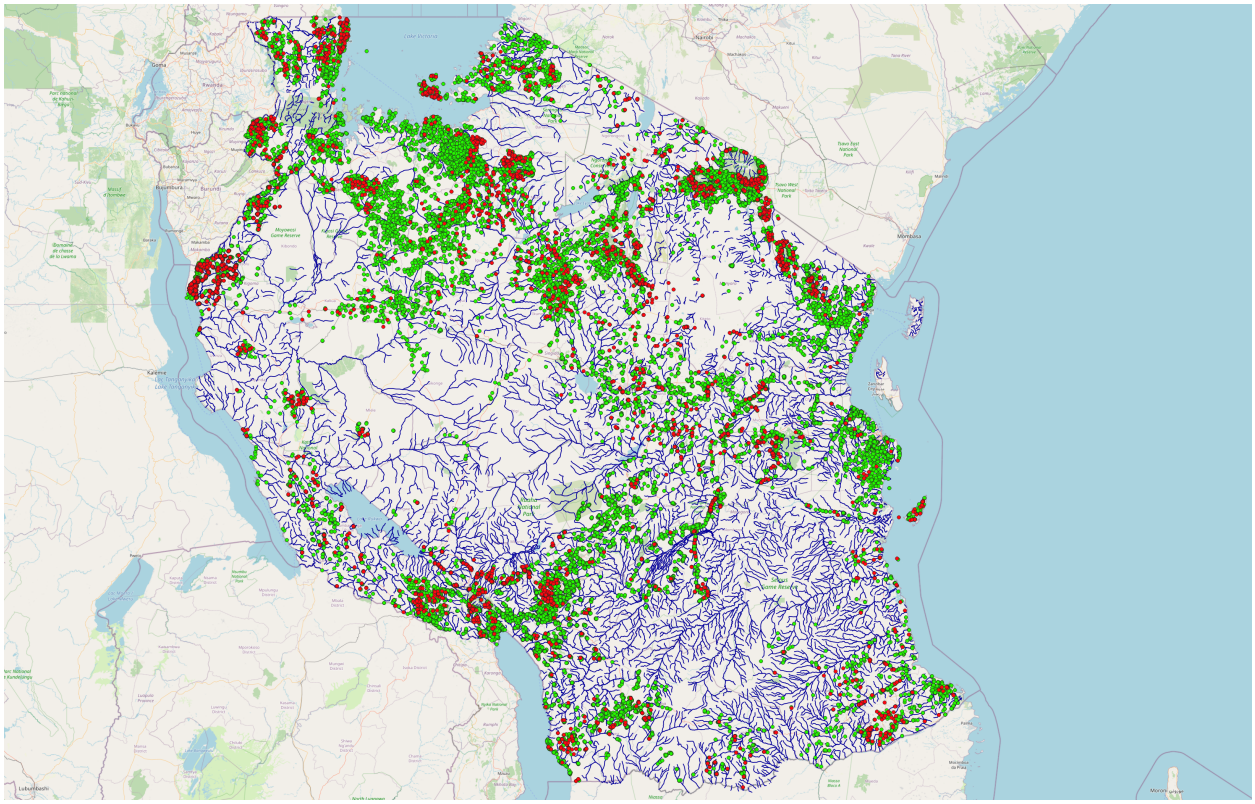
Knowing what pumps are functional/nonfunctional and being sure about it can prove essential for our predictive maitenance model. In this way, we can save resources by being sure which communities already have what they need vs communities that are more desperate for assistance and resources. There is a strong class imbalance in the tertiary model. In the future I would like to use more sophisticated methods to try to deal with the class imbalance and make predictions on all 3 labels. It could help to save even more money and resources to be able to accurately distinguish between functional needs repair and non functional. However, for now, I think building a reasonably accurate binary model is an excellent starting place for predictive maintenance.

In [7]:
```
need_repair_index = df['status_group'] == 'functional needs repair'
df_binary = df.copy()
df_binary.loc[need_repair_index, 'status_group'] = 'non functional'
```

In [8]:
```
df_binary['status_group'].value_counts()
```

Out[8]:
```
functional        32259
non functional    27141
Name: status_group, dtype: int64
```

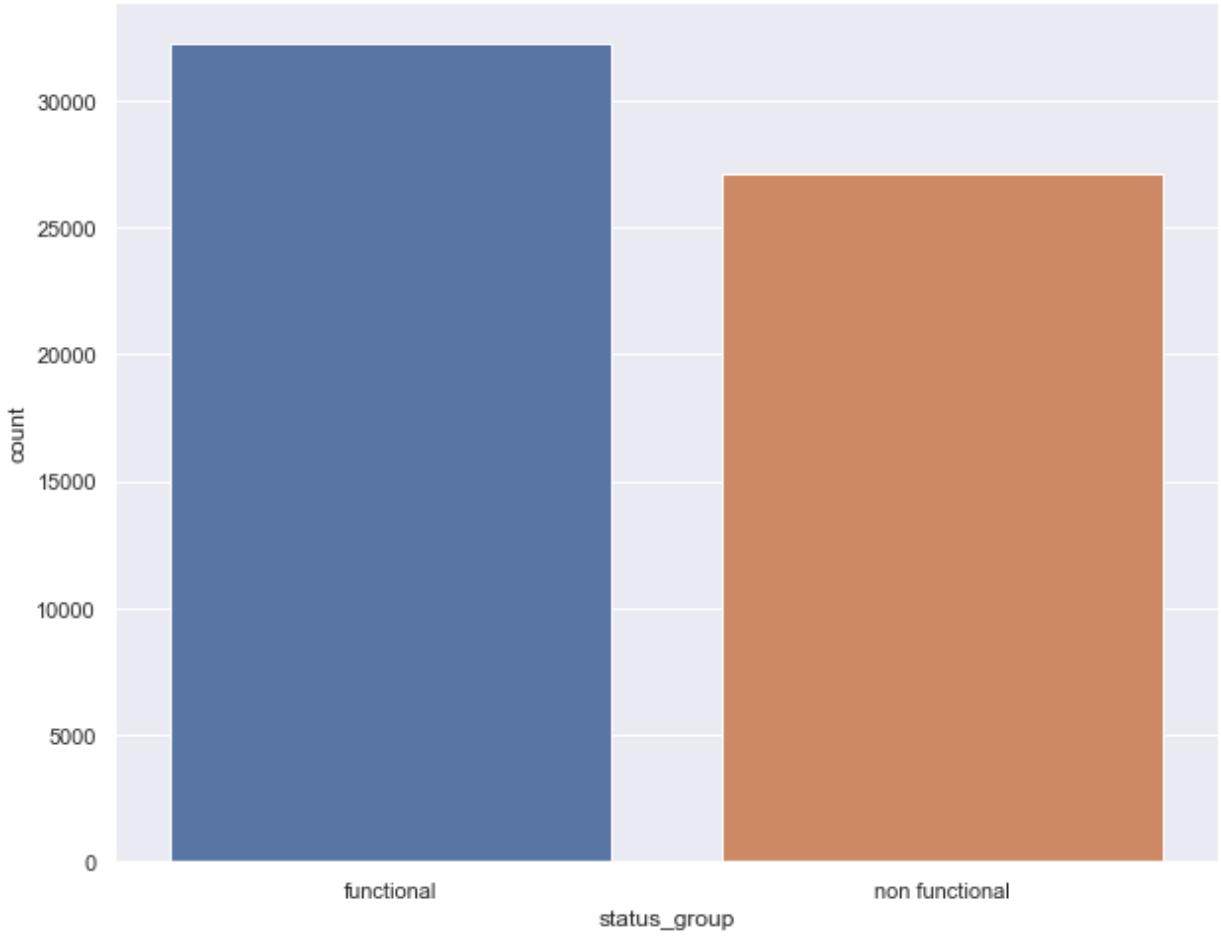
Below is an unpdated map for a binary classifcation model.



click below for a pdf version of map with zoom functionality.

water_pump_pdf (images/binary_map2.pdf)

In [9]:
```
fig = plt.figure(figsize=(10,8))
sns.countplot(x='status_group', data=df_binary)
#plt.savefig('images/binary_status.png')
plt.show();
```



In [10]:
```
river_df = pd.read_csv('data/river_dist2.csv')
river_df.head()
```

Out[10]:

	field_1	latitude	longitude	HubName	HubDist
0	0	-9.856322	34.938093	River/Stream	8.025861
1	1	-2.147466	34.698766	River/Stream	7.538778
2	2	-3.821329	37.460664	River/Stream	2.523575
3	3	-11.155298	38.486161	River/Stream	8.307942
4	4	-1.825359	31.130847	River/Stream	4.524439

In [11]:
```
#because some of the distance vectors were created with false coordinat
#I decided to fill in the incorrect distance values
#with the median distance for distance to nearest river
#there are about 1800 rows with incorrect lat/long coordinates
#these 1800 rows show lat/long values of zero which
#are obvious outliers when plotted on a map

index_riv = river_df[river_df['HubDist'] >66].index
river_median = river_df['HubDist'].median()
river_df.loc[index_riv, 'HubDist'] = river_median
river_df['HubDist'].describe()
```

Out[11]:
```
count    59400.000000
mean         8.520694
std          6.833602
min          0.035102
25%          4.237760
50%          7.115599
75%         10.669175
max         65.057665
Name: HubDist, dtype: float64
```

In [12]:
```
#create a booleon feature describing whether
#a water pump is within 8 km of a river

river_s = river_df['HubDist'].copy()
river_s.rename('near_river', inplace=True)
near_river = river_s[river_s < 8].apply(lambda x: 1 if not pd.isnull(x)
df = df.join(near_river)
df.near_river.fillna(0, inplace=True)
df.near_river.value_counts(normalize=True)
```

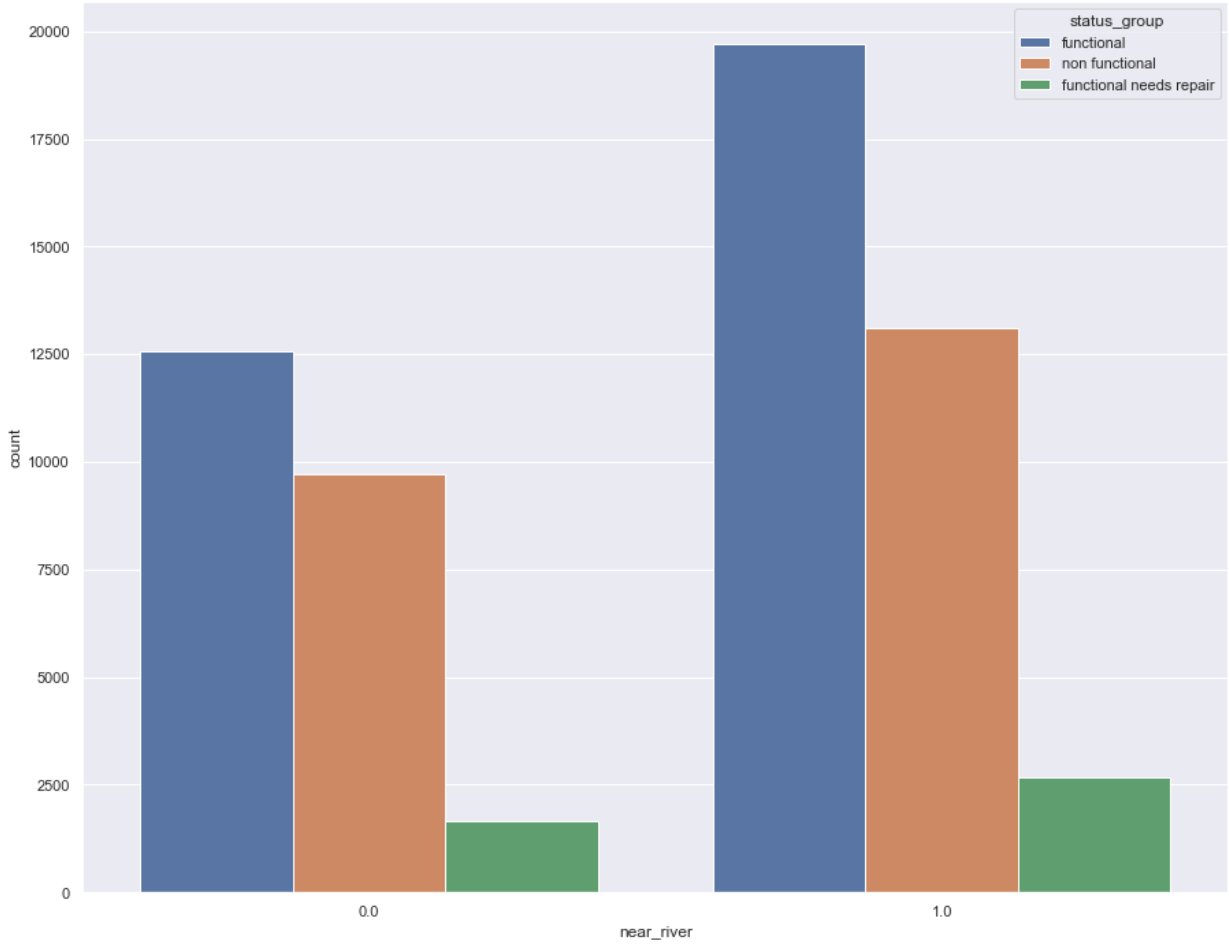
Out[12]:
```
1.0    0.597323
0.0    0.402677
Name: near_river, dtype: float64
```

In [13]:
```
display(df[df['near_river'] == 1]['status_group'].value_counts(normaliz
df[df['near_river'] == 0]['status_group'].value_counts(normalize=True)
```

```
functional                 0.555311
non functional             0.369663
functional needs repair    0.075026
Name: status_group, dtype: float64
```

Out[13]:
```
functional                 0.524938
non functional             0.405870
functional needs repair    0.069192
Name: status_group, dtype: float64
```

In [14]:
```
fig = plt.figure(figsize=(15,12))
sns.countplot(x='near_river', hue='status_group', data=df)
plt.show();
```



In [15]:
```
#profile = pandas_profiling.ProfileReport(df.copy())
#profile.to_file("output.html")
```

Adding Population data by ward

The column describing population is heavily skewed towards a value of zero, and it would seem very unlikely for so many wells to have a population of zero. Nearly 50% of the data is skewed towards a value of either zero or one. It is hard to trust the validaty of this column. I decided to drop this column and bring in population information by ward collected by government census in 2012. This data has its own issues but I believe it to be a more complete dataset and give a better idea about the number of people who could benefit from the presence of a functional well in their area. Ward is a pretty high level division of geological boundaries for Tanzania. May have to revisit this population data at a later date.

In [16]:
```
df_pop = pd.read_excel('data/tza-pop-popn-nbs-baselinedata-xlsx-1.xlsx'
display(df_pop.head())
df_pop['Ward_Name'].isna().sum()
```

	Reg_Code	Reg_Name	Dis_Code	Dis_Name	Ward_Code	Ward_Name	Division	PCode	total_bo
0	1	Dodoma	1	Kondoa	11	Bumbuta	NaN	101011	86
1	1	Dodoma	1	Kondoa	21	Pahi	NaN	101021	139
2	1	Dodoma	1	Kondoa	41	Haubi	NaN	101041	137
3	1	Dodoma	1	Kondoa	51	Kalamba	NaN	101051	139
4	1	Dodoma	1	Kondoa	61	Kwadelo	NaN	101061	115

5 rows × 21 columns

Out[16]: 0

In [17]:
```
#create a dictionary of values with format {Ward : Total Population}

pop_index = df_pop.groupby('Ward_Name')['total_both'].sum().index
pop_values = df_pop.groupby('Ward_Name')['total_both'].sum().values
pop_dict = dict(zip(pop_index, pop_values))

#create pandas Dataframe for merging
pop_dataframe = pd.DataFrame.from_dict(pop_dict, orient='index')
#rename column for clarity
pop_dataframe.rename(columns={0: 'ward_pop'}, inplace=True)
```

In [18]:
```
#merge dataframes
df_pop_merge = df.merge(pop_dataframe,
                                how='left',
                                left_on='ward',
                                right_index=True)

df_pop_merge.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 43 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object 
 3   funder                 55765 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              55745 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59400 non-null  object 
 9   num_private            59400 non-null  int64  
 10  basin                  59400 non-null  object 
 11  subvillage             59029 non-null  object 
 12  region                 59400 non-null  object 
 13  region_code            59400 non-null  int64  
 14  district_code          59400 non-null  int64  
 15  lga                    59400 non-null  object 
 16  ward                   59400 non-null  object 
 17  population             59400 non-null  int64  
 18  public_meeting         56066 non-null  object 
 19  recorded_by            59400 non-null  object 
 20  scheme_management      55523 non-null  object 
 21  scheme_name            31234 non-null  object 
 22  permit                 56344 non-null  object 
 23  construction_year      59400 non-null  int64  
 24  extraction_type        59400 non-null  object 
 25  extraction_type_group  59400 non-null  object 
 26  extraction_type_class  59400 non-null  object 
 27  management             59400 non-null  object 
 28  management_group       59400 non-null  object 
 29  payment                59400 non-null  object 
 30  payment_type           59400 non-null  object 
 31  water_quality          59400 non-null  object 
 32  quality_group          59400 non-null  object 
 33  quantity               59400 non-null  object 
 34  quantity_group         59400 non-null  object 
 35  source                 59400 non-null  object 
 36  source_type            59400 non-null  object 
 37  source_class           59400 non-null  object 
 38  waterpoint_type        59400 non-null  object 
 39  waterpoint_type_group  59400 non-null  object 
 40  status_group           59400 non-null  object 
 41  near_river             59400 non-null  float64
 42  ward_pop               53000 non-null  float64
```

```
dtypes: float64(5), int64(7), object(31)
memory usage: 22.4+ MB
```

In [19]:
```
#replace null values of ward population with
#median ward population

ward_pop_median = df_pop_merge['ward_pop'].median()
df_pop_merge.fillna(value=ward_pop_median, inplace=True)
df_pop_merge['ward_pop'].isna().sum()
```

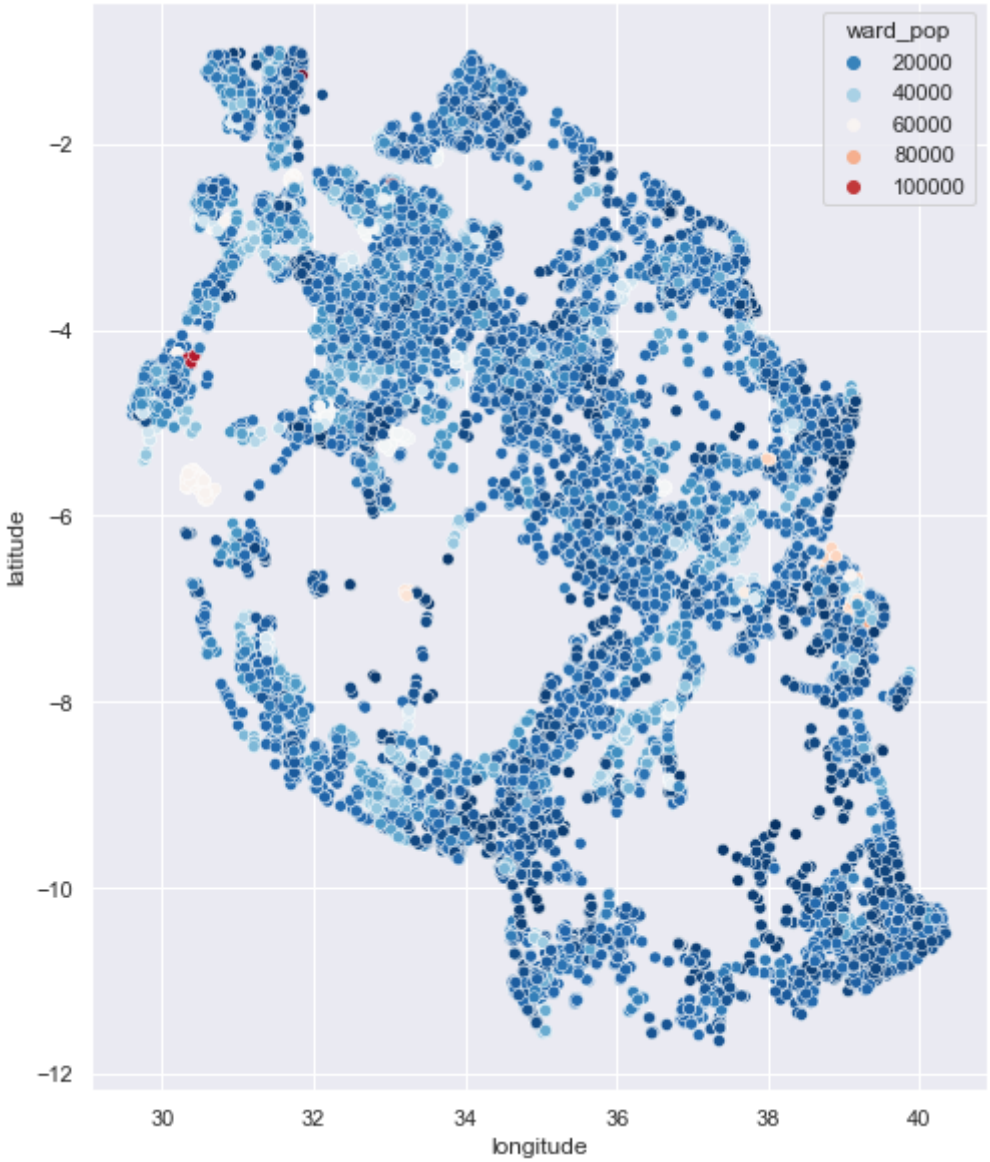
Out[19]: 0

In [20]:
```
ward_pop_s = df_pop_merge['ward_pop'].copy()
df = df.join(ward_pop_s)
df.drop(columns=['population'], axis=1, inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 42 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object 
 3   funder                 55765 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              55745 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59400 non-null  object 
 9   num_private            59400 non-null  int64  
 10  basin                  59400 non-null  object 
 11  subvillage             59029 non-null  object 
 12  region                 59400 non-null  object 
 13  region_code            59400 non-null  int64  
 14  district_code          59400 non-null  int64  
 15  lga                    59400 non-null  object 
 16  ward                   59400 non-null  object 
 17  public_meeting         56066 non-null  object 
 18  recorded_by            59400 non-null  object 
 19  scheme_management      55523 non-null  object 
 20  scheme_name            31234 non-null  object 
 21  permit                 56344 non-null  object 
 22  construction_year      59400 non-null  int64  
 23  extraction_type        59400 non-null  object 
 24  extraction_type_group  59400 non-null  object 
 25  extraction_type_class  59400 non-null  object 
 26  management             59400 non-null  object 
 27  management_group       59400 non-null  object 
 28  payment                59400 non-null  object 
 29  payment_type           59400 non-null  object 
 30  water_quality          59400 non-null  object 
 31  quality_group          59400 non-null  object 
 32  quantity               59400 non-null  object 
 33  quantity_group         59400 non-null  object 
 34  source                 59400 non-null  object 
 35  source_type            59400 non-null  object 
 36  source_class           59400 non-null  object 
 37  waterpoint_type        59400 non-null  object 
 38  waterpoint_type_group  59400 non-null  object 
 39  status_group           59400 non-null  object 
 40  near_river             59400 non-null  float64
 41  ward_pop               59400 non-null  float64
dtypes: float64(5), int64(6), object(31)
memory usage: 22.0+ MB
```

In [21]:
```
fig_df = df.copy()
to_drop_index = fig_df[fig_df['longitude'] == 0].index
fig_df = fig_df.drop(to_drop_index)
```

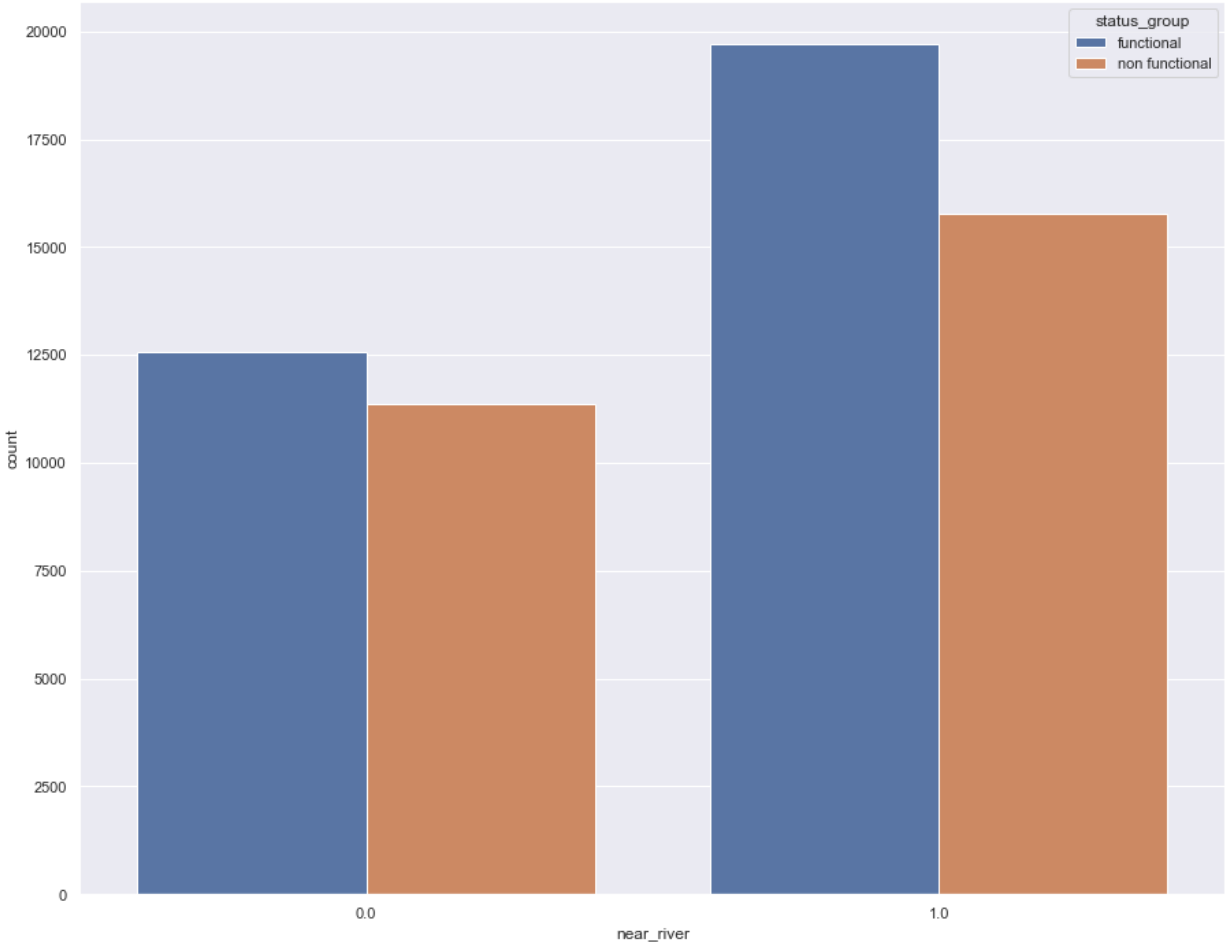
In [22]:
```
#wquick visualization of the density of population around pumps
#derived from ward population government census data
pop_fig = plt.figure(figsize=(8,10))
sns.scatterplot(x='longitude',
                y='latitude',
                hue='ward_pop',
                data=fig_df,
                palette="RdBu_r",
               )

#plt.savefig('images/ward_pop_map.png')
plt.show();
```



Binary Classification Model Binning

In [23]:
```
df_binary = df.copy()
df_binary.loc[need_repair_index, 'status_group'] = 'non functional'
```

In [24]:
```
fig = plt.figure(figsize=(15,12))
sns.countplot(x='near_river', hue='status_group', data=df_binary)
plt.show();
```



At this point, I have my dataframe that I will treat as my raw data.

Data Cleaning

Dropping Redundant and Uninformative Columns Overview

Below are the columns that I decided to drop initially and the reasoning behind dropping the column. This step will help overall model speeds and should reduce the chance of overfitting by cutting down on multicolinearity.

id: uninformitave
recorded_by: constant, unimportant for model
num_private: nearly 99% zeroes. Uninformative for model.
waterpoint_type_group: redundant. waterpoint_type covers same information.
source: Explains same information as source_type but with more variables. Keeping source_type.
source_class: Broadly explains same information as source and source_type. Keeping

source_type.
Source_type: This was NOT dropped. Kept it as a balance between the other two features of similar information.
extraction_type: explains similar information as extration_type_group and extraction_type_class. Dropped.
extraction_type_group: explains similar information as extration_type and extraction_type_class. Dropped.
extraction_type_class: broadly explains similar information as extraction_type and extraction_type_group. Kept.
payment: redundant information. Keep this and drop 'payment type'
payment_type: Same information as payment. Drop.
management: keep this and drop 'management_type'.
management_group: drop. Information contained within management column.
scheme_name: drop. Missing almost half of values. Large cardinality (nearly 2700 categories).
scheme_manager: drop. Contains similar information to management column.
water_quality: Keep this and drop 'quality group.' **water_quantity:** Keep this and drop water_quantity. They contain identical information. **date_recorded:** administrative. Not predictive.
latitude: No clear relationship between coordinate and pump status after viewing map. There is some obvious clustering though. Hope to get enough information from the other geological categorical features. Basin is likely to always show up in feature data as it is most general. Latitude and longitude for the pumps may even be imputed from mean or median values based on ward or some other common geological boundaries. Dropped. **longitude**: See above comments on latitude. Dropped.

In [25]:
```
1 df.columns
```

Out[25]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'wpt_name', 'num_private',
       'basin', 'subvillage', 'region', 'region_code', 'district_code',
'lga',
       'ward', 'public_meeting', 'recorded_by', 'scheme_management',
       'scheme_name', 'permit', 'construction_year', 'extraction_type',
       'extraction_type_group', 'extraction_type_class', 'management',
       'management_group', 'payment', 'payment_type', 'water_quality',
       'quality_group', 'quantity', 'quantity_group', 'source', 'source_t
ype',
       'source_class', 'waterpoint_type', 'waterpoint_type_group',
       'status_group', 'near_river', 'ward_pop'],
      dtype='object')
```

In [26]:
```
#view dataframe in different orientation
#to check for redundant information
df.head(10).transpose()
```

Out[26]:

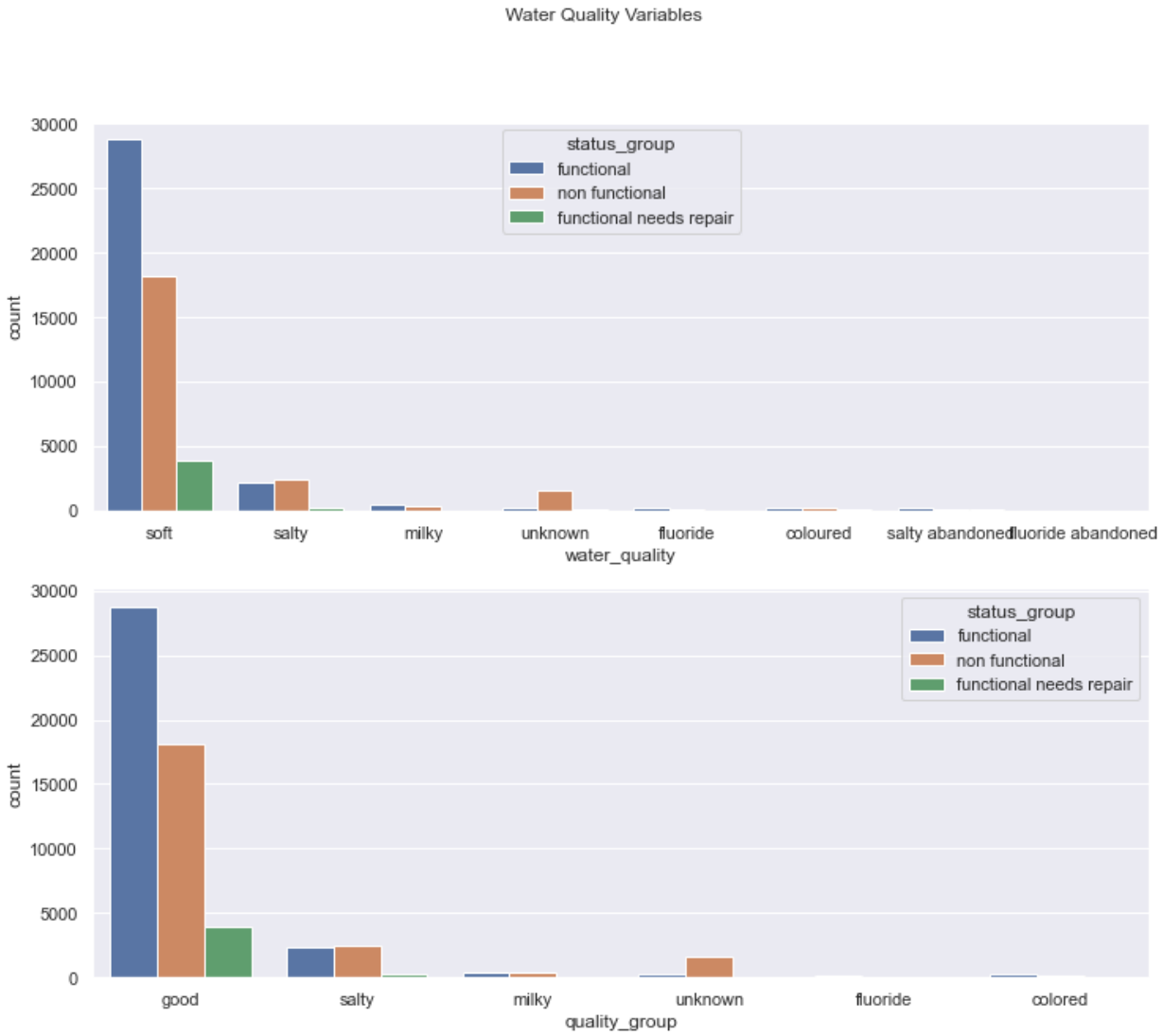
	0	1	2	3	4	5
id	69572	8776	34310	67743	19728	9944
amount_tsh	6000	0	25	0	0	20
date_recorded	2011-03-14	2013-03-06	2013-02-25	2013-01-28	2011-07-13	2011-03-13
funder	Roman	Grumeti	Lottery Club	Unicef	Action In A	Mkinga Distric Coun
gps_height	1390	1399	686	263	0	0
installer	Roman	GRUMETI	World vision	UNICEF	Artisan	DWE
longitude	34.9381	34.6988	37.4607	38.4862	31.1308	39.1728
latitude	-9.85632	-2.14747	-3.82133	-11.1553	-1.82536	-4.76559
wpt_name	none	Zahanati	Kwa Mahundi	Zahanati Ya Nanyumbu	Shuleni	Tajiri
num_private	0	0	0	0	0	0
basin	Lake Nyasa	Lake Victoria	Pangani	Ruvuma / Southern Coast	Lake Victoria	Pangani
subvillage	Mnyusi B	Nyamara	Majengo	Mahakamani	Kyanyamisa	Moa/Mwereme
region	Iringa	Mara	Manyara	Mtwara	Kagera	Tanga
region_code	11	20	21	90	18	4
district_code	5	2	4	63	1	8
lga	Ludewa	Serengeti	Simanjiro	Nanyumbu	Karagwe	Mkinga
ward	Mundindi	Natta	Ngorika	Nanyumbu	Nyakasimbi	Moa
public_meeting	True	NaN	True	True	True	True
recorded_by	GeoData Consultants Ltd	GeoData Consultants Ltd	GeoData Consultants Ltd	GeoData Consultants Ltd	GeoData Consultants Ltd	GeoData Consultants Ltd
scheme_management	VWC	Other	VWC	VWC	NaN	VWC
scheme_name	Roman	NaN	Nyumba ya mungu pipe scheme	NaN	NaN	Zingibali
permit	False	True	True	True	True	True
construction_year	1999	2010	2009	1986	0	2009
extraction_type	gravity	gravity	gravity	submersible	gravity	submersible
extraction_type_group	gravity	gravity	gravity	submersible	gravity	submersible
extraction_type_class	gravity	gravity	gravity	submersible	gravity	submersible

	0	1	2	3	4	5
management	vwc	wug	vwc	vwc	other	vwc
management_group	user-group	user-group	user-group	user-group	other	user-group
payment	pay annually	never pay	pay per bucket	never pay	never pay	pay per bucket
payment_type	annually	never pay	per bucket	never pay	never pay	per bucket
water_quality	soft	soft	soft	soft	soft	salty
quality_group	good	good	good	good	good	salty
quantity	enough	insufficient	enough	dry	seasonal	enough
quantity_group	enough	insufficient	enough	dry	seasonal	enough
source	spring	rainwater harvesting	dam	machine dbh	rainwater harvesting	other
source_type	spring	rainwater harvesting	dam	borehole	rainwater harvesting	other
source_class	groundwater	surface	surface	groundwater	surface	unknown
waterpoint_type	communal standpipe	communal standpipe	communal standpipe multiple	communal standpipe multiple	communal standpipe	communal standpipe multiple
waterpoint_type_group	communal standpipe	communal standpipe	communal standpipe	communal standpipe	communal standpipe	communal standpipe
status_group	functional	functional	functional	non functional	functional	functional
near_river	0	1	1	0	1	1
ward_pop	7346	12849	7417	10826	12803	4339

Water_quality vs Quality_group

Both of these columns contain essentially the same information, subgrouped differently. I decided to keep 'water_quality' and drop 'quality_group' in order to avoid overfitting issues and speed up the iterative modeling process.

In [27]:
```
fig, (ax1, ax2) = plt.subplots(2, figsize=(12,10))
fig.suptitle('Water Quality Variables')
sns.countplot(x='water_quality', hue='status_group', data=df, ax=ax1)
sns.countplot(x='quality_group', hue='status_group', data=df, ax=ax2)
plt.show();
```



In [28]:
```
display(df.groupby('quality_group')['status_group'].value_counts(normal
df.groupby('water_quality')['status_group'].value_counts(normalize=True
```

```
quality_group  status_group
colored        functional                 0.502041
               non functional             0.387755
               functional needs repair    0.110204
fluoride       functional                 0.723502
               non functional             0.216590
               functional needs repair    0.059908
good           functional                 0.565941
               non functional             0.357236
               functional needs repair    0.076823
milky          functional                 0.544776
               non functional             0.437811
               functional needs repair    0.017413
salty          non functional             0.482002
               functional                 0.460828
               functional needs repair    0.057170
unknown        non functional             0.840618
               functional                 0.140725
               functional needs repair    0.018657
Name: status_group, dtype: float64
```

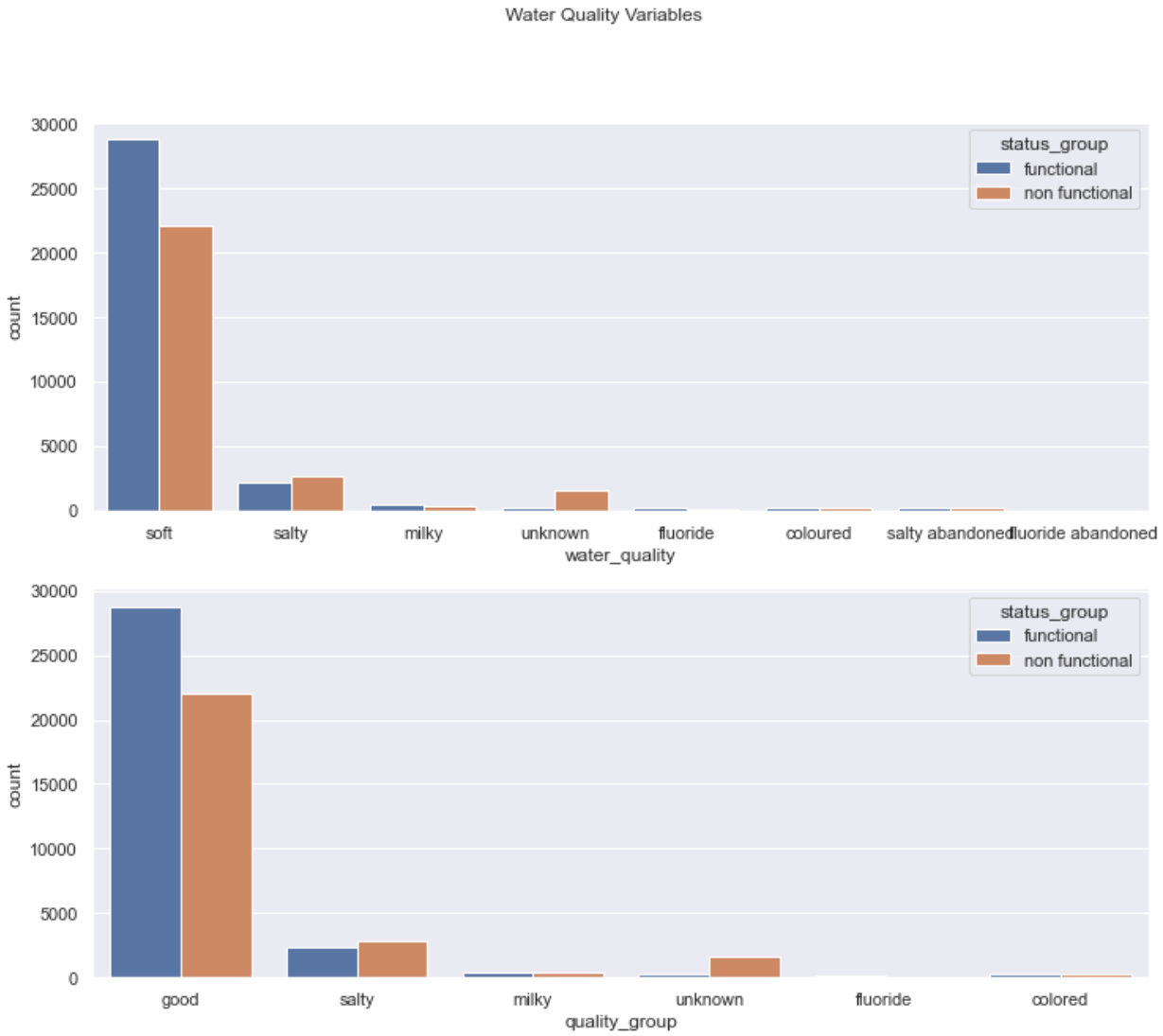
Out[28]:
```
water_quality       status_group
coloured            functional                 0.502041
                    non functional             0.387755
                    functional needs repair    0.110204
fluoride            functional                 0.755000
                    non functional             0.180000
                    functional needs repair    0.065000
fluoride abandoned  non functional             0.647059
                    functional                 0.352941
milky               functional                 0.544776
                    non functional             0.437811
                    functional needs repair    0.017413
salty               non functional             0.496499
                    functional                 0.457166
                    functional needs repair    0.046334
salty abandoned     functional                 0.513274
                    non functional             0.274336
                    functional needs repair    0.212389
soft                functional                 0.565941
                    non functional             0.357236
                    functional needs repair    0.076823
unknown             non functional             0.840618
                    functional                 0.140725
                    functional needs repair    0.018657
Name: status_group, dtype: float64
```

In [29]:
```
print('-----------------------------------------------------')
display(df_binary.groupby('quality_group')['status_group'].value_counts
df_binary.groupby('water_quality')['status_group'].value_counts(normali
```

```
-----------------------------------------------------

quality_group  status_group
colored        functional        0.502041
               non functional    0.497959
fluoride       functional        0.723502
               non functional    0.276498
good           functional        0.565941
               non functional    0.434059
milky          functional        0.544776
               non functional    0.455224
salty          non functional    0.539172
               functional        0.460828
unknown        non functional    0.859275
               functional        0.140725
Name: status_group, dtype: float64
```

Out[29]:
```
water_quality       status_group
coloured            functional        0.502041
                    non functional    0.497959
fluoride            functional        0.755000
                    non functional    0.245000
fluoride abandoned  non functional    0.647059
                    functional        0.352941
milky               functional        0.544776
                    non functional    0.455224
salty               non functional    0.542834
                    functional        0.457166
salty abandoned     functional        0.513274
                    non functional    0.486726
soft                functional        0.565941
                    non functional    0.434059
unknown             non functional    0.859275
                    functional        0.140725
Name: status_group, dtype: float64
```

In [30]:
```
fig, (ax1, ax2) = plt.subplots(2, figsize=(12,10))
fig.suptitle('Water Quality Variables')
sns.countplot(x='water_quality', hue='status_group', data=df_binary, ax
sns.countplot(x='quality_group', hue='status_group', data=df_binary, ax
plt.show();
```

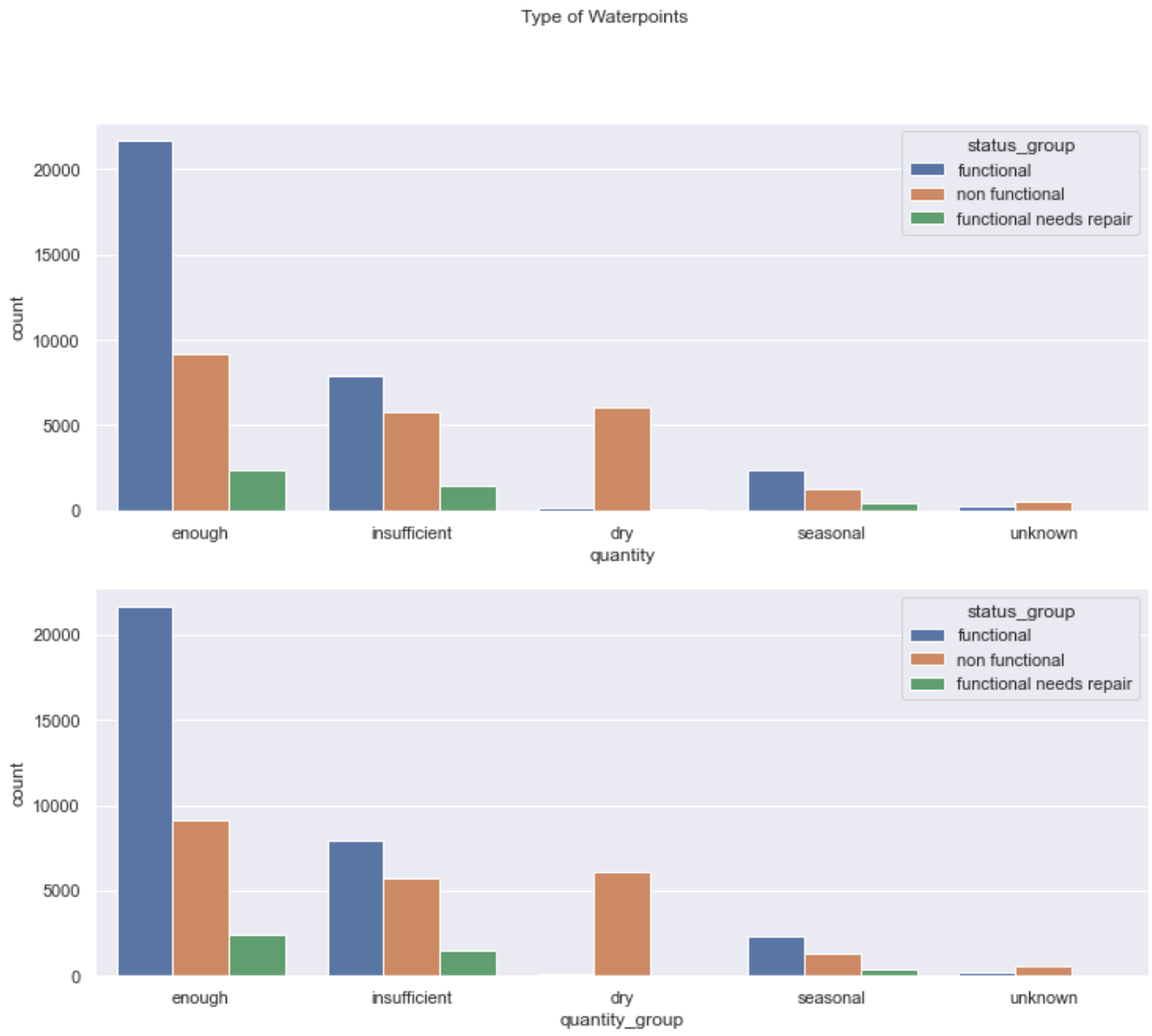


quantity and quantity_group

These columns are identical. Drop quantity group.

Quantity describes the amount of water avaiable. Dry pumps are non-functional, as expected. It is crucial that each pump has a sufficient water supply.

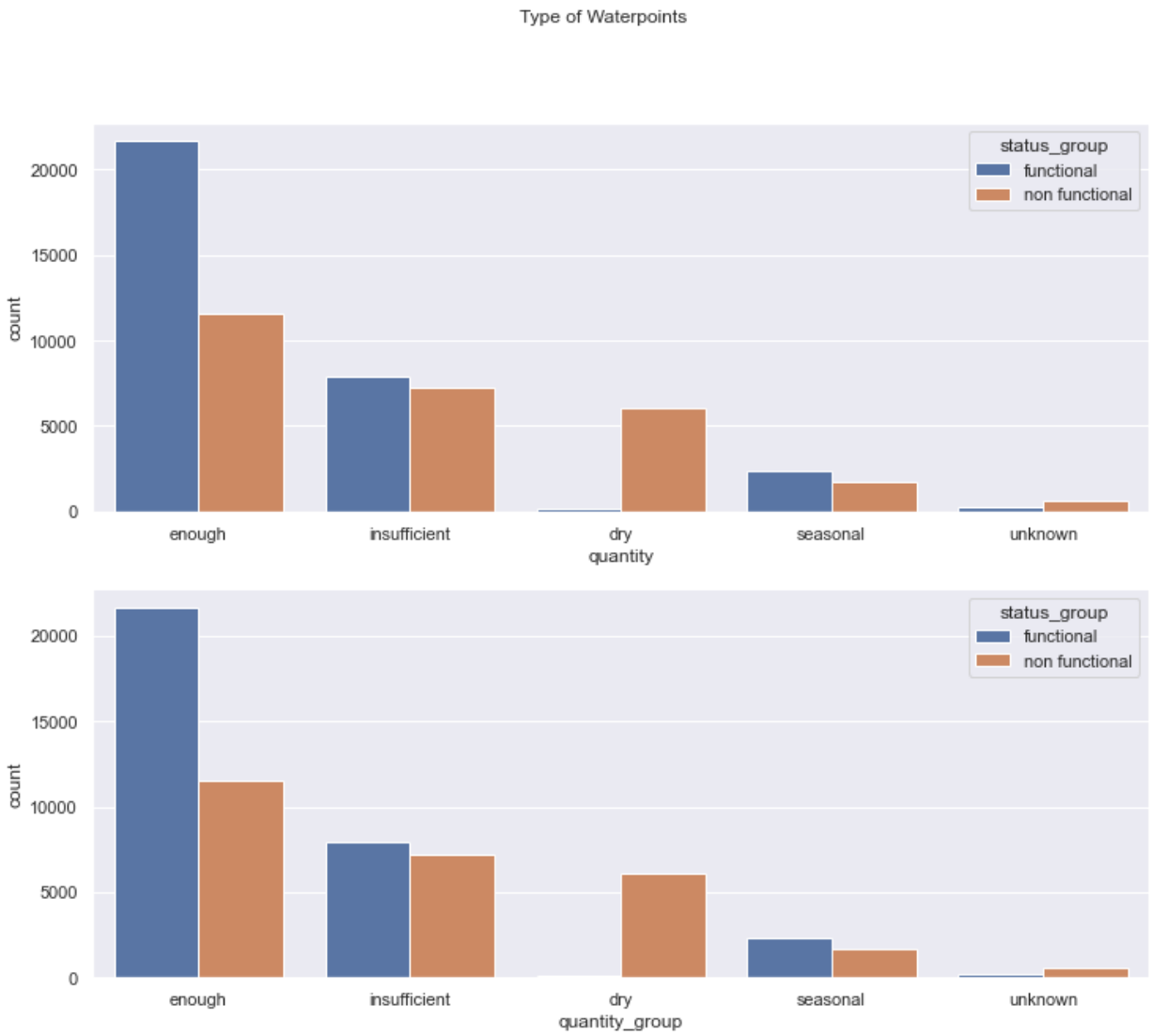
In [31]:
```
fig, (ax1, ax2) = plt.subplots(2, figsize=(12,10))
fig.suptitle('Type of Waterpoints')
sns.countplot(x='quantity', hue='status_group', data=df, ax=ax1)
sns.countplot(x='quantity_group', hue='status_group', data=df, ax=ax2)
plt.show();
```



Above: tertiary

Below: Binary

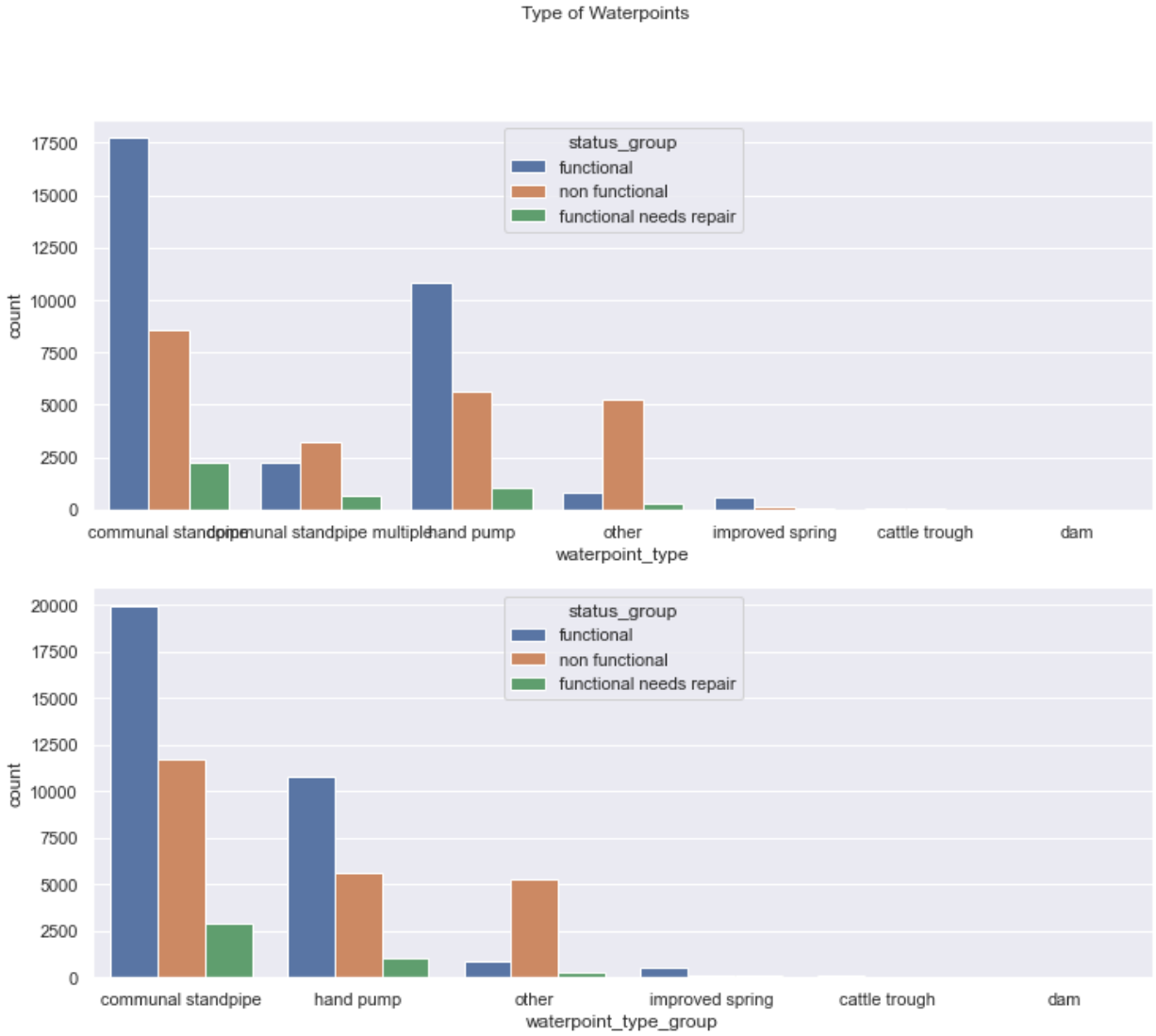
In [32]:
```
fig, (ax1, ax2) = plt.subplots(2, figsize=(12,10))
fig.suptitle('Type of Waterpoints')
sns.countplot(x='quantity', hue='status_group', data=df_binary, ax=ax1)
sns.countplot(x='quantity_group', hue='status_group', data=df_binary, a
plt.show();
```



waterpoint_type and waterpoint_type_group

Similar to what we saw above with water quality, both of these columns contain essentially the same information, subgrouped differently. I decided to keep 'waterpoint_type' and drop 'waterpoint_type_group' in order to avoid overfitting issues and speed up the iterative modeling process.

In [33]:
```
fig, (ax1, ax2) = plt.subplots(2, figsize=(12,10))
fig.suptitle('Type of Waterpoints')
sns.countplot(x='waterpoint_type', hue='status_group', data=df, ax=ax1)
sns.countplot(x='waterpoint_type_group', hue='status_group', data=df, a
plt.show();
```



Above: tertiary

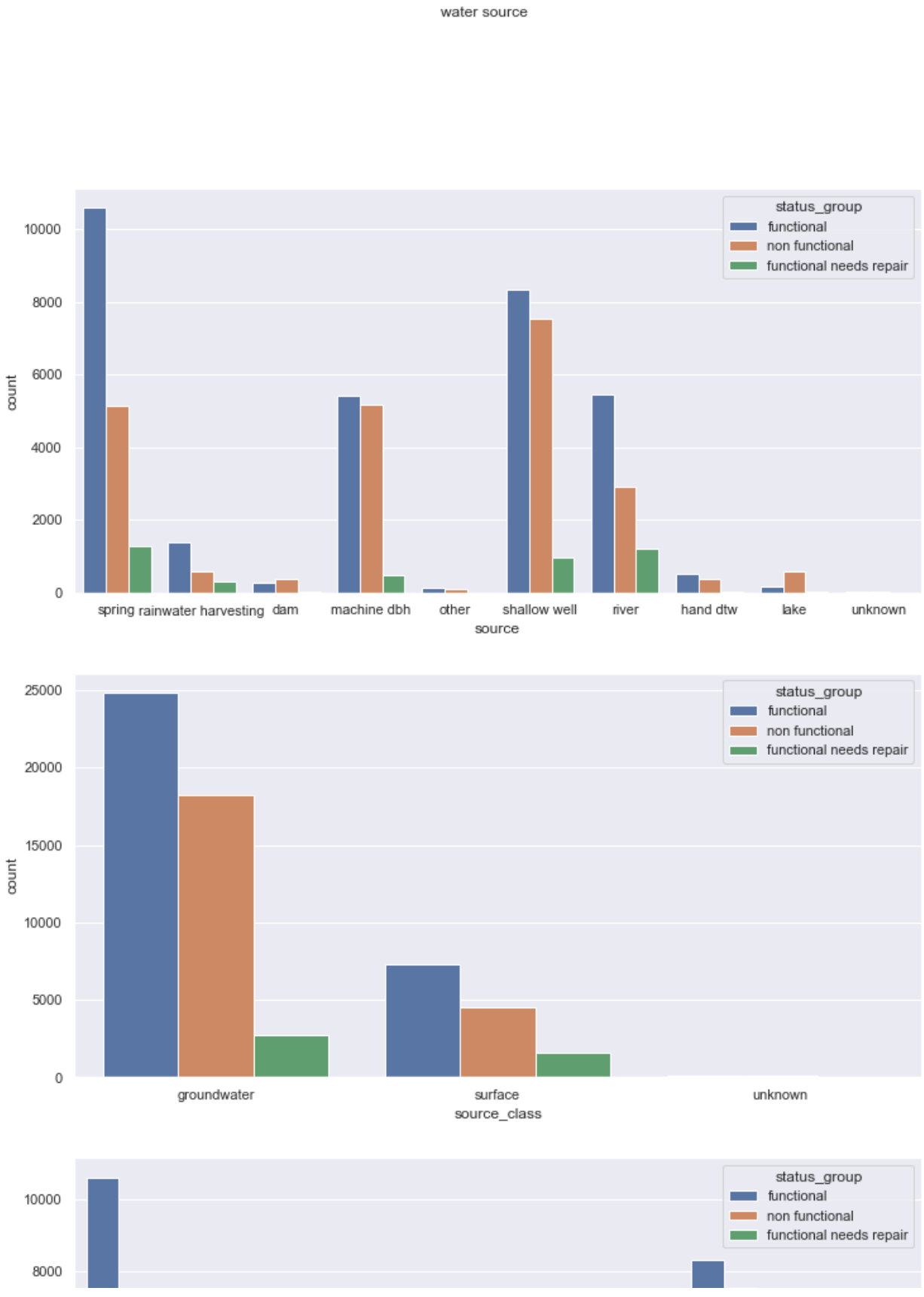
Below: Binary

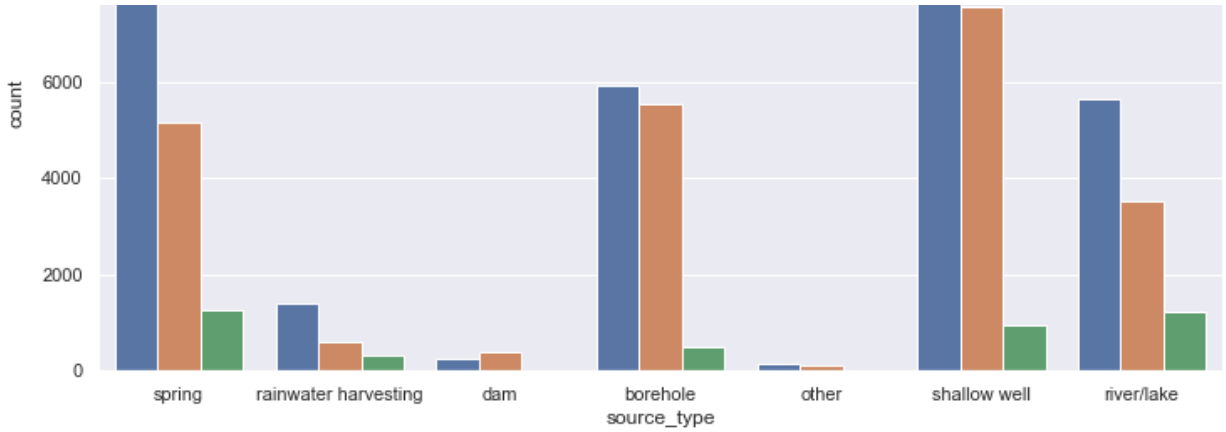
source, source_class, and source_type

source: Explains same information as source_type but with more variables. Keeping source_type.
source_class: Broadly explains same information as source and source_type. Keeping source_type.
Source_type: This was NOT dropped. Kept it as a balance between the other two features of similar information.

See below for visualization of the different groupings in terms of functional water pumps.

In [34]:
```
fig, (ax1, ax2, ax3) = plt.subplots(3, figsize=(12,20))
fig.suptitle('water source')
sns.countplot(x='source', hue='status_group', data=df, ax=ax1)
sns.countplot(x='source_class', hue='status_group', data=df, ax=ax2)
sns.countplot(x='source_type', hue='status_group', data=df, ax=ax3)
plt.show();
```

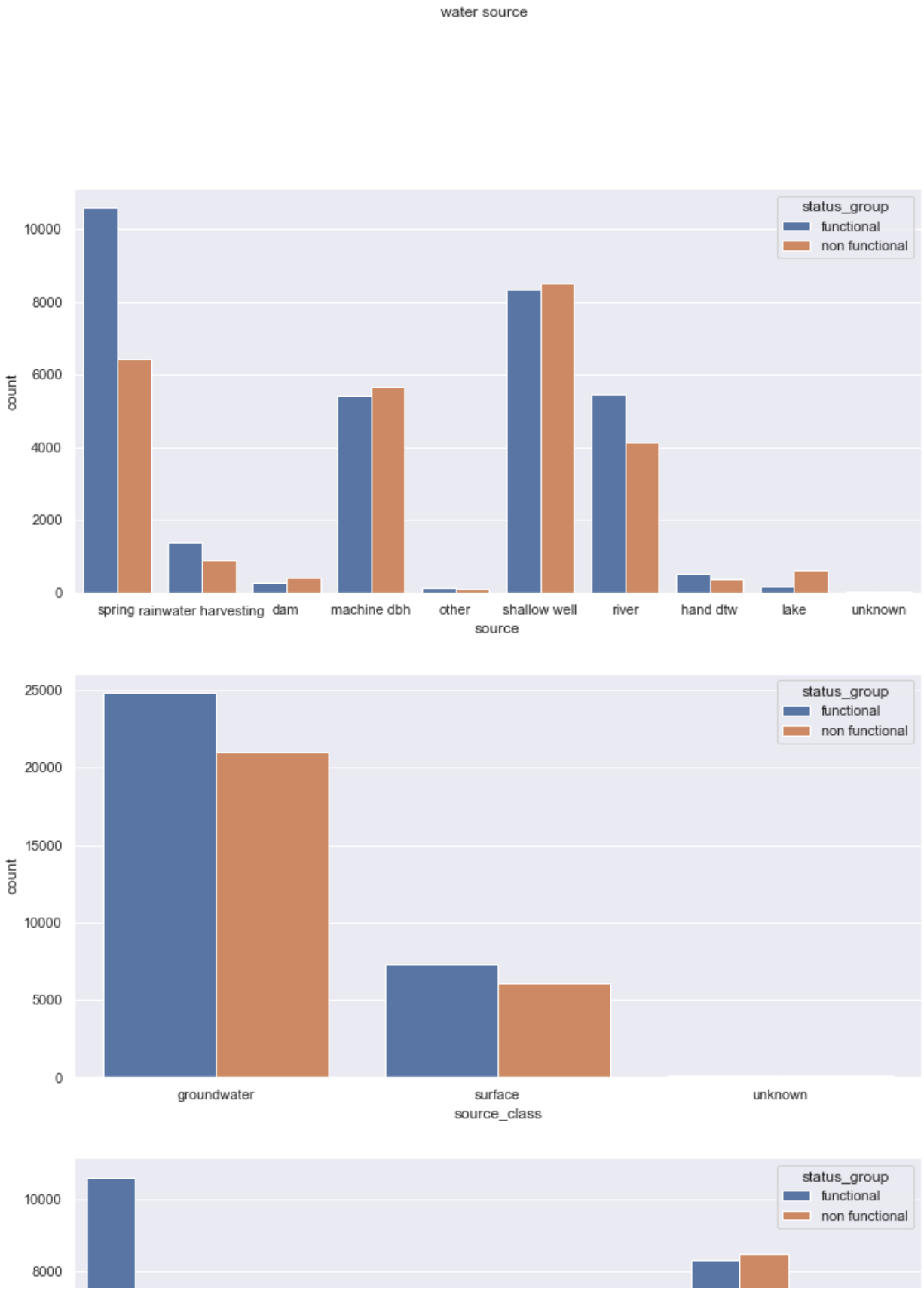


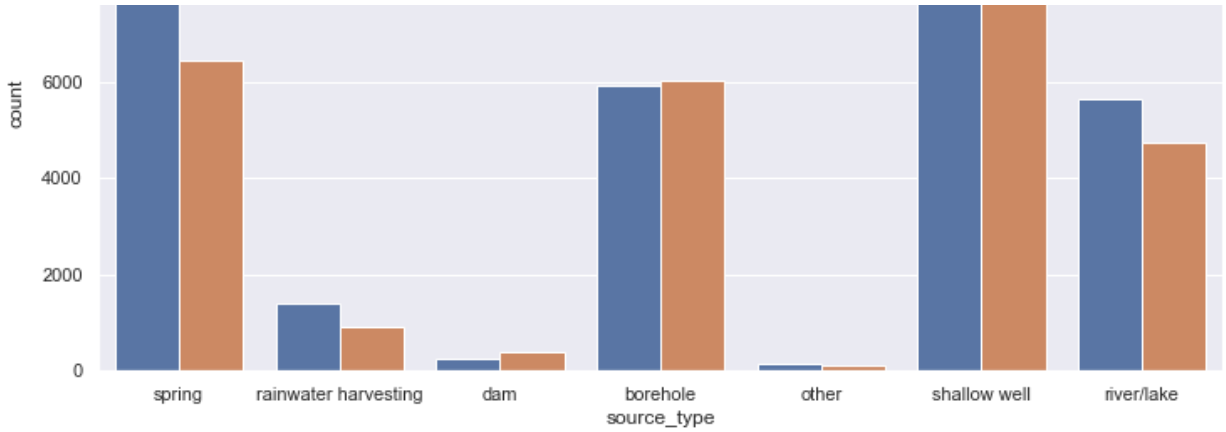


Above: tertiary

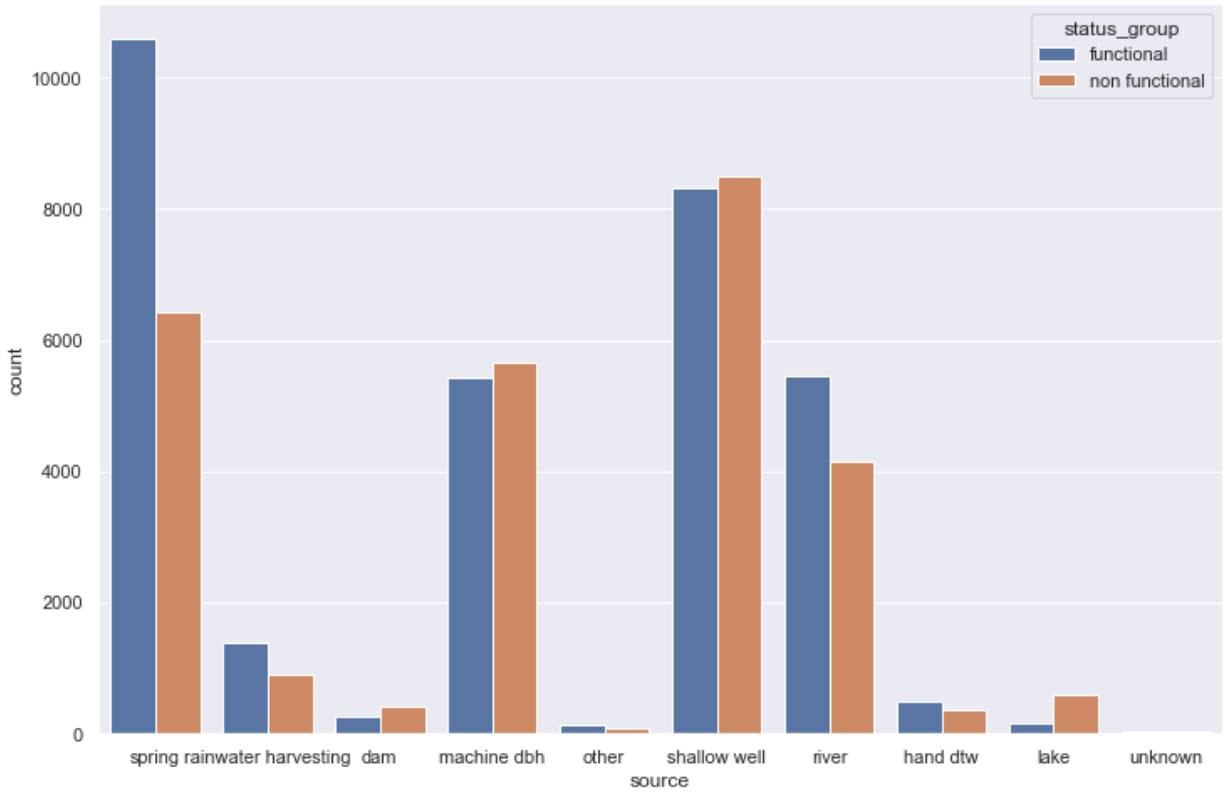
Below: Binary

In [35]:
```
fig, (ax1, ax2, ax3) = plt.subplots(3, figsize=(12,20))
fig.suptitle('water source')
sns.countplot(x='source', hue='status_group', data=df_binary, ax=ax1)
sns.countplot(x='source_class', hue='status_group', data=df_binary, ax=
sns.countplot(x='source_type', hue='status_group', data=df_binary, ax=a
plt.show();
```





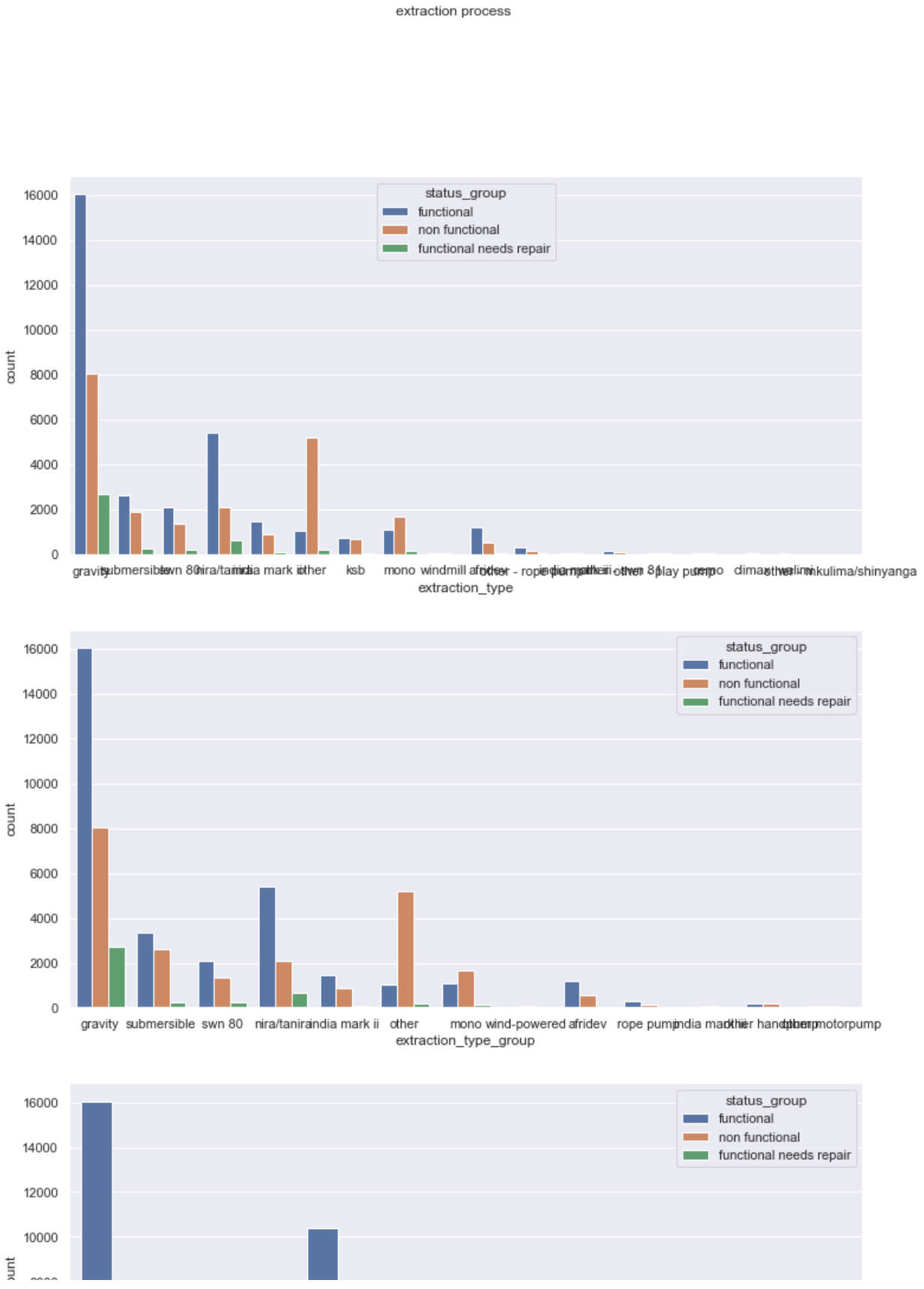
In [36]:
```
#save plot for presentation
fig, ax = plt.subplots(1, figsize=(12,8))
fig.suptitle('water source')
sns.countplot(x='source', hue='status_group', data=df_binary, ax=ax)
plt.savefig('images/')
plt.show();
```

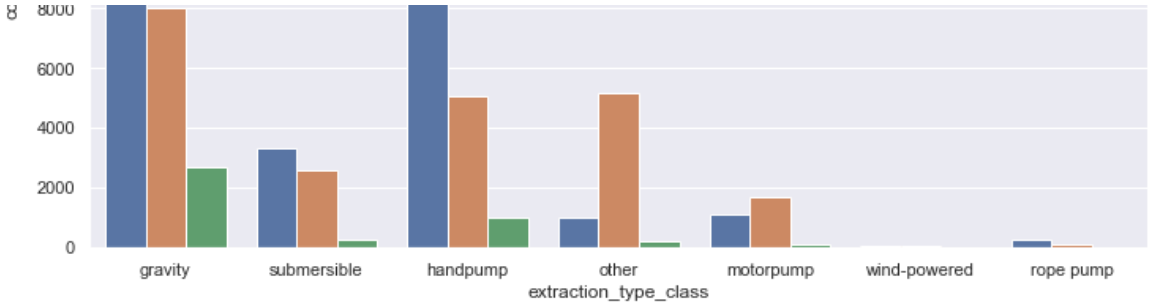


extraction_type, extraction_type_group, extraction_type_class

These three features explain a lot of the same information subgrouped in different ways. I decided to keep two and drop the third. The two that were dropped had columns with too little weight in the distrubtion for useful information.

In [37]:
```
fig, (ax1, ax2, ax3) = plt.subplots(3, figsize=(12,20))
fig.suptitle('extraction process')
sns.countplot(x='extraction_type', hue='status_group', data=df, ax=ax1)
sns.countplot(x='extraction_type_group', hue='status_group', data=df, a
sns.countplot(x='extraction_type_class', hue='status_group', data=df, a
plt.show();
```

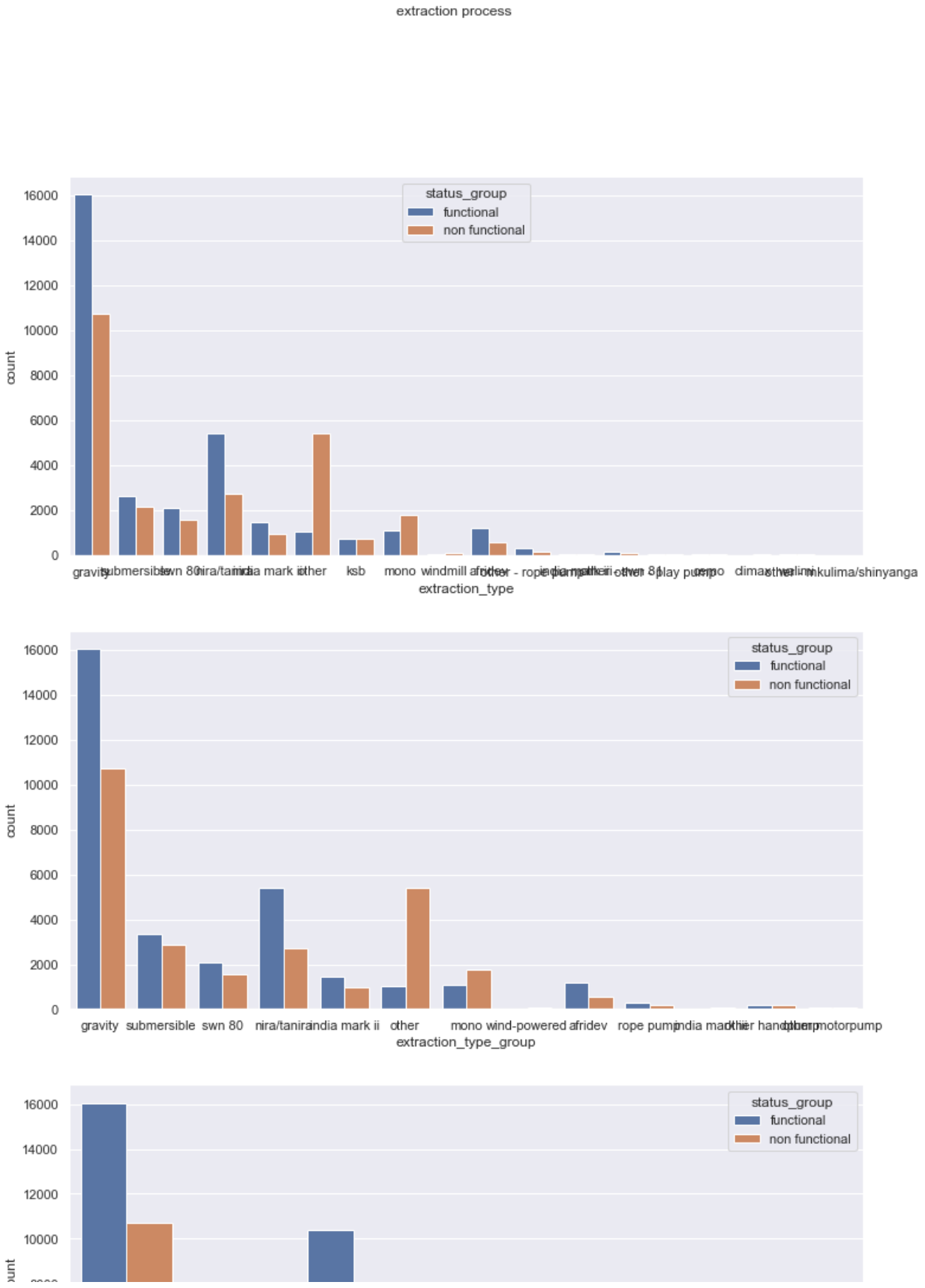


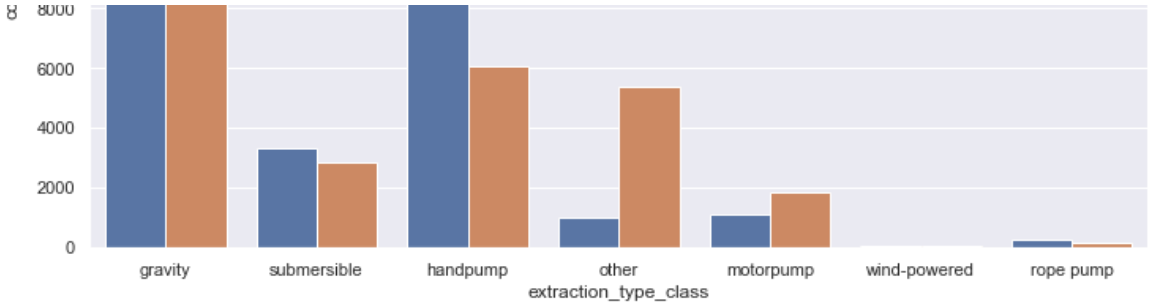


Above: tertiary

Below: Binary

In [38]:
```
fig, (ax1, ax2, ax3) = plt.subplots(3, figsize=(12,20))
fig.suptitle('extraction process')
sns.countplot(x='extraction_type', hue='status_group', data=df_binary,
sns.countplot(x='extraction_type_group', hue='status_group', data=df_bi
sns.countplot(x='extraction_type_class', hue='status_group', data=df_bi
plt.show();
```



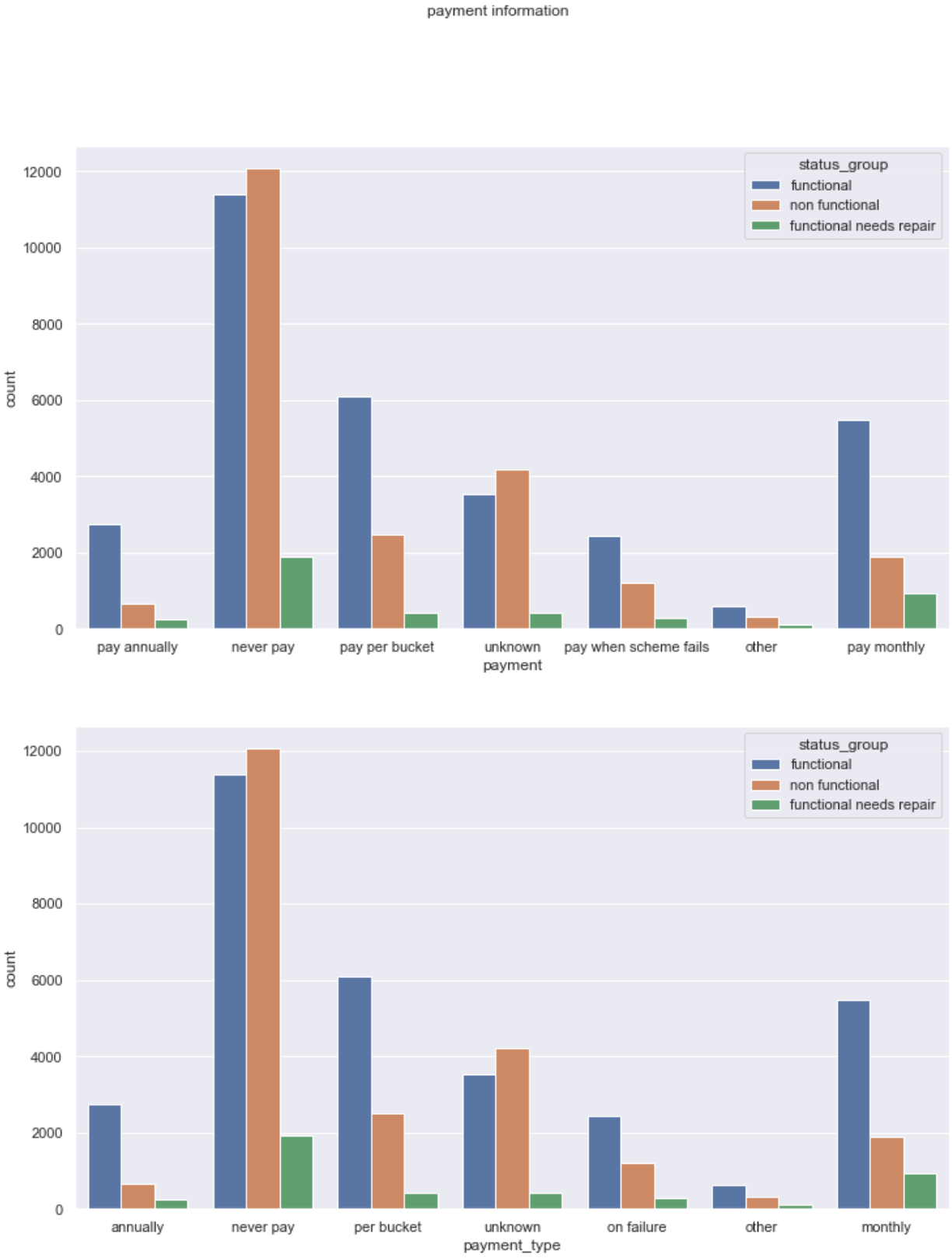


payment and payment_type

The information for both of these columns in nearly exactly identical. Drop 'payment_type' and keep 'payment'.

Most points that are not paid are not working. This may be due to a lack of maintenance resources. When a payment is added, the status changes.

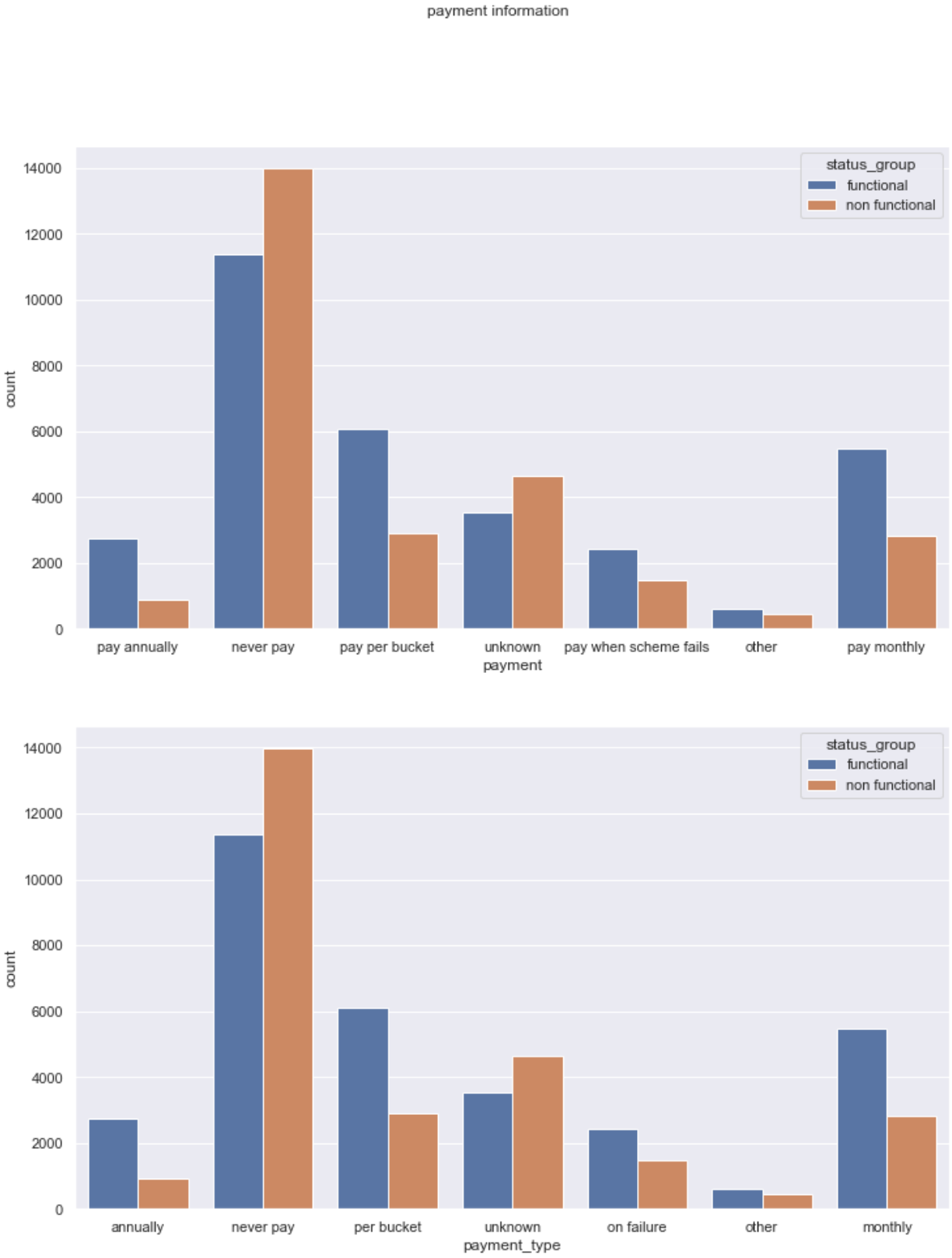
In [39]:
```
fig, (ax1, ax2) = plt.subplots(2, figsize=(12,15))
fig.suptitle('payment information')
sns.countplot(x='payment', hue='status_group', data=df, ax=ax1)
sns.countplot(x='payment_type', hue='status_group', data=df, ax=ax2)
plt.show();
```



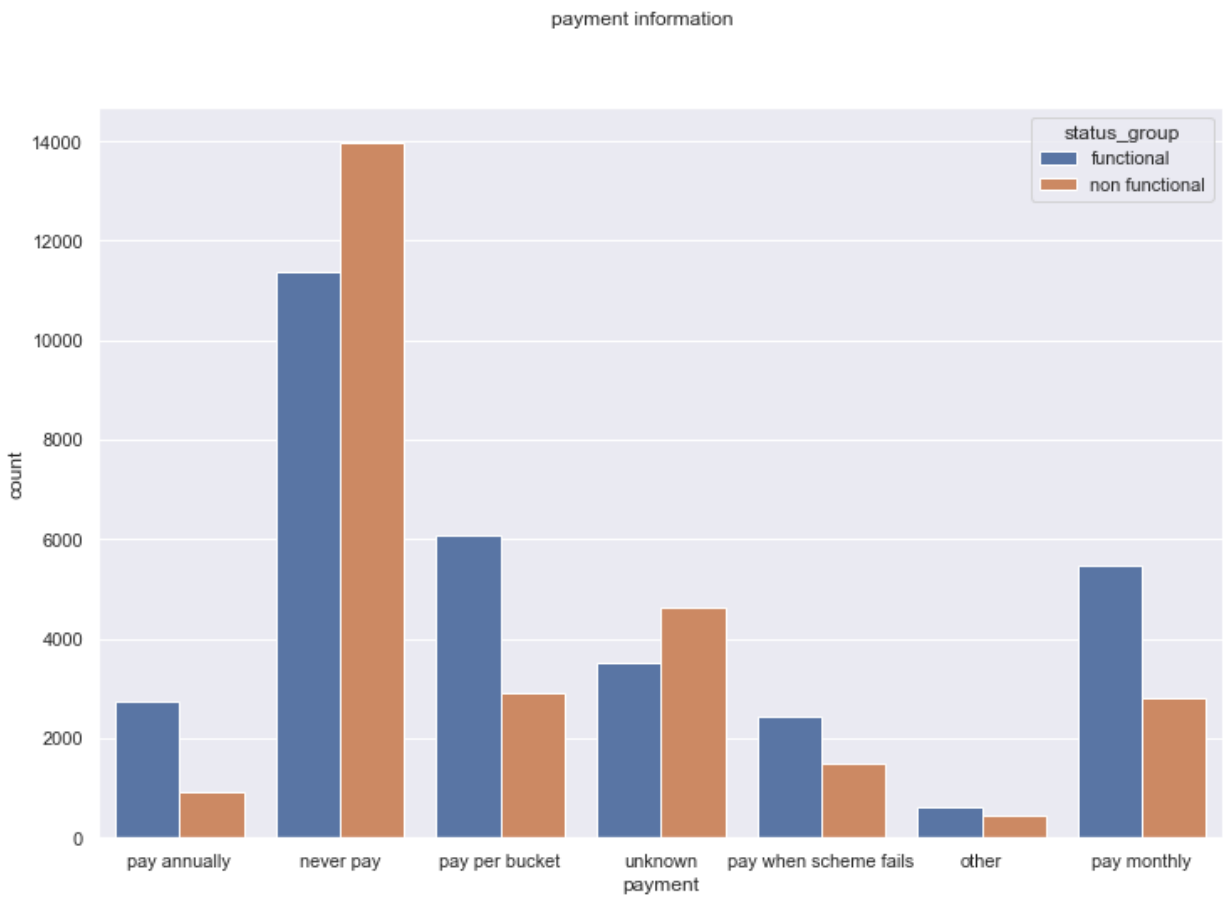
Above: tertiary

Below: Binary

In [40]:
```
fig, (ax1, ax2) = plt.subplots(2, figsize=(12,15))
fig.suptitle('payment information')
sns.countplot(x='payment', hue='status_group', data=df_binary, ax=ax1)
sns.countplot(x='payment_type', hue='status_group', data=df_binary, ax=
plt.show();
```



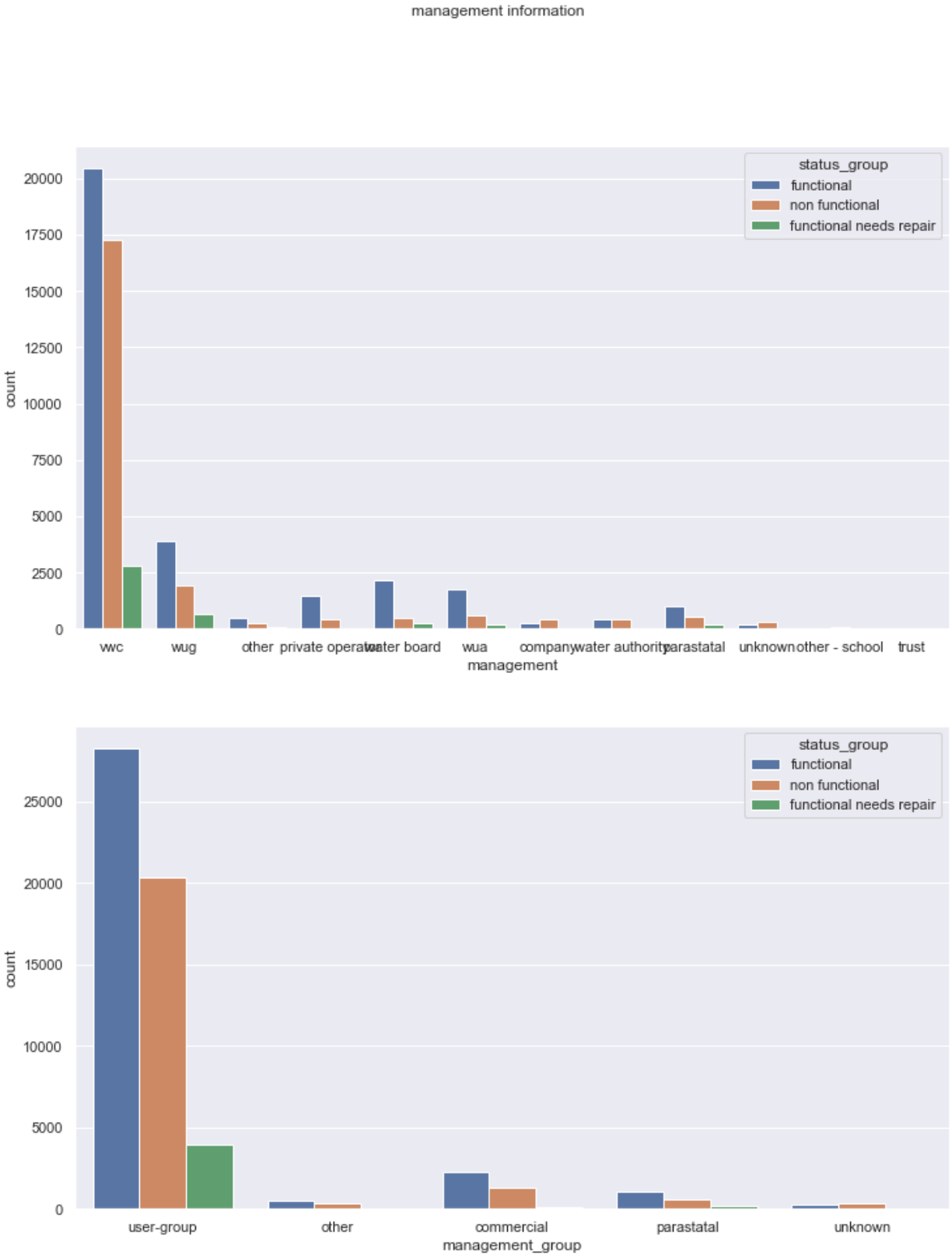
In [41]:
```
fig, ax = plt.subplots(1, figsize=(12,8))
fig.suptitle('payment information')
sns.countplot(x='payment', hue='status_group', data=df_binary, ax=ax)
plt.savefig('images/payment_graph')
plt.show();
```



management and management_group

I decided to keep the 'management' column and group the less specific 'management_group' column. Alot of the columns in the management column should have enough information to help the model make better predictions.

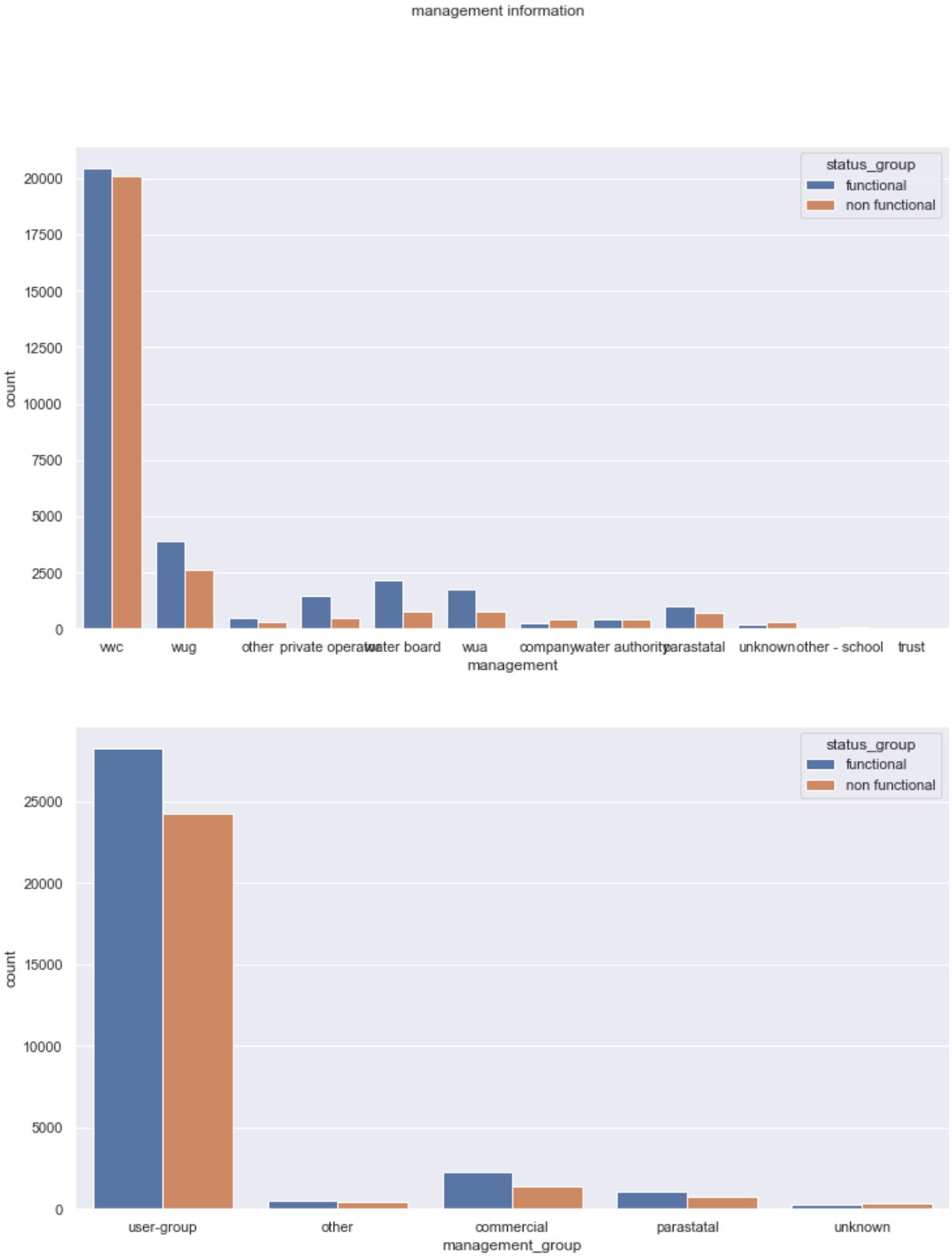
In [42]:
```
fig, (ax1, ax2) = plt.subplots(2, figsize=(12,15))
fig.suptitle('management information')
sns.countplot(x='management', hue='status_group', data=df, ax=ax1)
sns.countplot(x='management_group', hue='status_group', data=df, ax=ax2
plt.show();
```



Above: tertiary

Below: Binary

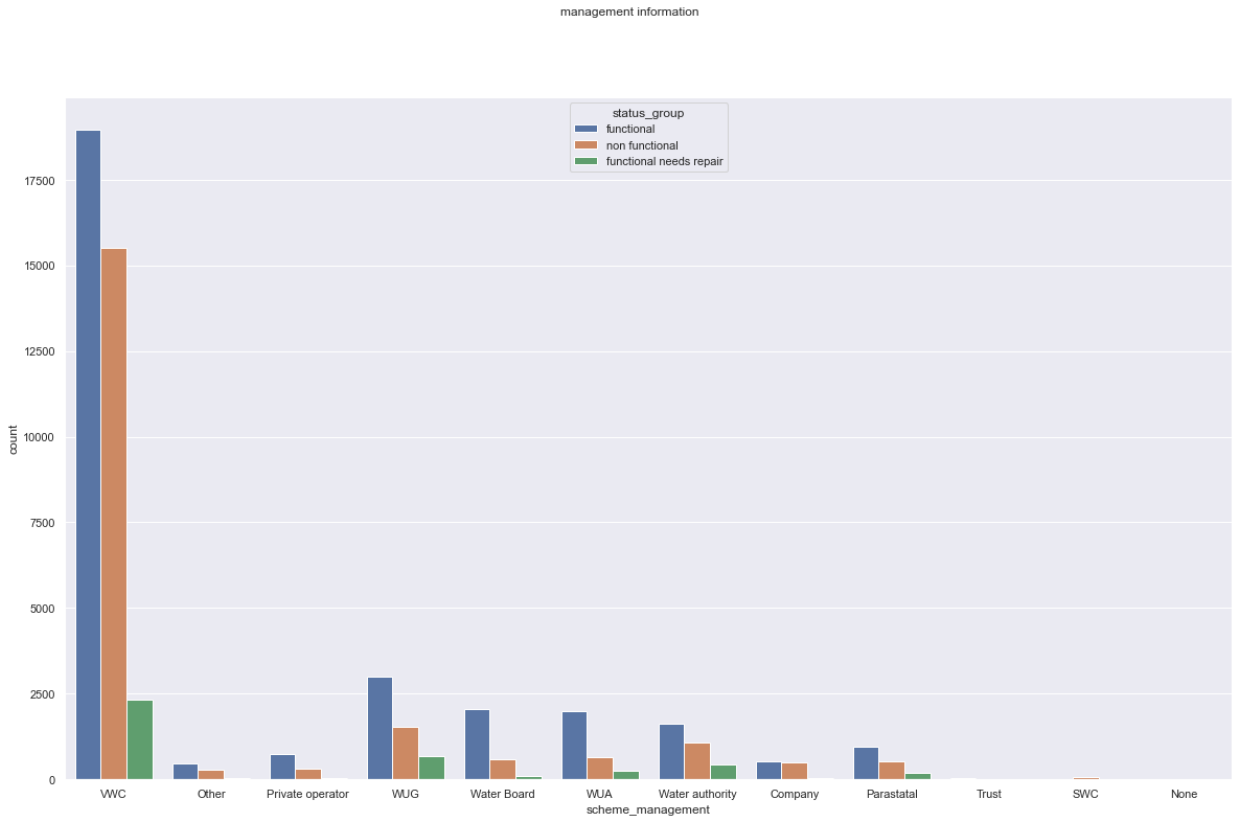
In [43]:
```
fig, (ax1, ax2) = plt.subplots(2, figsize=(12,15))
fig.suptitle('management information')
sns.countplot(x='management', hue='status_group', data=df_binary, ax=ax
sns.countplot(x='management_group', hue='status_group', data=df_binary,
plt.show();
```



scheme_name and scheme_management

scheme_name: drop. Missing almost half of values. Large cardinality (nearly 2700 categories).
scheme_manager: drop. Contains similar information to management column.

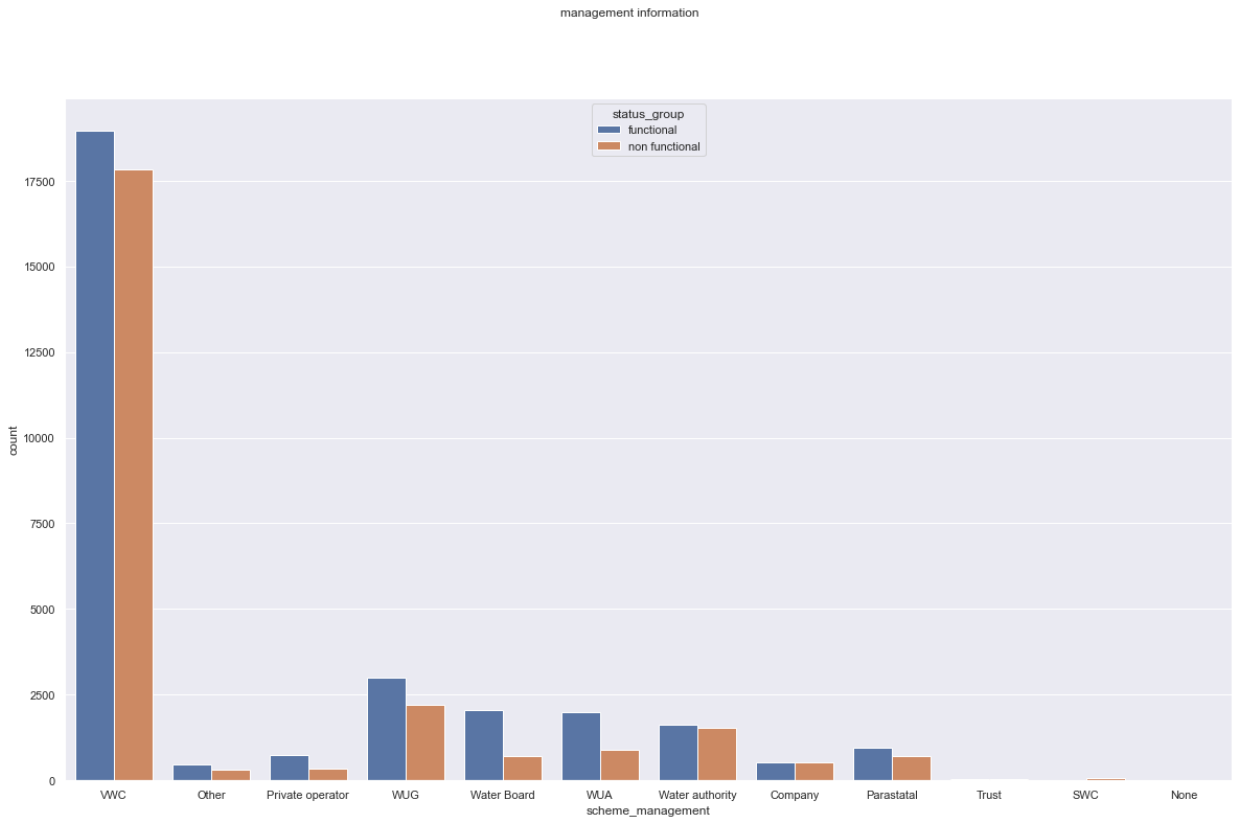
In [44]:
```
fig = plt.figure(figsize=(20,12))
fig.suptitle('management information')
sns.countplot(x='scheme_management', hue='status_group', data=df)
plt.show();
```



Above: tertiary

Below: Binary

In [45]:
```
fig = plt.figure(figsize=(20,12))
fig.suptitle('management information')
sns.countplot(x='scheme_management', hue='status_group', data=df_binary
plt.show();
```



In [46]:
```
to_drop = ['id', 'recorded_by', 'num_private',
           'waterpoint_type_group', 'source',
           'source_class', 'extraction_type',
           'extraction_type_group', 'payment_type',
           'management_group', 'scheme_name',
           'water_quality', 'quantity_group',
           'scheme_management', 'longitude',
           'latitude', 'date_recorded']
df2 = df.drop(to_drop, axis=1)
df2.head()
```

Out[46]:

	amount_tsh	funder	gps_height	installer	wpt_name	basin	subvillage	region	region_c
0	6000.0	Roman	1390	Roman	none	Lake Nyasa	Mnyusi B	Iringa	
1	0.0	Grumeti	1399	GRUMETI	Zahanati	Lake Victoria	Nyamara	Mara	
2	25.0	Lottery Club	686	World vision	Kwa Mahundi	Pangani	Majengo	Manyara	
3	0.0	Unicef	263	UNICEF	Zahanati Ya Nanyumbu	Ruvuma / Southern Coast	Mahakamani	Mtwara	
4	0.0	Action In A	0	Artisan	Shuleni	Lake Victoria	Kyanyamisa	Kagera	

5 rows × 25 columns

Date_Recorded: Understanding Time Frame of Data Collection and Current Capacity Limits

As show in the bargraph below, almost all of the data was originally recorded between the years 2011 and 2013. The highest capacity for the Ministry of Water was in the year 2011 when 28,674 pumps were visited. It is important to consider the time-scale of the data when considering the cost/resource anaylsis of predictive modeling vs the current maintenance being conducted with no modeling.

In [47]:
```
df3=df.copy()
df3['date_recorded'] = pd.to_datetime(df3['date_recorded'])
```

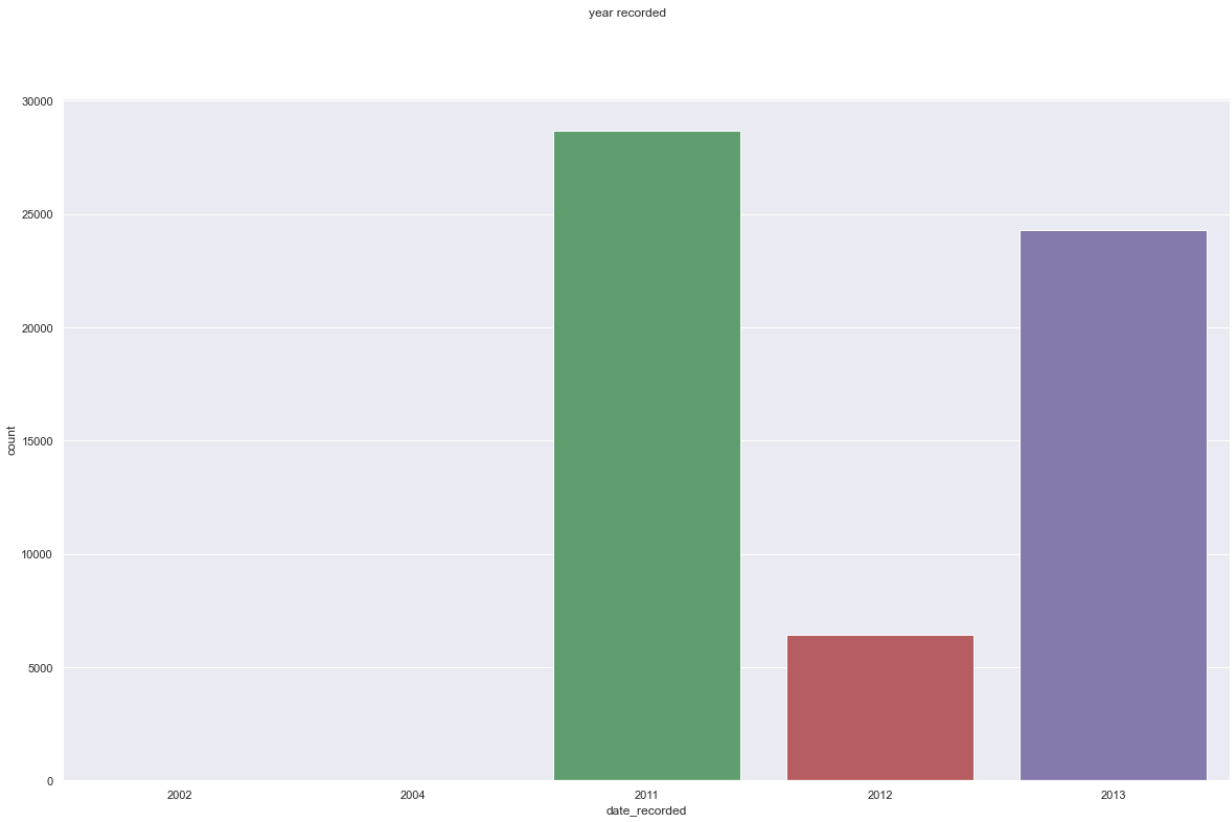
In [48]:
```
df3['date_recorded'].dt.year.value_counts()
```

Out[48]:
```
2011    28674
2013    24271
2012     6424
2004       30
2002        1
Name: date_recorded, dtype: int64
```

In [49]:
```
df3.shape
```

Out[49]: (59400, 42)

In [50]:
```
fig = plt.figure(figsize=(20,12))
fig.suptitle('year recorded')
sns.countplot(x=df3['date_recorded'].dt.year)
plt.show();
```



Speculate on the amount of labor required to physically check all of these pumps in a 2 to 3 year period. This will give a good understanding of the current cost and capacity without using any predictive maintenance.

Dealing with Null Values and '0' placeholder values

This section covers the handeling of null values in the data in preperation for modeling.

funder and Installer null values

In [51]:
```
print(df2['funder'].isna().sum())
print(df2['installer'].isna().sum())
df2[df2['funder'].isna()].index.isin(df2[df2['installer'].isna()].index
```

```
3635
3655
```

Out[51]: 3582

In [52]:
```
1 df2['installer'].value_counts()[:20]
```

Out[52]:
```
DWE                   17402
Government             1825
RWE                    1206
Commu                  1060
DANIDA                 1050
KKKT                    898
Hesawa                  840
0                       777
TCRS                    707
Central government      622
CES                     610
Community               553
DANID                   552
District Council        551
HESAWA                  539
World vision            408
LGA                     408
WEDECO                  397
TASAF                   396
District council        392
Name: installer, dtype: int64
```

In [53]:
```
1 df2['funder'].value_counts()[:20]
```

Out[53]:
```
Government Of Tanzania    9084
Danida                    3114
Hesawa                    2202
Rwssp                     1374
World Bank                1349
Kkkt                      1287
World Vision              1246
Unicef                    1057
Tasaf                      877
District Council           843
Dhv                        829
Private Individual         826
Dwsp                       811
0                          777
Norad                      765
Germany Republi            610
Tcrs                       602
Ministry Of Water          590
Water                      583
Dwe                        484
Name: funder, dtype: int64
```

In [54]:
```
installer_index_0 = df2['installer'] =='0'
funder_index_0 = df2['funder'] =='0'
#replace zero placeholders with 'unknown'
df2.loc[funder_index_0, 'funder'] = 'unknown'
df2.loc[funder_index_0, 'installer'] = 'unknown'
#replace null values as 'unkown'
df2['installer'].fillna(value='unknown', inplace=True)
df2['funder'].fillna(value='unknown', inplace=True)
#sanity check
display(df2['funder'].value_counts()[:20])
display(df2['installer'].value_counts()[:20])
df2.isna().sum()
```

```
Government Of Tanzania    9084
unknown                   4412
Danida                    3114
Hesawa                    2202
Rwssp                     1374
World Bank                1349
Kkkt                      1287
World Vision              1246
Unicef                    1057
Tasaf                      877
District Council           843
Dhv                        829
Private Individual         826
Dwsp                       811
Norad                      765
Germany Republi            610
Tcrs                       602
Ministry Of Water          590
Water                      583
Dwe                        484
Name: funder, dtype: int64

DWE                   17402
unknown                4433
Government             1825
RWE                    1206
Commu                  1060
DANIDA                 1050
KKKT                    898
Hesawa                  840
TCRS                    707
Central government      622
CES                     610
Community               553
DANID                   552
District Council        551
HESAWA                  539
World vision            408
LGA                     408
WEDECO                  397
TASAF                   396
District council        392
Name: installer, dtype: int64
```

Out[54]:
```
amount_tsh                0
funder                    0
gps_height                0
installer                 0
wpt_name                  0
basin                     0
subvillage              371
region                    0
region_code               0
district_code             0
lga                       0
ward                      0
public_meeting         3334
permit                 3056
construction_year         0
extraction_type_class     0
management                0
payment                   0
quality_group             0
quantity                  0
source_type               0
waterpoint_type           0
status_group              0
near_river                0
ward_pop                  0
dtype: int64
```

public meeting null values

In [55]:
```
1 display(df2['public_meeting'].value_counts(normalize=True))
2 df2['public_meeting'].value_counts(dropna=False,normalize=True)
```

```
True     0.909838
False    0.090162
Name: public_meeting, dtype: float64
```

Out[55]:
```
True     0.858771
False    0.085101
NaN      0.056128
Name: public_meeting, dtype: float64
```

In [56]:
```
#create copy of dataframe
df_pub_no_na = df2.copy()
#initialize boolean series for null values in pub meeting
filt = df_pub_no_na['public_meeting'].isna()
#initialize series in order to keep ratio of boolean the same
#after filling null values
probs = df2['public_meeting'].value_counts(normalize=True)
#fill null values with random selection of
#True or False but keep same probability as before filling NaNs
df_pub_no_na.loc[filt, 'public_meeting'] = np.random.choice([True, Fals
                    size=int(filt.sum()),
                    p = [probs[True], probs[False]])

#check to see NaNs are filled without changing probabilities
df_pub_no_na['public_meeting'].value_counts(dropna=False, normalize = T
```

Out[56]:
```
True     0.910084
False    0.089916
Name: public_meeting, dtype: float64
```

permit null values

In [57]:
```
df3 = df_pub_no_na.copy()
df3.isna().sum()
```

Out[57]:
```
amount_tsh                 0
funder                     0
gps_height                 0
installer                  0
wpt_name                   0
basin                      0
subvillage               371
region                     0
region_code                0
district_code              0
lga                        0
ward                       0
public_meeting             0
permit                  3056
construction_year          0
extraction_type_class      0
management                 0
payment                    0
quality_group              0
quantity                   0
source_type                0
waterpoint_type            0
status_group               0
near_river                 0
ward_pop                   0
dtype: int64
```

In [58]:
```
df3['permit'].value_counts(dropna=False, normalize=True)
```

Out[58]:
```
True     0.654074
False    0.294478
NaN      0.051448
Name: permit, dtype: float64
```

In [59]:
```
#initialize boolean series for null values in permit
filt2 = df3['permit'].isna()
#initialize series in order to keep ratio of boolean the same
#after filling null values
probs2 = df3['permit'].value_counts(normalize=True)
#fill null values with random selection of
#True or False but keep same probability as before filling NaNs
df3.loc[filt2, 'permit'] = np.random.choice([True, False],
                    size=int(filt2.sum()),
                    p = [probs2[True], probs2[False]])

df3['permit'].value_counts(dropna=False, normalize=True)
```

Out[59]:
```
True     0.690421
False    0.309579
Name: permit, dtype: float64
```

subvillage null values

In [60]:
```
#grab indexes of null values to fill for scheme_management column
subvillage_index_null = df3[df3['subvillage'].isna()].index
#fill null values with 'unknown'
df3.loc[subvillage_index_null, 'subvillage'] = 'unknown'

df3.isna().sum()
```

Out[60]:
```
amount_tsh              0
funder                  0
gps_height              0
installer               0
wpt_name                0
basin                   0
subvillage              0
region                  0
region_code             0
district_code           0
lga                     0
ward                    0
public_meeting          0
permit                  0
construction_year       0
extraction_type_class   0
management              0
payment                 0
quality_group           0
quantity                0
source_type             0
waterpoint_type         0
status_group            0
near_river              0
ward_pop                0
dtype: int64
```

High Cardinality Categorical Data

There are numerous ways to deal with categorical data with high cardinality. It is important when creating machine learning models to pay attetion to the dimensionality of the data. It can get out of hand really quickly if you do nothing to limit your cardinality. One of the simplest and easiest ways to follow is to take the categories with the highest frequencies (and therefore makeup the bulk of the distrubtion for that particular category) are left as is until a certain threshold of the data has been accounted for. After the threshold is met, all other categories for that column (which can sometimes be thousands of categories) will get lumped into a new category labled as 'other.'

This simple trick can easily reduce dimensionality of categorical data. While it is not the most sophisticated method, it should be good enough for the models I want to create for my project.

Below is a function I created in order to easily reduce cardinality in my categorical data by using the method described above. My default threshold value is 75%, meaning after 75% of the data is accounted for, all other categories of lower frequencies will be lumped together into the 'other' category.

This code was inspired by author Raj Sangani in his blog: Dealing with features that have high cardinality (https://towardsdatascience.com/dealing-with-features-that-have-high-cardinality-1c9212d7ff1b). Thank you for the well commented and easy to follow along code!

Here is the documentation for the import necessary for the function below from python collections library: Counter. collections.Counter (https://docs.python.org/3/library/collections.html#collections.Counter). Here we use the method 'most_common()' of collections.Counter.

From the documentation:

most_common([n]): Return a list of the n most common elements and their counts from the most common to the least. If n is omitted or None, most_common() returns all elements in the counter. Elements with equal counts are ordered in the order first encountered.

This function is ok for initial data exploration. However, it will need to be tweaked later in order to be implemeted approriately into a data processing pipeline. Instead of returning an updated column, future implementation will return a dictionary that will act as a value mapper in order to reduce cardinality of training and testing sets. The value mapper dictionary will be created by running the function on the entire dataset before carrying out the actual data processing/cleaning.

In [61]:
```
def cardinality_threshold(column,threshold=0.75,return_categories_list=
      #calculate the threshold value using
      #the frequency of instances in column
      threshold_value=int(threshold*len(column))
      #initialize a new list for lower cardinality column
      categories_list=[]
      #initialize a variable to calculate sum of frequencies
      s=0
      #Create a dictionary (unique_category: frequency)
      counts=Counter(column)

      #Iterate through category names and corresponding frequencies aft
      #by descending order of frequency
      for i,j in counts.most_common():
        #Add the frequency to the total sum
        s += dict(counts)[i]
        #append the category name to the categories list
        categories_list.append(i)
        #Check if the global sum has reached the threshold value, if so
        if s >= threshold_value:
            break
      #append the new 'Other' category to list
      categories_list.append('Other')

      #Take all instances not in categories below threshold
      #that were kept and lump them into the
      #new 'Other' category.
      new_column = column.apply(lambda x: x if x in categories_list els

      #Return the transformed column and
      #unique categories if return_categories = True
      if(return_categories_list):
        return new_column,categories_list
      #Return only the transformed column if return_categories=False
      else:
        return new_column
```

funder categorical column

This column has a lot of categories that seem to be abbreviations or mispellings of the same funders. Ideally, I would correct all of these inconsistencies in the data in order to have my model perform the best that it can perform. However, for the scope of this project, I am going to put this tedious task off for now.

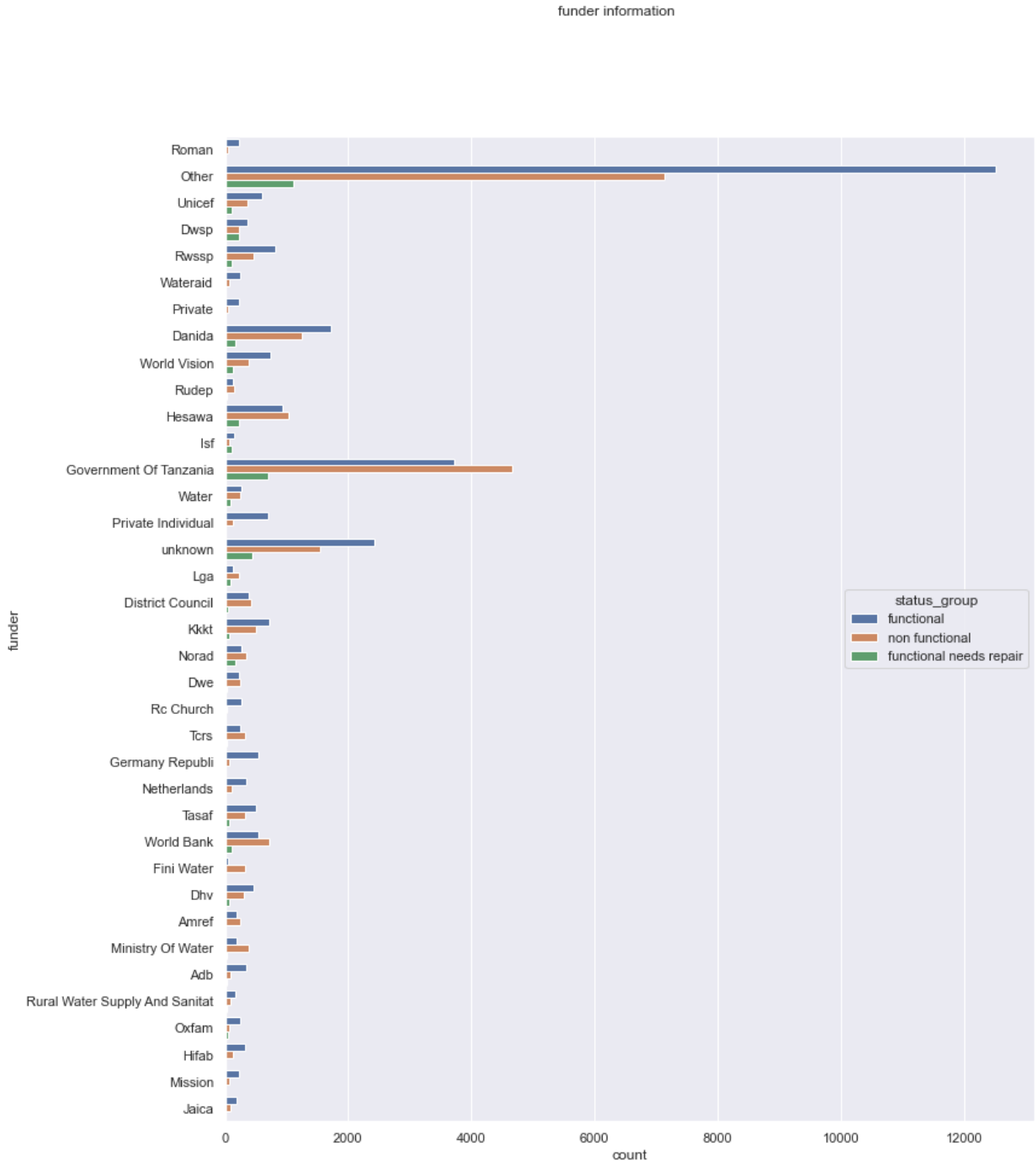
In [62]:
```
1 df3['funder'].sort_values().unique()[:200]
```

Out[62]:
```
array(['A/co Germany', 'Aar', 'Abas Ka', 'Abasia',
       'Abc-ihushi Development Cent', 'Abd', 'Abdala', 'Abddwe', 'Abdul',
       'Abood', 'Abs', 'Aco/germany', 'Acord', 'Acord Ngo', 'Acra', 'Ac
t',
       'Act Mara', 'Action Aid', 'Action Contre La Faim', 'Action In A',
       'Adap', 'Adb', 'Adf', 'Adp', 'Adp Bungu', 'Adp Mombo', 'Adp/w',
       'Adra', 'Af', 'Afdp', 'Afric', 'Africa',
       'Africa 2000 Network/undp', 'Africa Amini Alama',
       'Africa Project Ev Germany', 'African', 'African 2000 Network',
       'African Barrick Gold', 'African Development Bank',
       'African Development Foundation', 'African Muslim Agency',
       'African Realief Committe Of Ku', 'African Reflections Foundatio
n',
       'African Relie', 'Africaone Ltd', 'Africare', 'Afriican Reli',
       'Afroz Ismail', 'Afya Department Lindi Rural', 'Agape Churc',
       'Agt Church', 'Ahmadia', 'Ai', 'Aic', 'Aic Church', 'Aic Kij',
       'Aict', 'Aimgold', 'Aixos', 'Alia', 'Ambwene Mwaikek', 'Amref',
       'Amrefe', 'Anglican Church', 'Angrikana', 'Anjuman E Seifee',
       'Answeer Muslim Grou', 'Apm', 'Apm[africa Precious Metals Lt',
       'Aqua Blues Angels', 'Arab Community', 'Arabi', 'Arabs Community',
       'Ardhi Instute', 'Area', 'Artisan', 'Asb', 'Asdp',
       'Asgerali N Bharwan', 'Auwasa', 'Awf', 'B.A.P', 'Ba As', 'Babtes
t',
       'Babtist', 'Bahewasa', 'Bahresa', 'Bakari Chimkube', 'Bakwata',
       'Ballo', 'Balo', 'Balyehe', 'Banca Reale', 'Bank', 'Bao',
       'Baptist Church', 'Baric', 'Bathlomew Vicent', 'Batist Church',
       'Belgian Government', 'Belgij', 'Bened', 'Benguka', 'Bffs', 'Bfw
d',
       'Bgm', 'Bgss', 'Bgssws', 'Bhws', 'Bilila', 'Bingo Foundation',
       'Bingo Foundation Germany', 'Bio Fuel Company', 'Biore', 'Birage',
       'Bkhws', 'Boazi', 'Boazi /o', 'Bobby', 'Bokera W', 'Boma Saving',
       'Bong-kug Ohh/choonlza Lee', 'Bonite Bottles Ltd', 'Br', 'Bra',
       'Brad', 'Brdp', 'Bread For The Wor', 'Bread Of The Worl',
       'Bridge North', 'British Colonial Government', 'British Tanza',
       'Brown', 'Bruder', 'Bs', 'Bsf', 'Bukumbi', 'Bukwang Church Saint',
       'Bukwang Church Saints', 'Buluga Subvillage Community',
       'Bulyahunlu Gold Mine', 'Bumabu', 'Buptist', 'Busoga Trust', 'C',
       'Cafod', 'Caltas', 'Caltas Tanzania', 'Caltaz Kahama', 'Caltus',
       'Calvary Connect', 'Camartec', 'Camavita', 'Canada', 'Canada Aid',
       'Care Int', 'Care International', 'Care/cipro', 'Care/dwe',
       'Caritas', 'Carmatech', 'Cartas Tanzania', 'Cast', 'Cathoric',
       'Cbhi', 'Cc Motor Day 2010', 'Ccp', 'Ccpk', 'Ccps', 'Cct', 'Cdcg',
       'Cdft', 'Cdg', 'Cdtf', 'Cdtfdistrict Council', 'Cefa',
       'Cefa-njombe', 'Cefa/rcchurch', 'Ces (gmbh)', 'Ces(gmbh)', 'Cg',
       'Cg/rc', 'Cgc', 'Cgi', 'Ch', 'Chacha', 'Chacha Issame',
       'Chai Wazir', 'Chama Cha Ushirika', 'Chamavita', 'Chani',
       'Charlotte Well', 'Cheni', 'China Government', 'Chmavita',
       'Chongolo', 'Christan Outrich', 'Christian Outrich', 'Chuo',
       'Churc'], dtype=object)
```

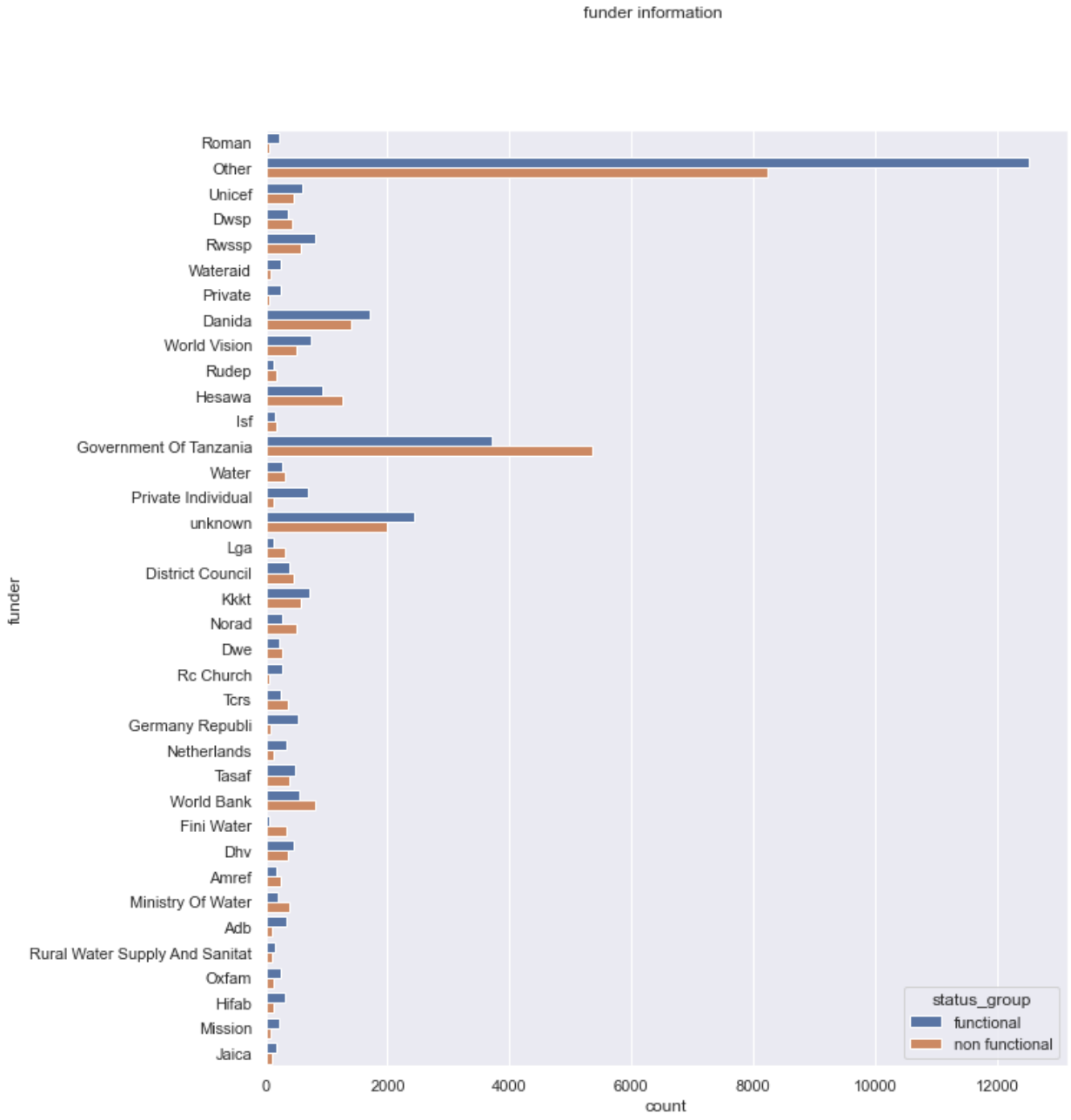
In [63]:
```
transformed_funder = cardinality_threshold(df3['funder'],
                                           threshold=0.65,
                                           return_categories_list=False

transformed_funder.value_counts()
```

Out[63]:
```
Other                              20765
Government Of Tanzania              9084
unknown                             4412
Danida                              3114
Hesawa                              2202
Rwssp                               1374
World Bank                          1349
Kkkt                                1287
World Vision                        1246
Unicef                              1057
Tasaf                                877
District Council                     843
Dhv                                  829
Private Individual                   826
Dwsp                                 811
Norad                                765
Germany Republi                      610
Tcrs                                 602
Ministry Of Water                    590
Water                                583
Dwe                                  484
Netherlands                          470
Hifab                                450
Adb                                  448
Lga                                  442
Amref                                425
Fini Water                           393
Oxfam                                359
Wateraid                             333
Rc Church                            321
Isf                                  316
Rudep                                312
Mission                              301
Private                              295
Jaica                                280
Roman                                275
Rural Water Supply And Sanitat       270
Name: funder, dtype: int64
```

In [64]:
```
df_transformed = df3.copy()
df_transformed['funder'] = transformed_funder

fig = plt.figure(figsize=(12,15))
fig.suptitle('funder information')
sns.countplot(y= 'funder', hue='status_group', data=df_transformed)
plt.show();
```



In [65]:
```
df_binary['funder'] = transformed_funder

fig = plt.figure(figsize=(10,12))
fig.suptitle('funder information')
sns.countplot(y= 'funder', hue='status_group', data=df_binary)
plt.savefig('images/funder_graph')
plt.show();
```

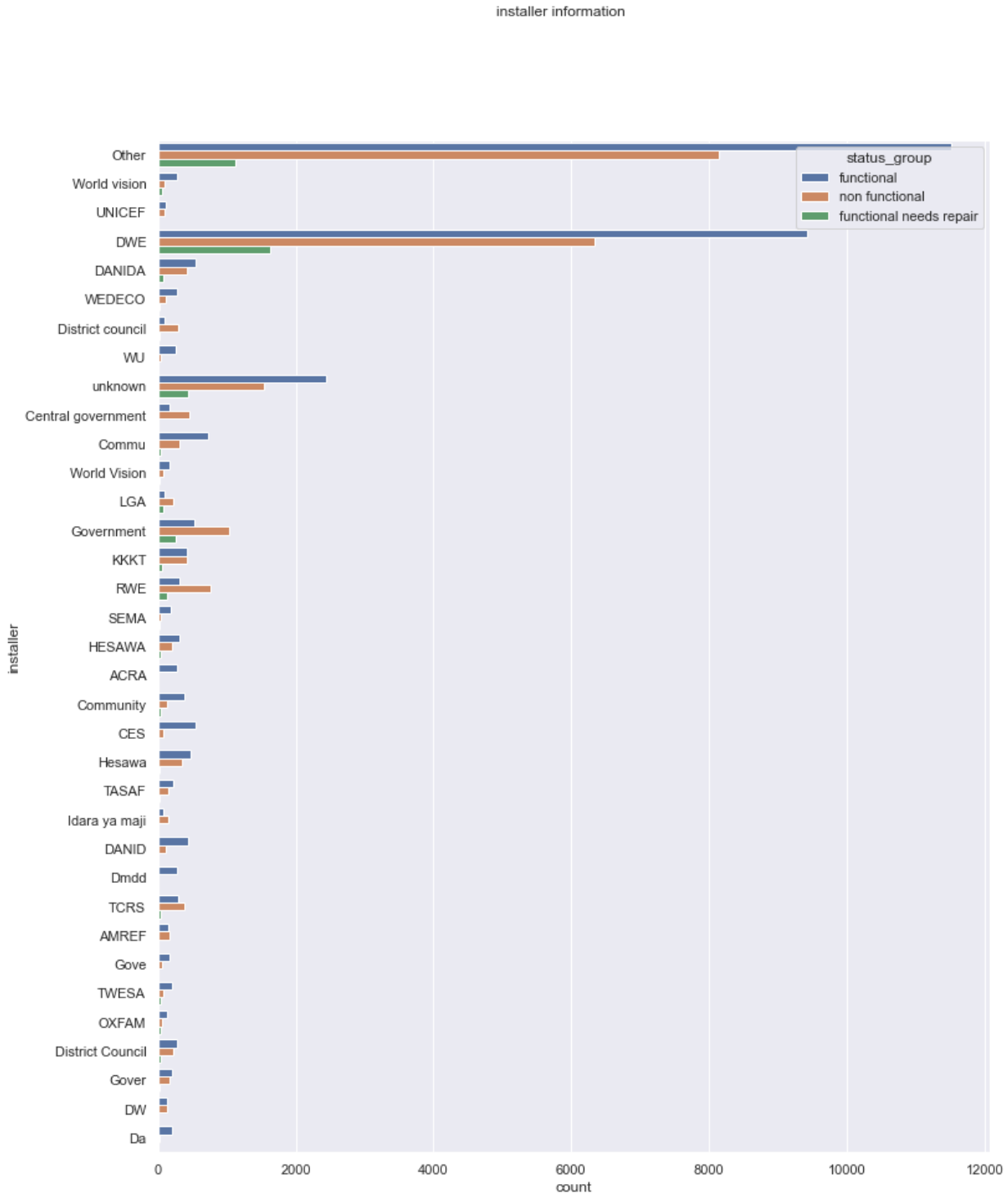


Transforming installer column

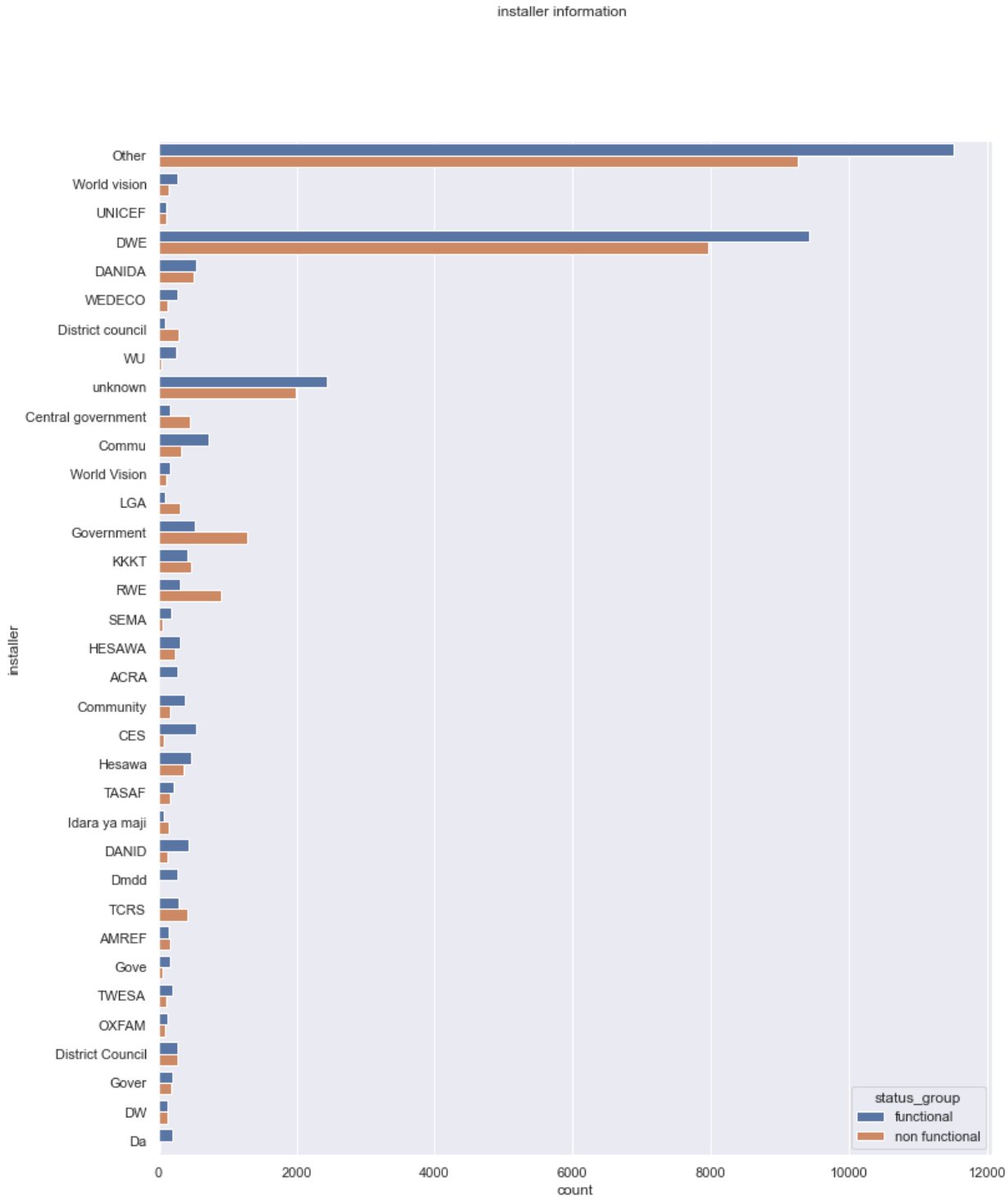
In [66]:
```
transformed_installer = cardinality_threshold(df3['installer'],
                                              threshold=0.65,
                                              return_categories_list=False

transformed_installer.value_counts()
```

Out[66]:
```
Other                  20768
DWE                    17402
unknown                 4433
Government              1825
RWE                     1206
Commu                   1060
DANIDA                  1050
KKKT                     898
Hesawa                   840
TCRS                     707
Central government       622
CES                      610
Community                553
DANID                    552
District Council         551
HESAWA                   539
LGA                      408
World vision             408
WEDECO                   397
TASAF                    396
District council         392
Gover                    383
AMREF                    329
TWESA                    316
WU                       301
Dmdd                     287
ACRA                     278
World Vision             270
SEMA                     249
DW                       246
OXFAM                    234
Da                       224
Idara ya maji            222
Gove                     222
UNICEF                   222
Name: installer, dtype: int64
```

In [67]:
```
df_transformed['installer'] = transformed_installer

fig = plt.figure(figsize=(12,15))
fig.suptitle('installer information')
sns.countplot(y= 'installer', hue='status_group', data=df_transformed)
plt.show();
```



In [68]:
```
df_binary['installer'] = transformed_installer

fig = plt.figure(figsize=(12,15))
fig.suptitle('installer information')
sns.countplot(y= 'installer', hue='status_group', data=df_binary)
plt.savefig('images/installer_graph')
plt.show();
```

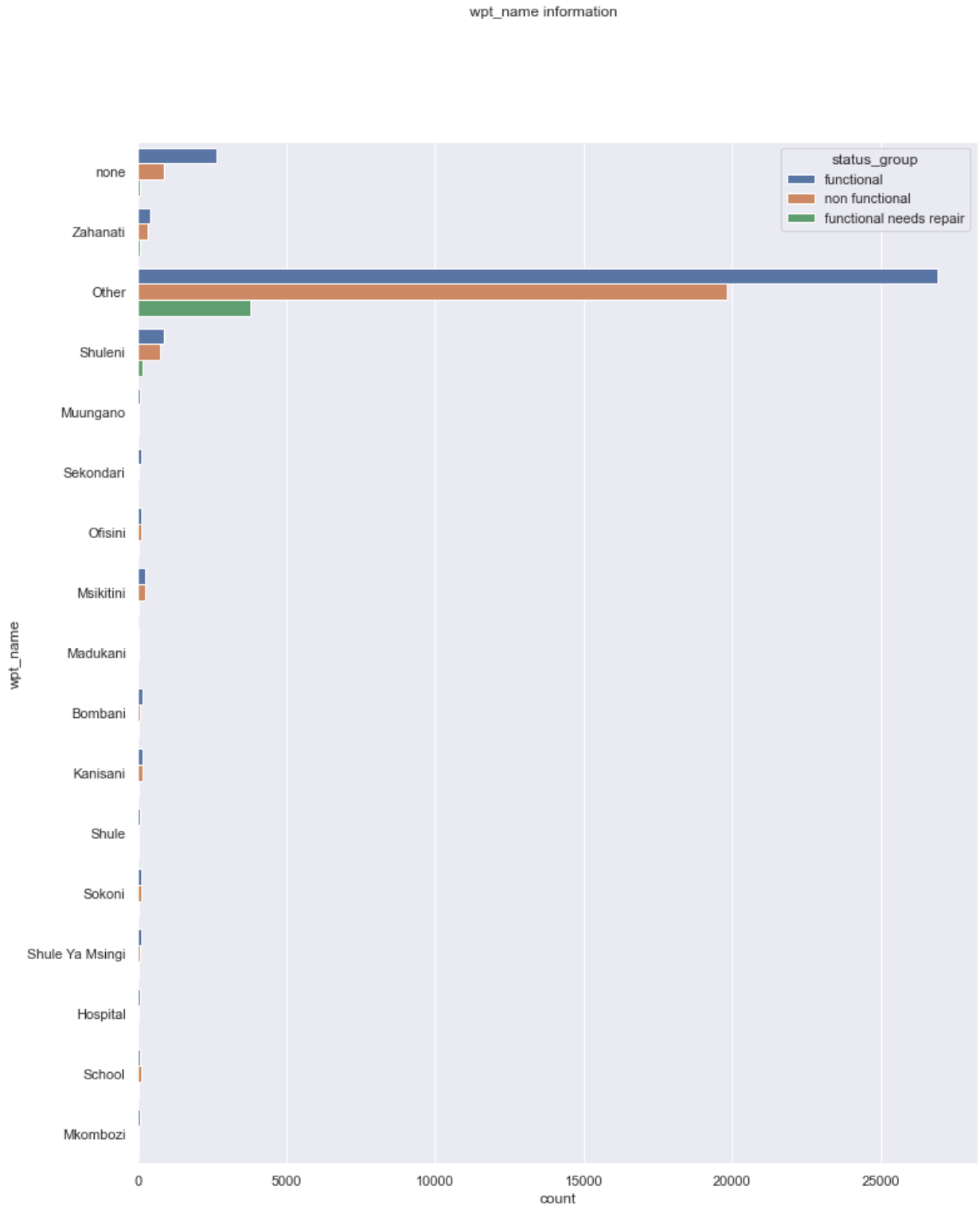


wpt_name transformation

In [69]:
```
transformed_wpt_name = cardinality_threshold(df3['wpt_name'],
                                             threshold=0.15,
                                             return_categories_list=False

transformed_wpt_name.value_counts()
```

Out[69]:
```
Other              50469
none                3563
Shuleni             1748
Zahanati             830
Msikitini            535
Kanisani             323
Bombani              271
Sokoni               260
Ofisini              254
School               208
Shule Ya Msingi      199
Shule                152
Sekondari            146
Muungano             133
Mkombozi             111
Madukani             104
Hospital              94
Name: wpt_name, dtype: int64
```

In [70]:
```
df_transformed['wpt_name'] = transformed_wpt_name

fig = plt.figure(figsize=(12,15))
fig.suptitle('wpt_name information')
sns.countplot(y= 'wpt_name', hue='status_group', data=df_transformed)
plt.show();
```

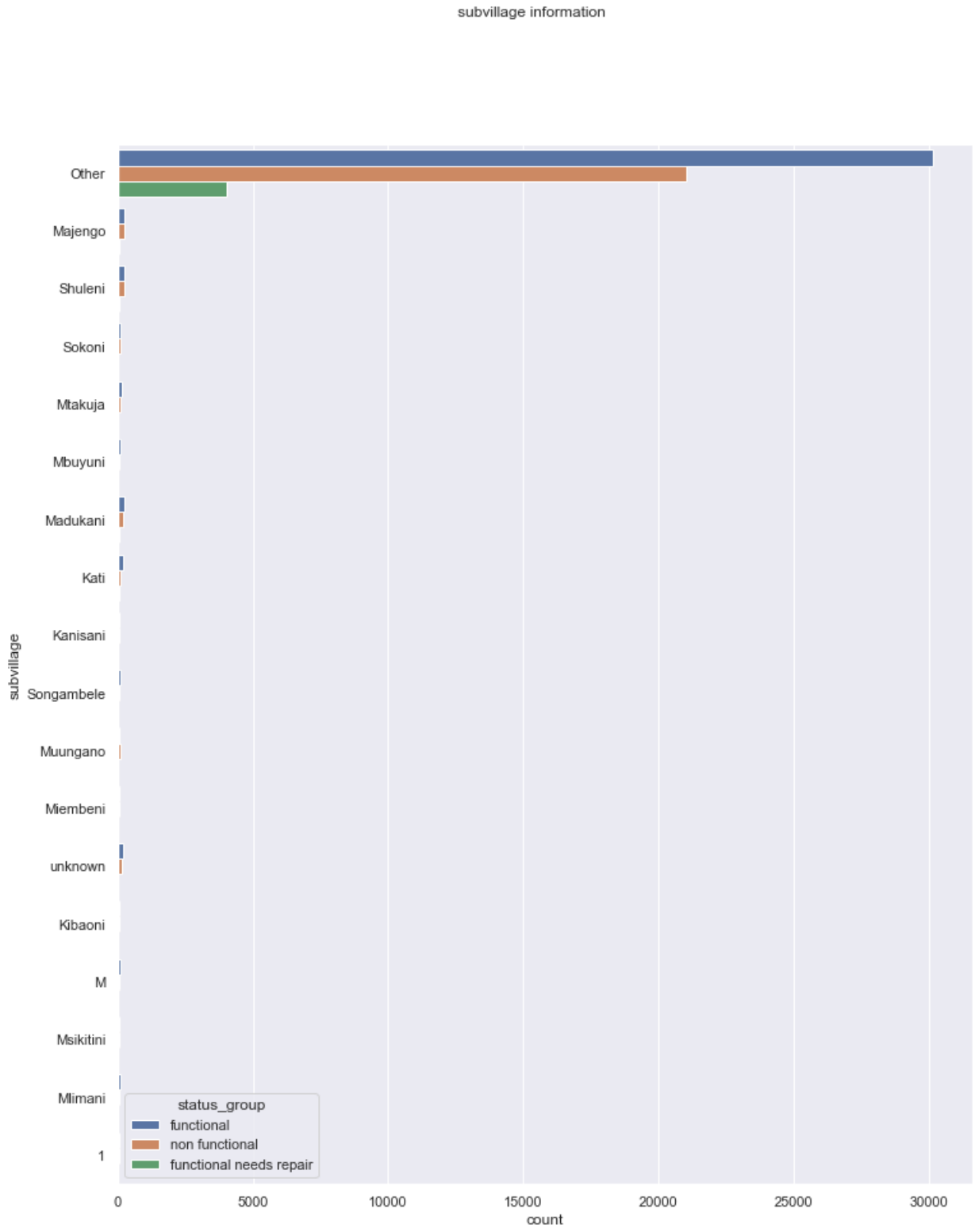


subvillage transformation

In [71]:
```
transformed_subvillage = cardinality_threshold(df3['subvillage'],
                                               threshold=0.07,
                                               return_categories_list=False

transformed_subvillage.value_counts()
```

Out[71]:
```
Other         55199
Madukani        508
Shuleni         506
Majengo         502
Kati            373
unknown         371
Mtakuja         262
Sokoni          232
M               187
Muungano        172
Mbuyuni         164
Mlimani         152
Songambele      147
Miembeni        134
Msikitini       134
1               132
Kibaoni         114
Kanisani        111
Name: subvillage, dtype: int64
```

In [72]:
```
df_transformed['subvillage'] = transformed_subvillage

fig = plt.figure(figsize=(12,15))
fig.suptitle('subvillage information')
sns.countplot(y= 'subvillage', hue='status_group', data=df_transformed)
plt.show();
```

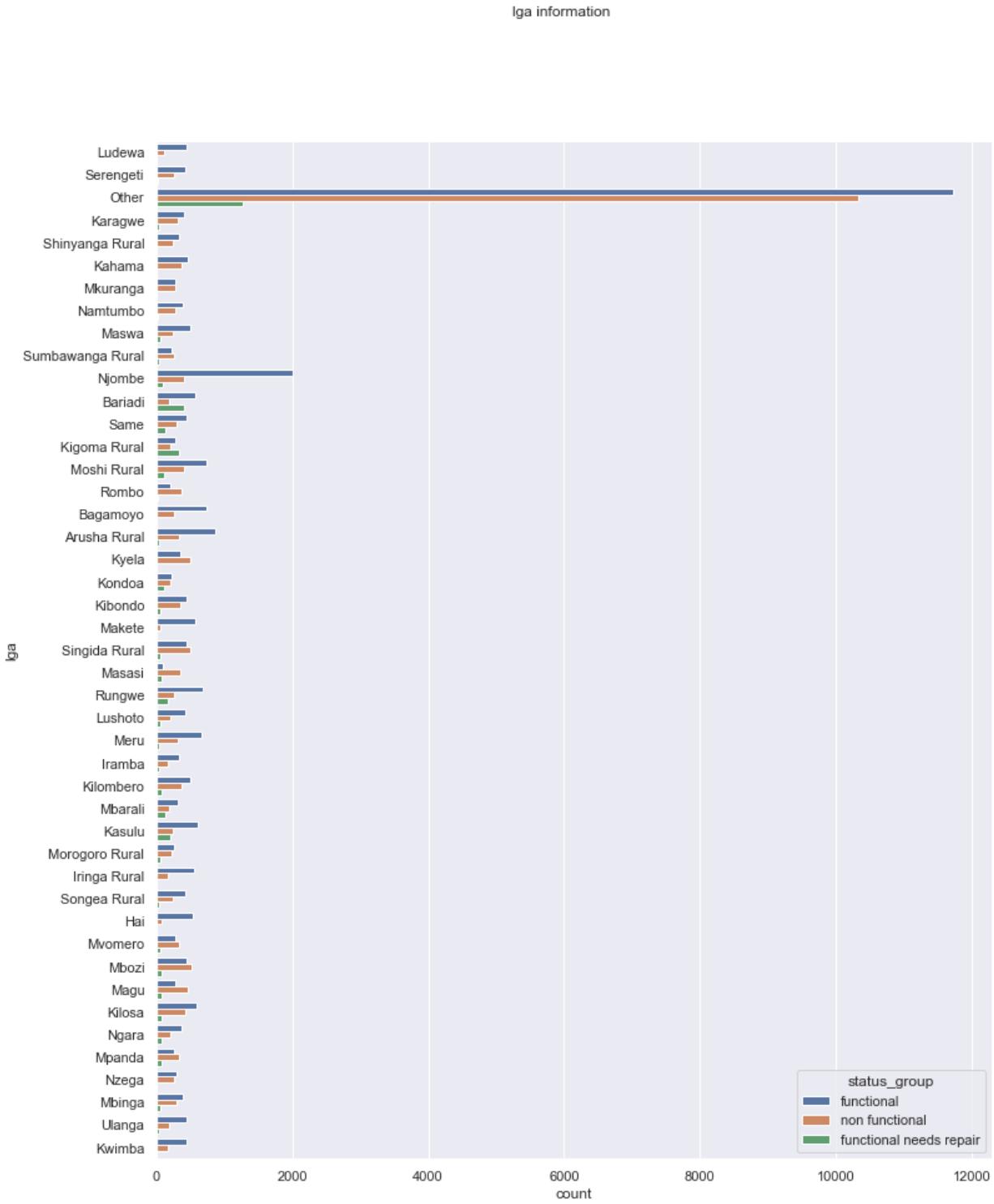


lga transformation

In [73]:
```
transformed_lga = cardinality_threshold(df3['lga'],
                                        threshold=0.6,
                                        return_categories_list=False

transformed_lga.value_counts()
```

Out[73]:
```
Other              23317
Njombe              2503
Arusha Rural        1252
Moshi Rural         1251
Bariadi             1177
Rungwe              1106
Kilosa              1094
Kasulu              1047
Mbozi               1034
Meru                1009
Bagamoyo             997
Singida Rural        995
Kilombero            959
Same                 877
Kibondo              874
Kyela                859
Kahama               836
Magu                 824
Kigoma Rural         824
Maswa                809
Karagwe              771
Mbinga               750
Iringa Rural         728
Serengeti            716
Lushoto              694
Namtumbo             694
Songea Rural         693
Mpanda               679
Mvomero              671
Ngara                669
Ulanga               665
Makete               630
Kwimba               627
Mbarali              626
Hai                  625
Rombo                594
Shinyanga Rural      588
Nzega                575
Ludewa               564
Mkuranga             560
Iramba               544
Masasi               528
Kondoa               523
Morogoro Rural       521
Sumbawanga Rural     521
Name: lga, dtype: int64
```

In [74]:
```
df_transformed['lga'] = transformed_lga

fig = plt.figure(figsize=(12,15))
fig.suptitle('lga information')
sns.countplot(y= 'lga', hue='status_group', data=df_transformed)
plt.show();
```



ward transformation

In [75]:
```
transformed_ward = cardinality_threshold(df3['ward'],
                                         threshold=0.05,
                                         return_categories_list=False

transformed_ward.value_counts()
```

Out[75]:
```
Other           56323
Igosi             307
Imalinyi          252
Siha Kati         232
Mdandu            231
Nduruma           217
Kitunda           203
Mishamo           203
Msindo            201
Chalinze          196
Maji ya Chai      190
Usuka             187
Ngarenanyuki      172
Chanika           171
Vikindu           162
Mtwango           153
Name: ward, dtype: int64
```

In [76]:
```
df_transformed['ward'] = transformed_ward

fig = plt.figure(figsize=(12,15))
fig.suptitle('ward information')
sns.countplot(y= 'ward', hue='status_group', data=df_transformed)
plt.show();
```

In [77]:
```
1 df3.columns
```

Out[77]:
```
Index(['amount_tsh', 'funder', 'gps_height', 'installer', 'wpt_name', 'basin',
       'subvillage', 'region', 'region_code', 'district_code', 'lga', 'ward',
       'public_meeting', 'permit', 'construction_year',
       'extraction_type_class', 'management', 'payment', 'quality_group',
       'quantity', 'source_type', 'waterpoint_type', 'status_group',
       'near_river', 'ward_pop'],
      dtype='object')
```

zero skewed data

population

The column describing population is heavily skewed towards a value of zero, and it would seem very unlikely for so many wells to have a population of zero. Nearly 50% of the data is skewed towards a value of either zero or one. It is hard to trust the validaty of this column. I decided to drop this column and bring in population information by ward collected by government census in 2012. This data has its own issues but I believe it to be a more complete dataset and give a better idea about the number of people who could benefit from the presence of a functional well in their area. Ward is a pretty high level division of geological boundaries for Tanzania. May have to revisit this population data at a later date. See beginning of notebook to see how population data was added by ward.

construction_year

This column is heavily skewed towards a value of zero. Zero seems to be a placeholder for unkown construction year. This column will be turned into a categorical column with binned decades and a column to replace zeroes with 'unknown'.

In [78]:
```
1 #with zeroes
2 df['construction_year'].describe()
```

Out[78]:
```
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 [79]:
```
#without zeroes (placeholder values)
construction_zero_index = df3[df3['construction_year'] == 0].index
df_construction = df3.drop(construction_zero_index)
df_construction['construction_year'].describe()
```

Out[79]:
```
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 [80]:
```
sns.countplot(x='construction_year', hue='status_group', data = df_cons
```

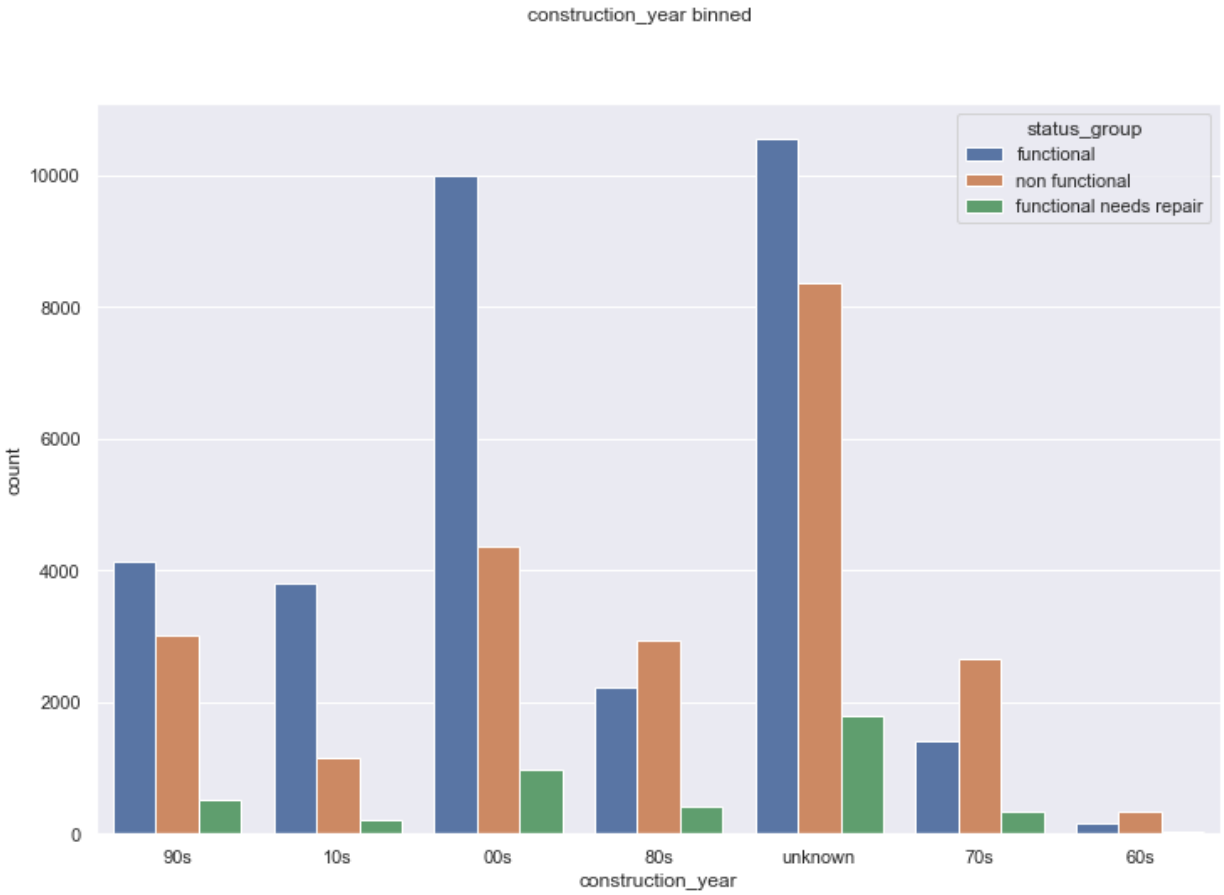
Out[80]:
```
<AxesSubplot:xlabel='construction_year', ylabel='count'>
```

In [81]:
```
#bin construction year into decades and 'unknown' for zeroes


def construction_wrangler(row):
    if row['construction_year'] >= 1960 and row['construction_year'] <
        return '60s'
    elif row['construction_year'] >= 1970 and row['construction_year']
        return '70s'
    elif row['construction_year'] >= 1980 and row['construction_year']
        return '80s'
    elif row['construction_year'] >= 1990 and row['construction_year']
        return '90s'
    elif row['construction_year'] >= 2000 and row['construction_year']
        return '00s'
    elif row['construction_year'] >= 2010:
        return '10s'
    else:
        return 'unknown'

df_transformed['construction_year'] = df_transformed.apply(lambda row:
```

In [82]:
```
df_transformed['construction_year'].value_counts()
```

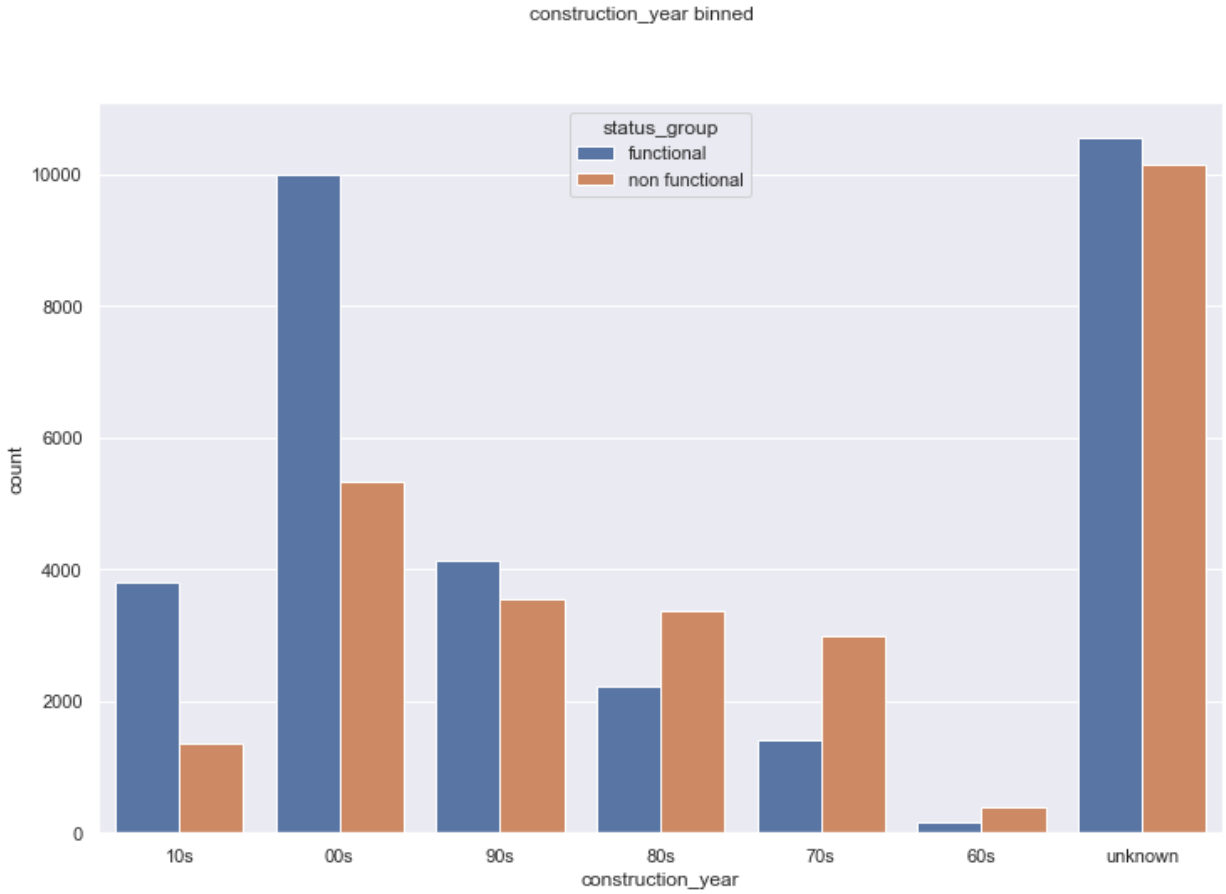
Out[82]:
```
unknown    20709
00s        15330
90s         7678
80s         5578
10s         5161
70s         4406
60s          538
Name: construction_year, dtype: int64
```

In [83]:
```
fig = plt.figure(figsize=(12,8))
fig.suptitle('construction_year binned')
sns.countplot(x = 'construction_year', hue='status_group', data=df_tran
plt.show();
```



In [84]:
```
df_binary['construction_year'] = df_binary.apply(lambda row: constructi
```

In [85]:
```
fig = plt.figure(figsize=(12,8))
fig.suptitle('construction_year binned')
sns.countplot(x = 'construction_year',
              hue='status_group',
              order=['10s',
                     '00s',
                     '90s',
                     '80s',
                     '70s',
                     '60s',
                     'unknown'],
              data=df_binary)
plt.savefig('images/construction_graph')
plt.show();
```



amount_tsh

In [86]:
```
df_transformed['amount_tsh'].sort_values(ascending=False)[:50]
```

Out[86]:
```
10812    350000.0
22191    250000.0
22817    200000.0
45067    170000.0
9961     138000.0
9917     120000.0
45470    117000.0
57811    117000.0
54595    117000.0
5558     117000.0
37459    117000.0
44381    117000.0
10615    117000.0
3228     100000.0
38137    100000.0
6591     100000.0
21567     70000.0
53968     60000.0
50494     50000.0
12895     50000.0
51260     50000.0
47201     50000.0
26130     45000.0
39114     45000.0
11349     45000.0
59375     40000.0
44803     40000.0
7364      40000.0
3245      40000.0
41790     40000.0
31976     40000.0
543       40000.0
49244     38000.0
23252     30000.0
45421     30000.0
31013     30000.0
34335     30000.0
17794     30000.0
48611     30000.0
57770     30000.0
20500     30000.0
23087     26000.0
27536     26000.0
45540     25000.0
55981     25000.0
58566     25000.0
30955     25000.0
22487     25000.0
194       25000.0
43712     25000.0
Name: amount_tsh, dtype: float64
```

Amount tsh

This column describes the total static head of each pump. It could be very useful in determining the amount of water available at each well. However, the data is extremely skewed towards the value of zero. There also seems to be extreme outliers in the other direction as well, with a value of 350000. Also, there are no dimensions in the data to know what the scale is. It could be feet or meters or something else.

Dealing with the large skew (over 70%) towards the value of zero is out of the scope for my project. I will drop this column for now and move on.

In [87]:
```
df_transformed.drop(columns=['amount_tsh'], axis=1, inplace=True)
```

GPS height

This column also has a skew towards zero. Nearly 35% of the values are zero. I am going to drop this column for now.

In [88]:
```
df_transformed.drop(columns=['gps_height'], axis=1, inplace=True)
```

In [89]:
```
df_transformed.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 23 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   funder                 59400 non-null  object 
 1   installer              59400 non-null  object 
 2   wpt_name               59400 non-null  object 
 3   basin                  59400 non-null  object 
 4   subvillage             59400 non-null  object 
 5   region                 59400 non-null  object 
 6   region_code            59400 non-null  int64  
 7   district_code          59400 non-null  int64  
 8   lga                    59400 non-null  object 
 9   ward                   59400 non-null  object 
 10  public_meeting         59400 non-null  object 
 11  permit                 59400 non-null  object 
 12  construction_year      59400 non-null  object 
 13  extraction_type_class  59400 non-null  object 
 14  management             59400 non-null  object 
 15  payment                59400 non-null  object 
 16  quality_group          59400 non-null  object 
 17  quantity               59400 non-null  object 
 18  source_type            59400 non-null  object 
 19  waterpoint_type        59400 non-null  object 
 20  status_group           59400 non-null  object 
 21  near_river             59400 non-null  float64
 22  ward_pop               59400 non-null  float64
dtypes: float64(2), int64(2), object(19)
memory usage: 13.4+ MB
```

In [90]:
```
df_transformed.columns
```

Out[90]:
```
Index(['funder', 'installer', 'wpt_name', 'basin', 'subvillage', 'regio
n',
       'region_code', 'district_code', 'lga', 'ward', 'public_meeting',
       'permit', 'construction_year', 'extraction_type_class', 'managemen
t',
       'payment', 'quality_group', 'quantity', 'source_type',
       'waterpoint_type', 'status_group', 'near_river', 'ward_pop'],
      dtype='object')
```

In [91]:
```
df_transformed.drop(columns=['region_code', 'district_code'], axis=1, i
```

In [92]:
```
df_transformed.columns
```

Out[92]:
```
Index(['funder', 'installer', 'wpt_name', 'basin', 'subvillage', 'regio
n',
       'lga', 'ward', 'public_meeting', 'permit', 'construction_year',
       'extraction_type_class', 'management', 'payment', 'quality_group',
       'quantity', 'source_type', 'waterpoint_type', 'status_group',
       'near_river', 'ward_pop'],
      dtype='object')
```

Below is some additional geographical/census/population data that could prove useful in improving modeling in future work. Due to time constraints, the data was not thoroughly explored.

I kept it below for now as an example of ways to bring in more information from government resources in order to explore new ways to improve predictive capabilities of any future modeling.

In [93]:
```
# df1 = pd.read_csv('data/region_points.csv')

# df2 = pd.read_csv('data/ObservationData_eqpqcq.csv')
# region_list = list(train_features['region'].unique())
# df_2 = df2[df2['region'].isin(region_list)]

# df3 = pd.read_csv('data/ObservationData_mzztfvd.csv')
```

In [94]:
```
# len(df3[df3['location'].isin(region_list)]['location'].unique())
# df2[df2['indicator'] == 'Revenue Collection (Tshs)'].groupby('region'
# df_2.groupby(['region', 'indicator']).mean()
# df3[df3['variable'] == 'Mean Maximum Temperature (°C)'].groupby('loca
# dfT = pd.read_csv('data/ObservationData_eqpqcq.csv')
# dfT2 = pd.read_csv('data/ObservationData_mzztfvd.csv')

# dfT2.head()
```

End of Exploratory Notebook

This is the end of data exploration and of this jupyter notebook. Please feel free to reach me at the following email for any questions or comments. Please continue on to my modeling notebook which contains information about what classification metrics are most important to consider given my buisness problem, all data preprocessing steps, and all modeling steps. Thank you!

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Github: Dddey Github (https://github.com/ddey117/Tanzanian_Water_Pump_Classification)