Final Project Submission

Please fill out:

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- Student pace: full time
- Scheduled project review date/time: 4/23/2021 11am CST
- Instructor name: Claude Fried
- Blog post URL:

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency

from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler, MinMaxScaler
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
from sklearn.pipeline import make_pipeline
from sklearn.impute import KNNImputer
import xgboost
```

In [2]:

```
df =pd.read_csv("./data/train_values.csv")
tr_labels = pd.read_csv("./data/train_labels.csv")
```

Business Problem:

- WaterAid has hired us to analyze some waterpoint mapping data they have collected.
- They would like us to make a model to predict whether a waterpoint is in need of repair.
- From that model, they would like to know which factures most affect failure rates.
- Of particular interest is to find out which Local Government Authorities are struggling the most.

1. Data Overview

We will be using the Tanzania Waterpoint Mapping data released in 2012. Dataset is from an active competition on datadriven.org.

Feature descriptions:

- amount_tsh - Total static head (amount water available to waterpoint)

- date_recorded - The date the row was entered
- funder - Who funded the well
- gps_height - Altitude of the well
- installer - Organization that installed the well
- longitude - GPS coordinate
- latitude - GPS coordinate
- wpt_name - Name of the waterpoint if there is one
- num_private -
- basin - Geographic water basin
- subvillage - Geographic location
- region - Geographic location
- region_code - Geographic location (coded)
- district_code - Geographic location (coded)
- lga - Geographic location
- ward - Geographic location
- population - Population around the well
- public_meeting - True/False
- recorded_by - Group entering this row of data
- scheme_management - Who operates the waterpoint
- scheme_name - Who operates the waterpoint
- permit - If the waterpoint is permitted
- construction_year - Year the waterpoint was constructed
- extraction_type - The kind of extraction the waterpoint uses
- extraction_type_group - The kind of extraction the waterpoint uses
- extraction_type_class - The kind of extraction the waterpoint uses
- management - How the waterpoint is managed
- management_group - How the waterpoint is managed
- payment - What the water costs
- payment_type - What the water costs
- water_quality - The quality of the water
- quality_group - The quality of the water
- quantity - The quantity of water
- quantity_group - The quantity of water
- source - The source of the water
- source_type - The source of the water
- source_class - The source of the water
- waterpoint_type - The kind of waterpoint

- waterpoint_type_group - The kind of waterpoint

1.1 Cursory Look

In [3]:
```
df.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
```

- There are 40 columns here, and many appear to be duplicates

In [4]:
```
df.head()
```

Out[4]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_private	...	payment_type	water_quality	quality_group	quantity	quantity_group	sourc
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	none	0	...	annually	soft	good	enough	enough	sprin
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zahanati	0	...	never pay	soft	good	insufficient	insufficient	rainwate harvestin
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Kwa Mahundi	0	...	per bucket	soft	good	enough	enough	dar
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	Zahanati Ya Nanyumbu	0	...	never pay	soft	good	dry	dry	machin db
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	Shuleni	0	...	never pay	soft	good	seasonal	seasonal	rainwate harvestin

5 rows × 40 columns

- We can see that a lot of our data appears to be categorical. Let's see how many columns could be continuous.

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

Out[5]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	region_code	district_code	population	construction_year
count	59400.000000	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.000000	59400.000000	59400.000000	59400.000000	59400.000000
mean	37115.131768	317.650385	668.297239	34.077427	-5.706033e+00	0.474141	15.297003	5.629747	179.909983	1300.652475
std	21453.128371	2997.574558	693.116350	6.567432	2.946019e+00	12.236230	17.587406	9.633649	471.482176	951.620547
min	0.000000	0.000000	-90.000000	0.000000	-1.164944e+01	0.000000	1.000000	0.000000	0.000000	0.000000
25%	18519.750000	0.000000	0.000000	33.090347	-8.540621e+00	0.000000	5.000000	2.000000	0.000000	0.000000
50%	37061.500000	0.000000	369.000000	34.908743	-5.021597e+00	0.000000	12.000000	3.000000	25.000000	1986.000000
75%	55656.500000	20.000000	1319.250000	37.178387	-3.326156e+00	0.000000	17.000000	5.000000	215.000000	2004.000000
max	74247.000000	350000.000000	2770.000000	40.345193	-2.000000e-08	1776.000000	99.000000	80.000000	30500.000000	2013.000000

- We have 10 columns that appear to be continuous right now, but that is deceiving.
  - region_code and district_code have numbers, but they are categorical.
  - id and num_private seem to be for internal record keeping.
  - amount_tsh, gps_height, population and construction_year have at least 25% values of 0 which are null
  - I suspect there are zero numbers in latitude and longitude as well

1.2 Dealing with the Target Variable

In [6]:
```
tr_labels.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   id            59400 non-null  int64 
 1   status_group  59400 non-null  object
dtypes: int64(1), object(1)
memory usage: 928.2+ KB
```

In [7]:
```
tr_labels.head()
```

Out[7]:

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

In [8]:
```
tr_labels.status_group.value_counts(normalize=True)
```

Out[8]:
```
functional                 0.543081
non functional             0.384242
functional needs repair    0.072677
Name: status_group, dtype: float64
```

- The majority of the waterpoints are functional, but we need to combine the non functional and functional needs repair

In [9]:
```
tr_labels['status_group'] = tr_labels['status_group'].map(lambda x: 'needs repair' if x != 'functional' else 'no repair')
df = df.merge(tr_labels, how='left', on='id')
tr_labels.status_group.value_counts(normalize=True)
```

Out[9]:
```
no repair       0.543081
needs repair    0.456919
Name: status_group, dtype: float64
```

- This works better and we see that the counts are more even. We have a binary classification now.

1.3 Dropping Excess Columns

In [10]:
```
df =df.drop([ 'funder', 'gps_height', 'installer', 'wpt_name'
            , 'num_private', 'population', 'public_meeting', 'recorded_by', 'permit',
            'scheme_management', 'scheme_name', 'quantity_group', 'extraction_type',
            'extraction_type_group', 'source', 'payment', 'waterpoint_type' ], axis=1)
```

- Here, we're dropping some duplicate and problematic columns.
- We can get them back, if necessary.

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 24 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   longitude              59400 non-null  float64
 4   latitude               59400 non-null  float64
 5   basin                  59400 non-null  object 
 6   subvillage             59029 non-null  object 
 7   region                 59400 non-null  object 
 8   region_code            59400 non-null  int64  
 9   district_code          59400 non-null  int64  
 10  lga                    59400 non-null  object 
 11  ward                   59400 non-null  object 
 12  construction_year      59400 non-null  int64  
 13  extraction_type_class  59400 non-null  object 
 14  management             59400 non-null  object 
 15  management_group       59400 non-null  object 
 16  payment_type           59400 non-null  object 
 17  water_quality          59400 non-null  object 
 18  quality_group          59400 non-null  object 
 19  quantity               59400 non-null  object 
 20  source_type            59400 non-null  object 
 21  source_class           59400 non-null  object 
 22  waterpoint_type_group  59400 non-null  object 
 23  status_group           59400 non-null  object 
dtypes: float64(3), int64(4), object(17)
memory usage: 11.3+ MB
```

- Down to 22 categories. We will eventually have to cut more.

2. Data Analysis and Feature Engineering

2.1 Taking care of some oddities

In [12]:
```
df['date_recorded'] = pd.to_datetime(df['date_recorded'])
df['year_recorded'] = df['date_recorded'].apply(lambda x: x.strftime('%Y')).astype(int)
df['date_recorded'] = df['date_recorded'].apply(lambda x: x.strftime('%Y-%m'))
```

- Didn't end up using this, but it could be useful if more complete construction_year data comes in.

In [13]:
```
df.amount_tsh.value_counts(normalize=True)
```

Out[13]:
```
0.0         0.700993
500.0       0.052222
50.0        0.041616
1000.0      0.025051
20.0        0.024630
              ...
8500.0      0.000017
6300.0      0.000017
220.0       0.000017
138000.0    0.000017
12.0        0.000017
Name: amount_tsh, Length: 98, dtype: float64
```

- I suspect(confidently) that 0s have been placed in place of the null values
- Simple logic: If you have 64% of the sources functional, you can't have 70% with 0 tsh.
- Ignore category
- Similar issues with the population and construction year.

In [14]:
```
df.describe()
```

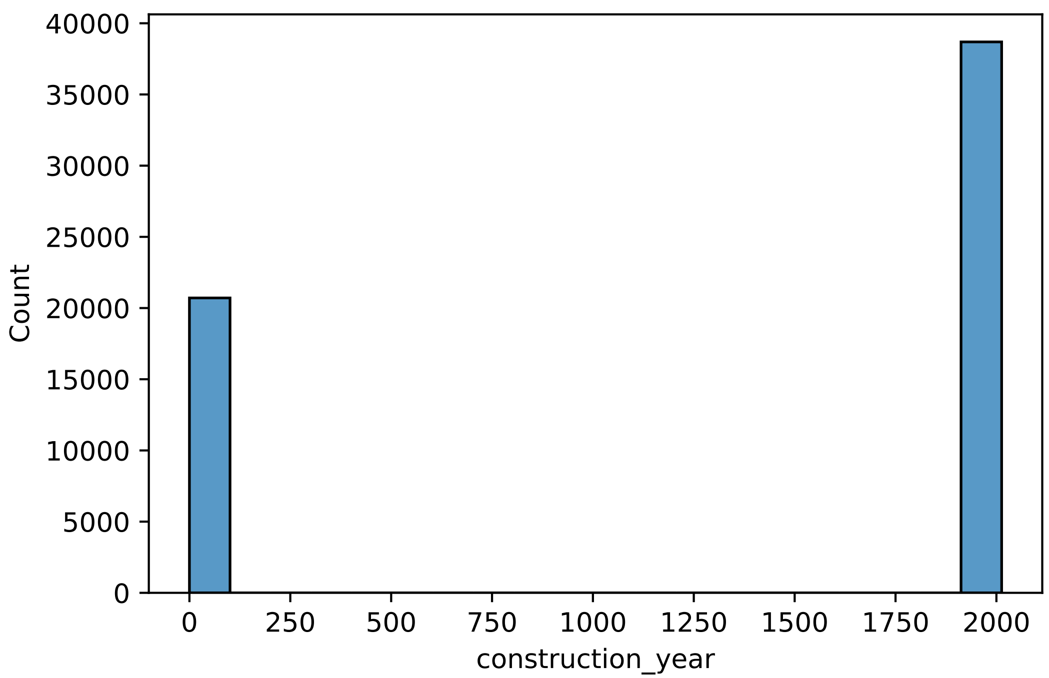
Out[14]:

	id	amount_tsh	longitude	latitude	region_code	district_code	construction_year	year_recorded
count	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.000000	59400.000000	59400.000000	59400.000000
mean	37115.131768	317.650385	34.077427	-5.706033e+00	15.297003	5.629747	1300.652475	2011.921667
std	21453.128371	2997.574558	6.567432	2.946019e+00	17.587406	9.633649	951.620547	0.958758
min	0.000000	0.000000	0.000000	-1.164944e+01	1.000000	0.000000	0.000000	2002.000000
25%	18519.750000	0.000000	33.090347	-8.540621e+00	5.000000	2.000000	0.000000	2011.000000

	id	amount_tsh	longitude	latitude	region_code	district_code	construction_year	year_recorded
50%	37061.500000	0.000000	34.908743	-5.021597e+00	12.000000	3.000000	1986.000000	2012.000000
75%	55656.500000	20.000000	37.178387	-3.326156e+00	17.000000	5.000000	2004.000000	2013.000000
max	74247.000000	350000.000000	40.345193	-2.000000e-08	99.000000	80.000000	2013.000000	2013.000000

In [15]:
```
sns.histplot(df.construction_year, bins=20)
```

Out[15]: <AxesSubplot:xlabel='construction_year', ylabel='Count'>



- We can't drop 20% of our data and it's not possible to umpute those values in a way that would be helpful.
- Column has to go

In [16]:
```
'''def cat_comb(df, category, threshold=5):
    series = pd.value_counts(df[category])
    mask = (series / series.sum() * 100).lt(threshold)
    df[category] = np.where(df[category].isin(series[mask].index),'other', df[category])
    return df[category]
'''
```

Out[16]:
```
"def cat_comb(df, category, threshold=5):\n    series = pd.value_counts(df[category])\n    mask = (series / series.sum() * 100).lt(threshold)\n    df[category] = np.where(d
f[category].isin(series[mask].index),'other', df[category])\n    return df[category]\n"
```

In [17]:
```
df.basin.value_counts(normalize=True)
```

Out[17]:
```
Lake Victoria              0.172525
Pangani                    0.150505
Rufiji                     0.134276
Internal                   0.131061
Lake Tanganyika            0.108283
Wami / Ruvu                0.100791
Lake Nyasa                 0.085606
Ruvuma / Southern Coast    0.075640
Lake Rukwa                 0.041313
Name: basin, dtype: float64
```

- There seem to be some basins combined.

def hashit(df, column): return df[column].apply(lambda x: mmh3.hash(x, seed=42, signed=True)&100)

In [18]:
```
#df['region'] = hashit(df, 'region')
df.lga.value_counts(normalize=True)
```

Out[18]:
```
Njombe          0.042138
Arusha Rural    0.021077
Moshi Rural     0.021061
Bariadi         0.019815
Rungwe          0.018620
                  ...
Moshi Urban     0.001330
Kigoma Urban    0.001195
Arusha Urban    0.001061
Lindi Urban     0.000354
Nyamagana       0.000017
Name: lga, Length: 125, dtype: float64
```

In [19]:
```
df['lga'] = df['lga'].apply(lambda x: x.split(" ")[0])
df.lga.value_counts()
```

Out[19]:
```
Njombe       2503
Moshi        1330
Arusha       1315
Bariadi      1177
Singida      1172
             ...
Ilemela       142
Mafia         132
Tanga          99
Kinondoni      93
Nyamagana       1
Name: lga, Length: 114, dtype: int64
```

Single value for Nyamangana is peculiar. Let's look at it.

In [20]:
```
df[df['lga'] == 'Nyamagana']
```

Out[20]:

	id	amount_tsh	date_recorded	longitude	latitude	basin	subvillage	region	region_code	district_code	...	management_group	payment_type	water_quality	quality_group	quantity	sou
3676	16551	0.0	2011-07	32.863271	-2.623808	Lake Victoria	Luchelele Ziwani	Mwanza	19	3	...	user-group	never pay	soft	good	enough	sha

1 rows × 25 columns

- Appears to be in a water rich area where such waterpoints aren't necessary.

sns.histplot(df.status_group)

fig = plt.figure(figsize=(20,15)) ax = sns.scatterplot(data=working[working['construction_year'] != 0], x='longitude', y='latitude', alpha=0.2, hue='construction_year', marker='.') ''' ax.set(xlabel='Budget($100 Million)', ylabel='Return on Investment(%)', title='Returns by Budget', xticks=np.arange(0, 340000000, 50000000), yticks=np.arange(0, 51, 10),) '''

plt.xlim([29,41]) plt.ylim([-12,0]) plt.show()

In [21]:
```
df = df.drop(['id', 'amount_tsh', 'date_recorded', 'year_recorded', 'construction_year', 'management'], axis=1)
```

- These features don't have much use to us at this point.

2.2 Categoricals and Continuous Variables

2.2.1 Split

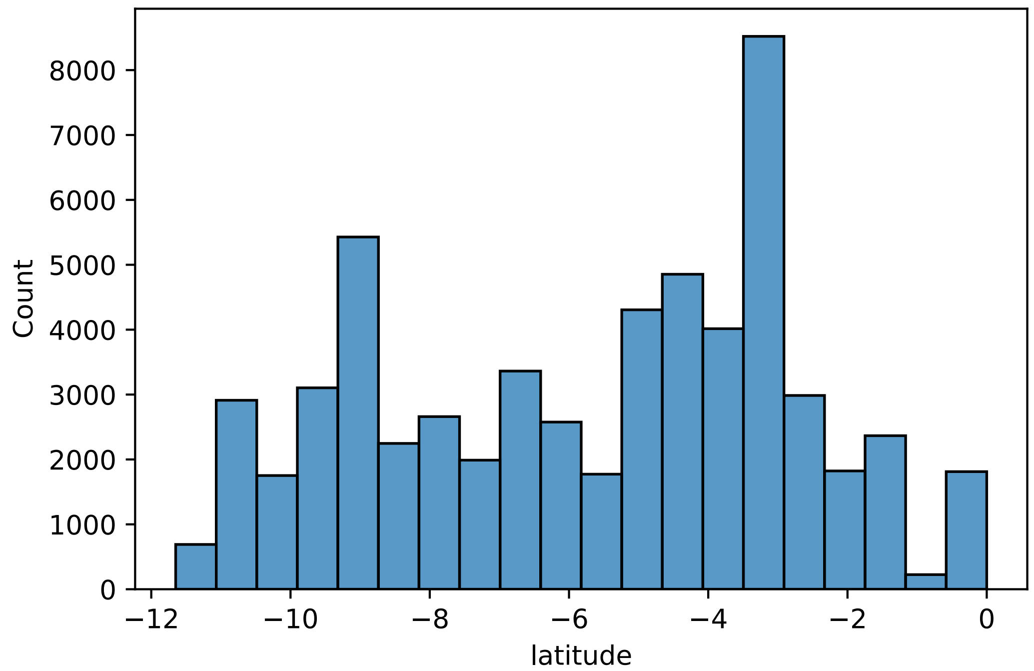
In [22]:
```
df_cont = df[['latitude', 'longitude']]
df_cat = df.drop(['latitude', 'longitude'], axis=1)
```

2.2.2 Continuous Variables

In [23]:
```
df_cont = pd.DataFrame(df_cont)
```

In [24]:
```
sns.histplot(df_cont.latitude, bins=20)
```

Out[24]:
```
<AxesSubplot:xlabel='latitude', ylabel='Count'>
```

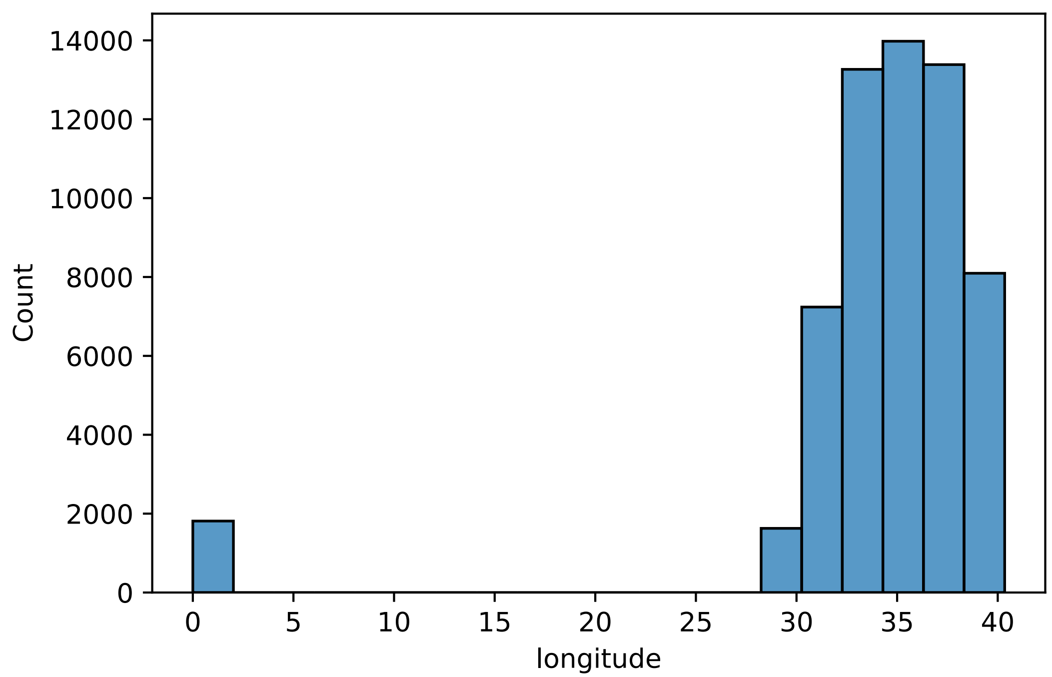


In [25]:

```
sns.histplot(df_cont.longitude, bins=20)
```

Out[25]:

```
<AxesSubplot:xlabel='longitude', ylabel='Count'>
```



- Alright, we got some problematic 0 values which are a placeholder for null
- Using SimpleImputer with mean or mode would be more problematic.
- For now, we'll stick with the strategy='ignore' which leaves 0s.

In [26]:
```
scaler = StandardScaler()

df_cont = scaler.fit_transform(df_cont)
df_cont = pd.DataFrame(df_cont)
```

2.2.3 Categorical Variables

In [27]:
```
for column in df_cat:
    print(column)
    print (len(df_cat[column].value_counts()))
```

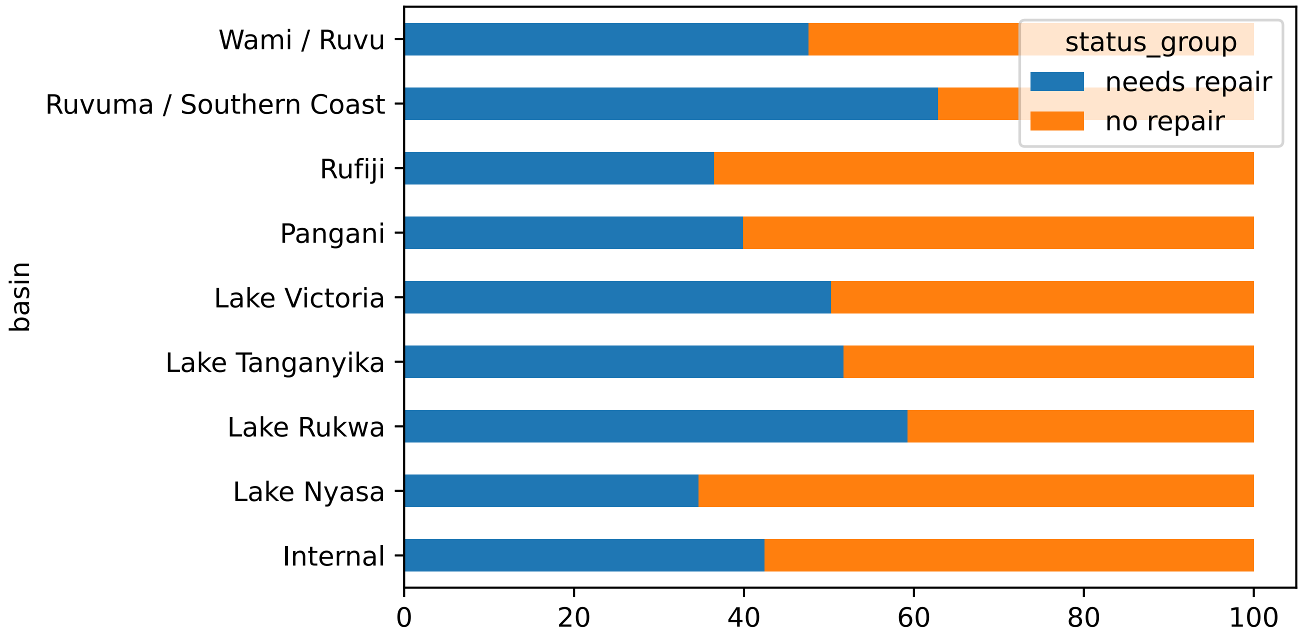
```
basin
9
subvillage
19287
region
21
region_code
27
district_code
20
lga
114
ward
2092
extraction_type_class
7
management_group
5
payment_type
7
water_quality
8
quality_group
6
quantity
5
source_type
7
source_class
3
waterpoint_type_group
6
status_group
2
```

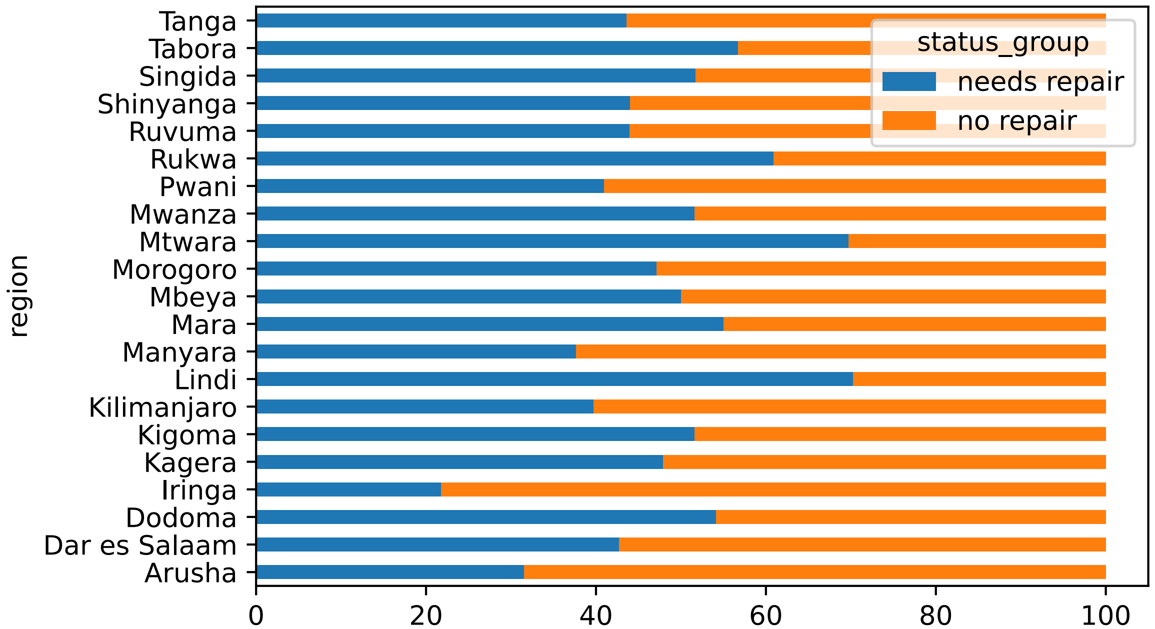
In [ ]:

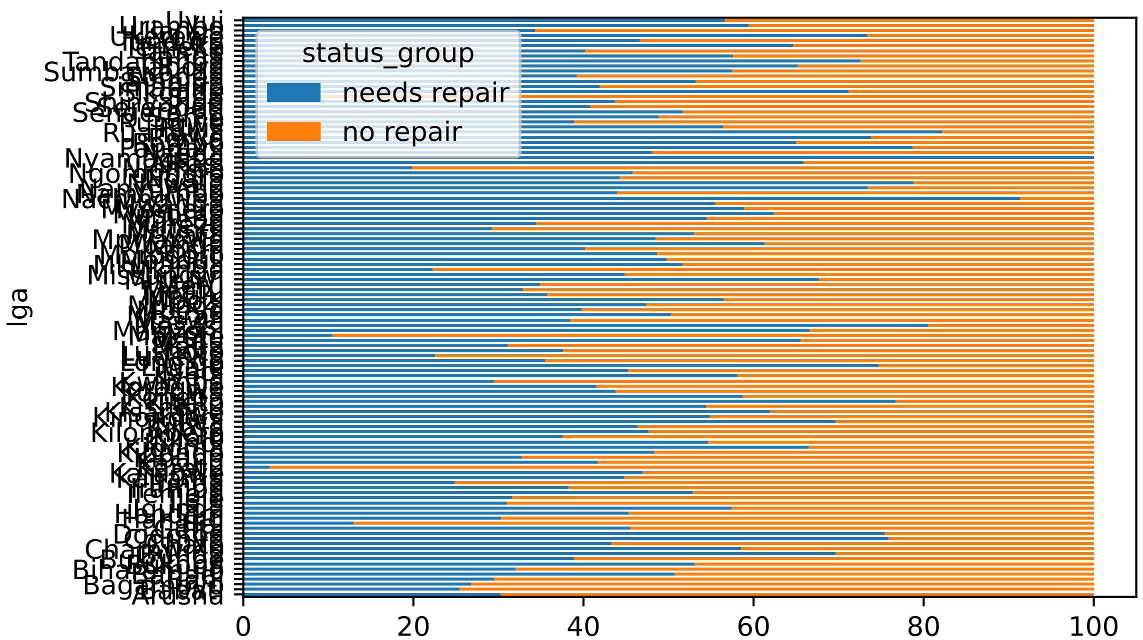
In [28]:
```
df_cat = df_cat.drop(['subvillage', 'ward', 'source_class', 'water_quality', 'region_code', 'district_code'], axis=1)
```

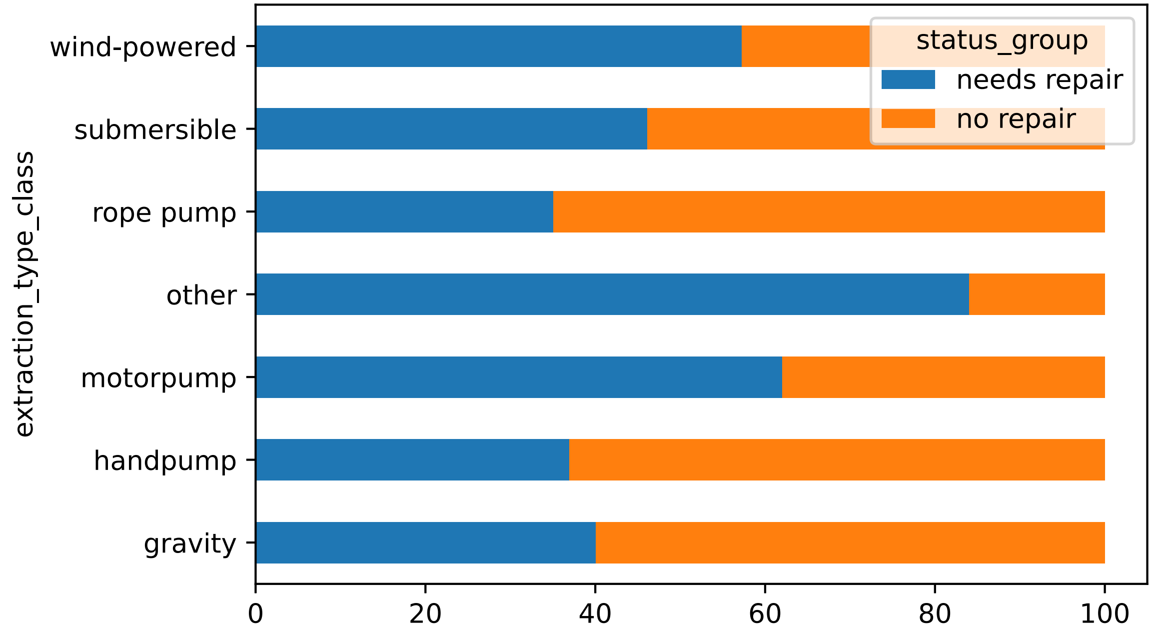
In [ ]:

In [29]:
```
for column in df_cat:
    pd.crosstab(df_cat[column], tr_labels['status_group']
                        ).apply(lambda x: x/x.sum()*100, axis=1
                        ).plot(kind="barh",stacked=True)
```

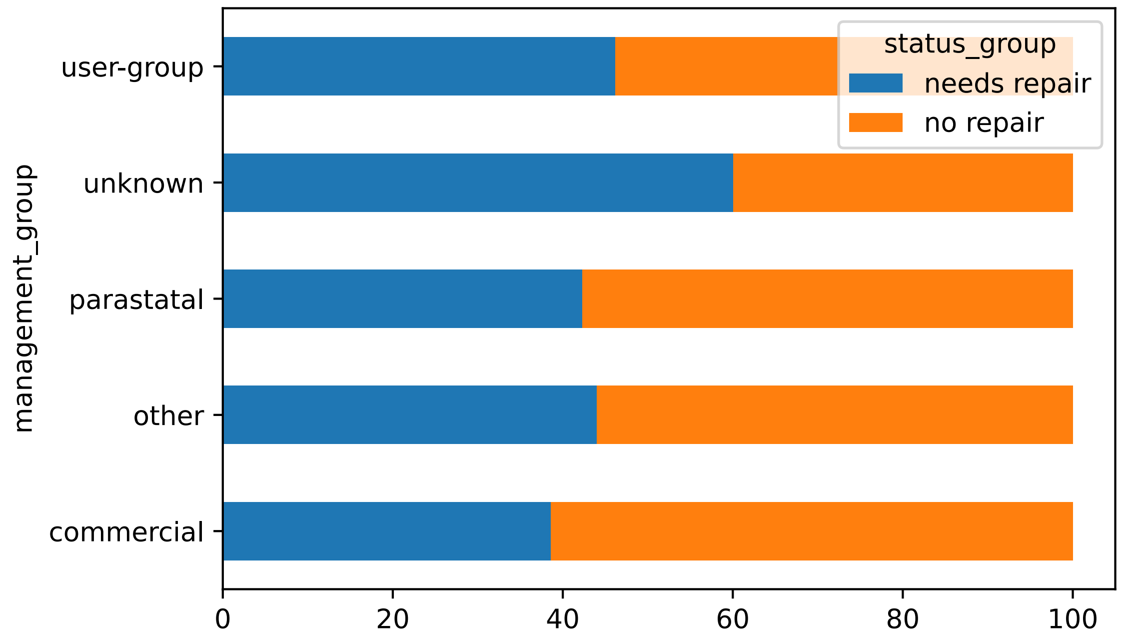



status_group
needs repair
no repair
region
Tanga
Tabora
Singida
Shinyanga
Ruvuma
Rukwa
Pwani
Mwanza
Mtwara
Morogoro
Mbeya
Mara
Manyara
Lindi
Kilimanjaro
Kigoma
Kagera
Iringa
Dodoma
Dar es Salaam
Arusha
0
20
40
60
80
100

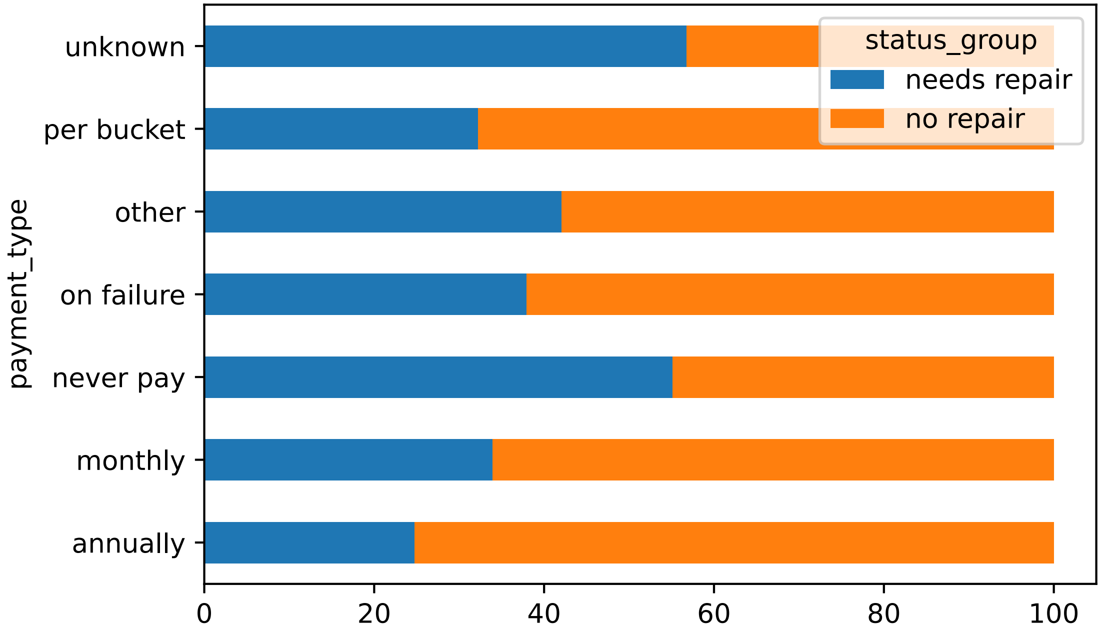

status_group
needs repair
no repair
lga
0
20
40
60
80
100



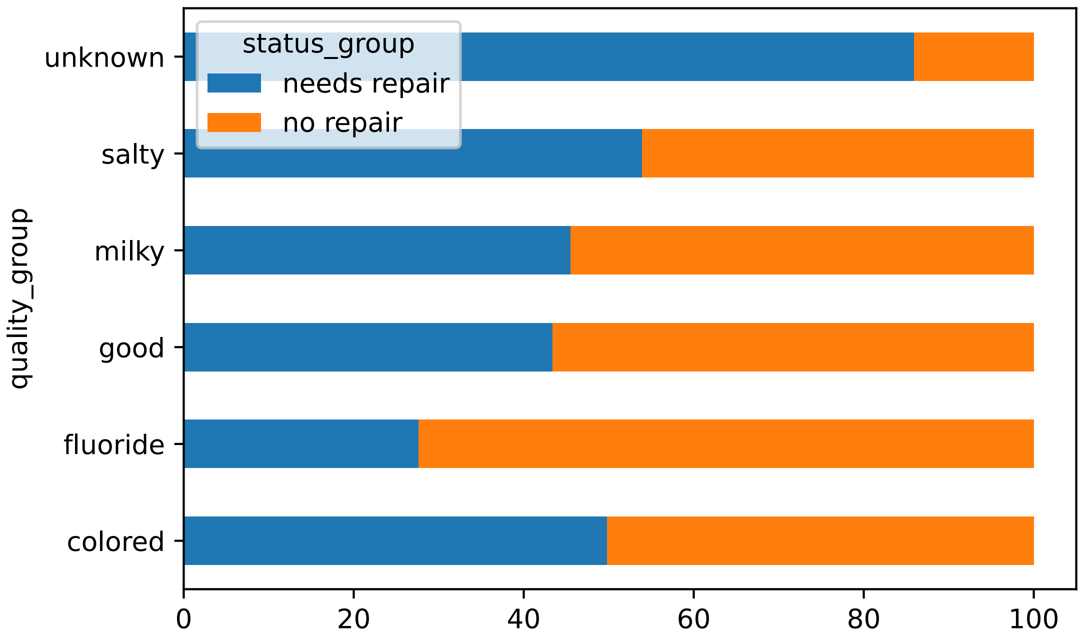
wind-powered
submersible
rope pump
other
motorpump
handpump
gravity
extraction_type_class
0
20
40
60
80
100
status_group
needs repair
no repair



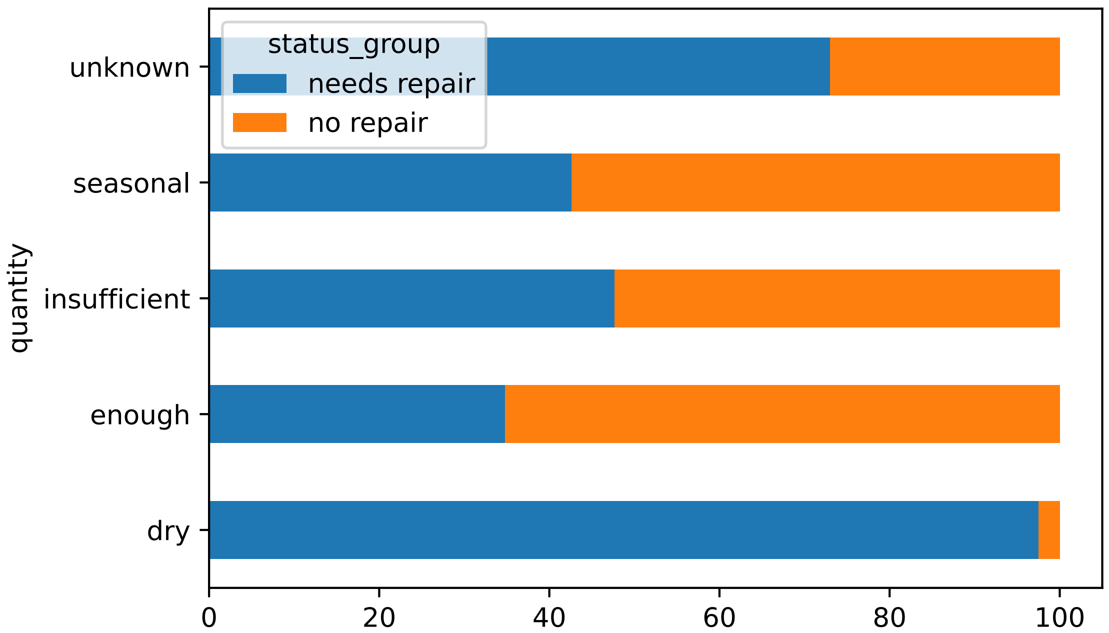
user-group
unknown
parastatal
other
commercial
management_group
0
20
40
60
80
100
status_group
needs repair
no repair

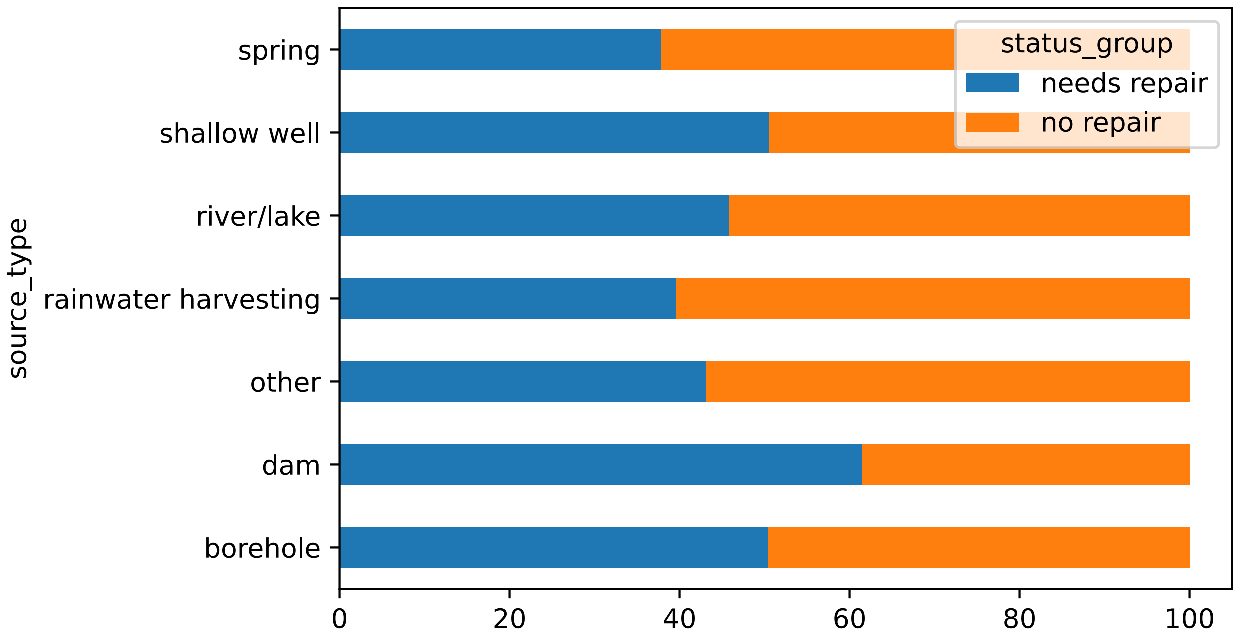


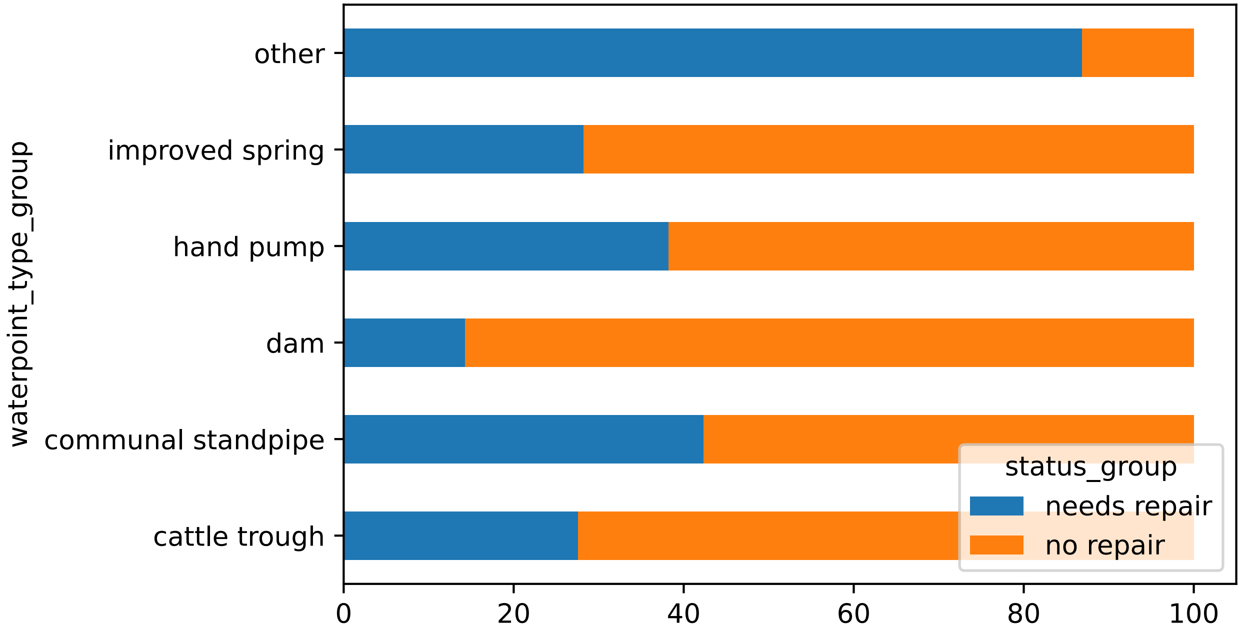
payment_type
unknown
per bucket
other
on failure
never pay
monthly
annually
0
20
40
60
80
100
status_group
needs repair
no repair

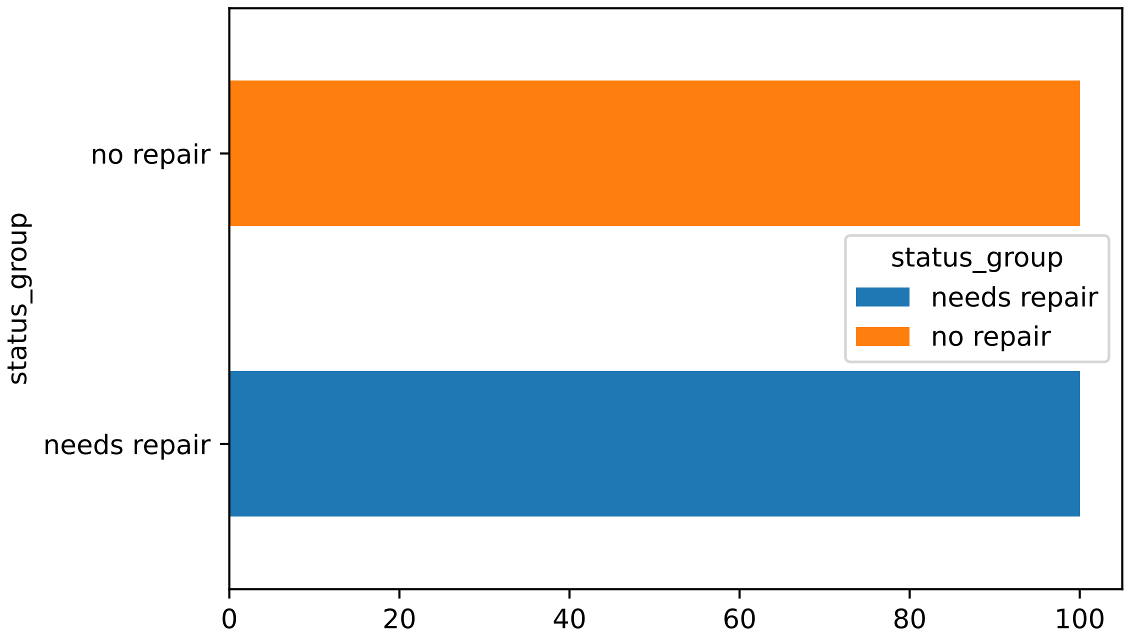


quality_group
unknown
salty
milky
good
fluoride
colored
0
20
40
60
80
100
status_group
needs repair
no repair


status_group
needs repair
no repair
quantity
unknown
seasonal
insufficient
enough
dry
0
20
40
60
80
100


status_group
needs repair
no repair
source_type
spring
shallow well
river/lake
rainwater harvesting
other
dam
borehole
0
20
40
60
80
100





In [30]:
```
for column in df_cat:
    print(df_cat[column].value_counts(normalize=True))
```

```
Lake Victoria              0.172525
Pangani                    0.150505
Rufiji                     0.134276
Internal                   0.131061
Lake Tanganyika            0.108283
```

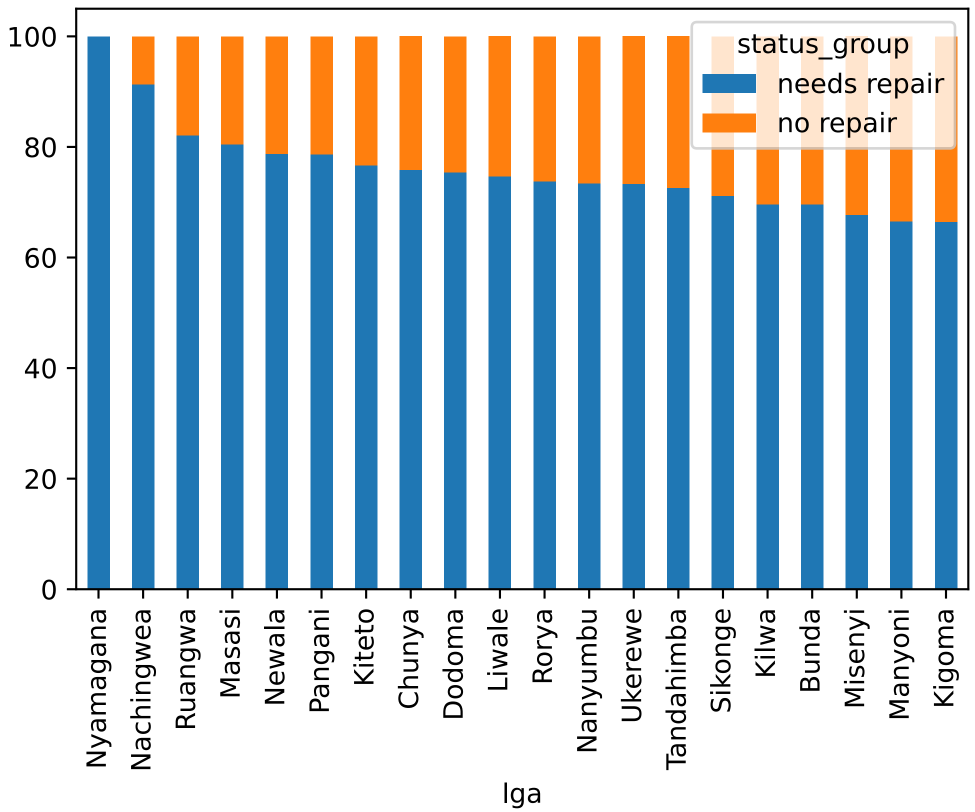
```
Wami / Ruvu                0.100791
Lake Nyasa                 0.085606
Ruvuma / Southern Coast    0.075640
Lake Rukwa                 0.041313
Name: basin, dtype: float64
Iringa           0.089125
Shinyanga        0.083872
Mbeya            0.078098
Kilimanjaro      0.073721
Morogoro         0.067441
Arusha           0.056397
Kagera           0.055825
Mwanza           0.052222
Kigoma           0.047407
Ruvuma           0.044444
Pwani            0.044360
Tanga            0.042879
Dodoma           0.037054
Singida          0.035236
Mara             0.033148
Tabora           0.032980
Rukwa            0.030438
Mtwara           0.029125
Manyara          0.026650
Lindi            0.026027
Dar es Salaam    0.013552
Name: region, dtype: float64
Njombe       0.042138
Moshi        0.022391
Arusha       0.022138
Bariadi      0.019815
Singida      0.019731
               ...
Ilemela      0.002391
Mafia        0.002222
Tanga        0.001667
Kinondoni    0.001566
Nyamagana    0.000017
Name: lga, Length: 114, dtype: float64
gravity         0.450842
handpump        0.277037
other           0.108249
submersible     0.104024
motorpump       0.050286
rope pump       0.007593
wind-powered    0.001970
Name: extraction_type_class, dtype: float64
user-group    0.883670
commercial    0.061246
parastatal    0.029764
other         0.015875
unknown       0.009444
Name: management_group, dtype: float64
never pay     0.426734
```

```
per bucket    0.151263
monthly       0.139731
unknown       0.137323
on failure    0.065892
annually      0.061313
other         0.017744
Name: payment_type, dtype: float64
good        0.855522
salty       0.087458
unknown     0.031582
milky       0.013535
colored     0.008249
fluoride    0.003653
Name: quality_group, dtype: float64
enough          0.558687
insufficient    0.254697
dry             0.105152
seasonal        0.068182
unknown         0.013283
Name: quantity, dtype: float64
spring                  0.286549
shallow well            0.283232
borehole                0.201162
river/lake              0.174697
rainwater harvesting    0.038636
dam                     0.011044
other                   0.004680
Name: source_type, dtype: float64
communal standpipe    0.582912
hand pump             0.294411
other                 0.107407
improved spring       0.013199
cattle trough         0.001953
dam                   0.000118
Name: waterpoint_type_group, dtype: float64
no repair       0.543081
needs repair    0.456919
Name: status_group, dtype: float64
```

- Thints that stand out:
  - Quantity of dry has a huge effect and that's about 10% of wells
  - Payment type of never_pay and unknown have higer repair needs.
    - That's 43% and 14% of all waterpoints
  - LGA has a high amount of variability, so it is very important.

In [31]:
```
repairc =pd.crosstab(df_cat['lga'], tr_labels['status_group']).apply(lambda x: x/x.sum()*100, axis=1)
repairc =repairc.sort_values(by='needs repair', ascending=False).head(20)
repairc.plot(kind='bar', stacked=True)
```

Out[31]:
```
<AxesSubplot:xlabel='lga'>
```



- These are the 20 LGAs that have the highest repair needs by %
- We notice Nyamagana here.
- Let's do this for waterpoints where the quantity of water isn't enough.

In [32]:
```
df_ne = df_cat[df_cat['quantity'] != 'enough']
df_ne.info()
```

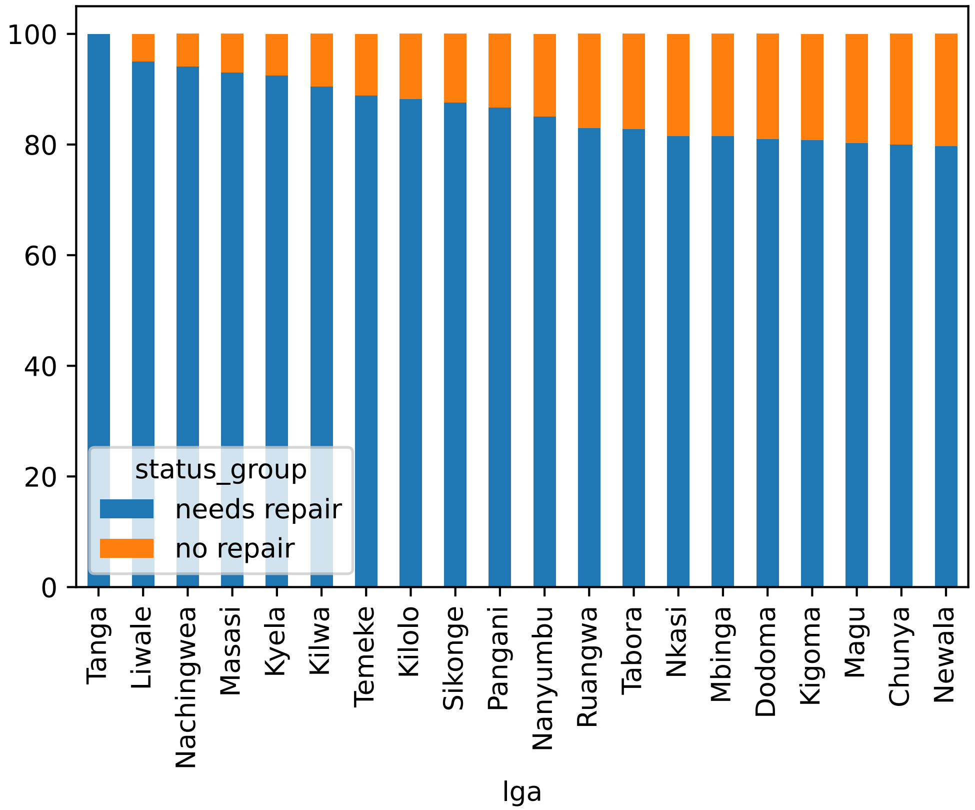
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26214 entries, 1 to 59398
Data columns (total 11 columns):
 #   Column                 Non-Null Count  Dtype 
---  ------                 --------------  ----- 
 0   basin                  26214 non-null  object
 1   region                 26214 non-null  object
 2   lga                    26214 non-null  object
 3   extraction_type_class  26214 non-null  object
 4   management_group       26214 non-null  object
 5   payment_type           26214 non-null  object
 6   quality_group          26214 non-null  object
 7   quantity               26214 non-null  object
 8   source_type            26214 non-null  object
 9   waterpoint_type_group  26214 non-null  object
 10  status_group           26214 non-null  object
```

```
dtypes: object(11)
memory usage: 2.4+ MB
```

In [33]:

```python
repairc =pd.crosstab(df_ne['lga'], df_ne['status_group']).apply(lambda x: x/x.sum()*100, axis=1)
repairc =repairc.sort_values(by='needs repair', ascending=False).head(20)
repairc.plot(kind='bar', stacked=True)
```

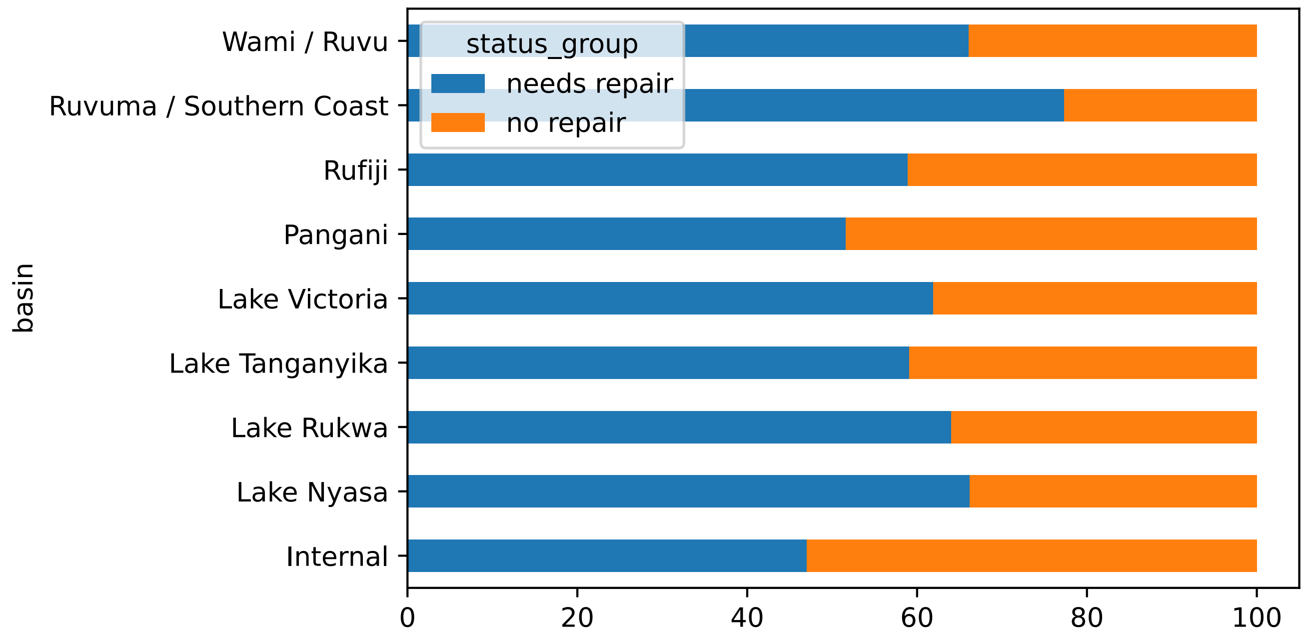
Out[33]: <AxesSubplot:xlabel='lga'>

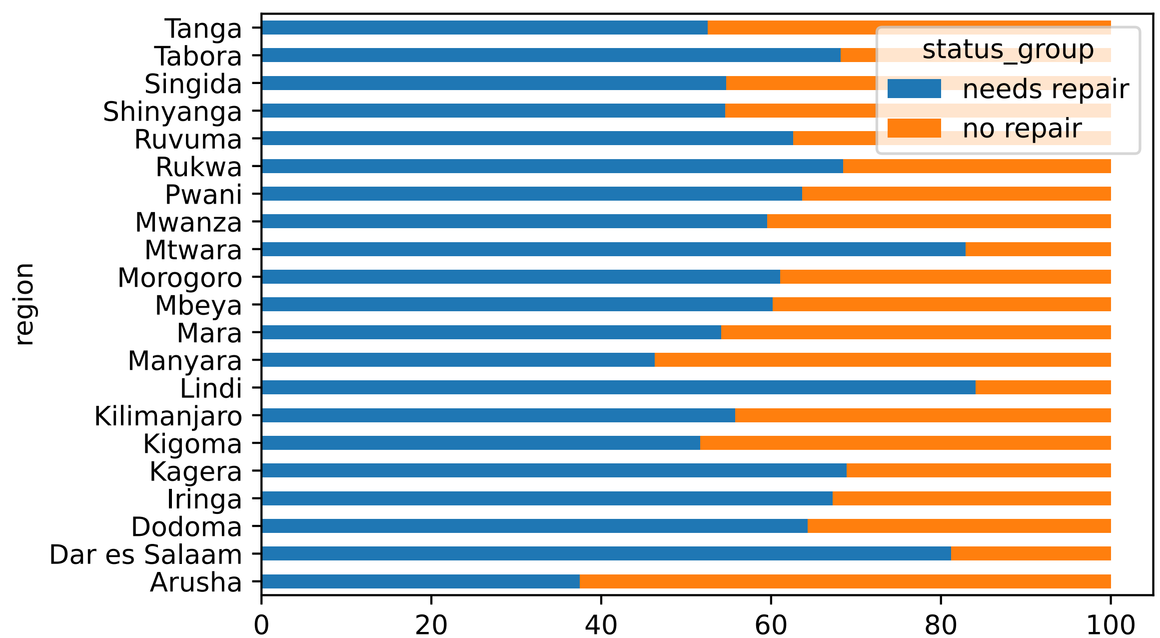


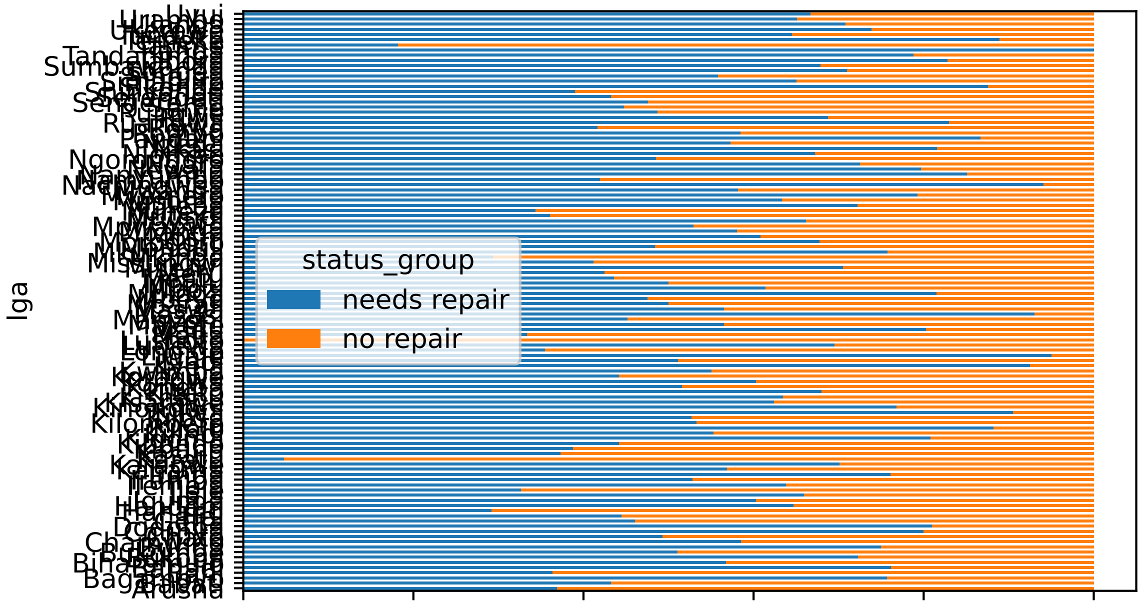
- Wow. The LGAs with the highest repair needs are all above 80%

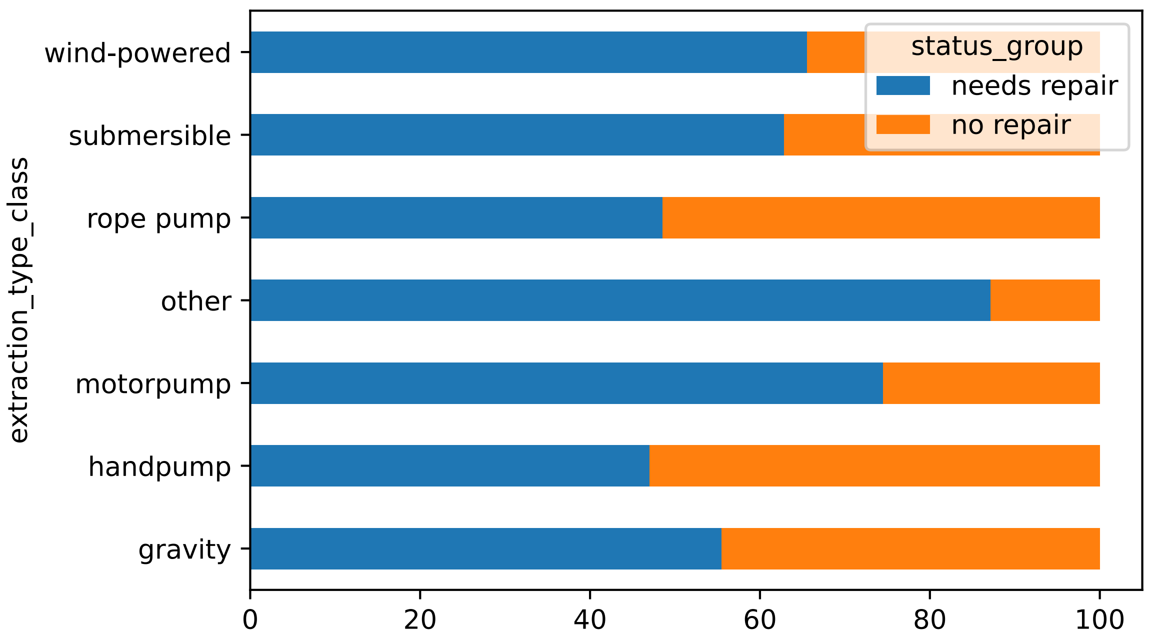
In [34]:

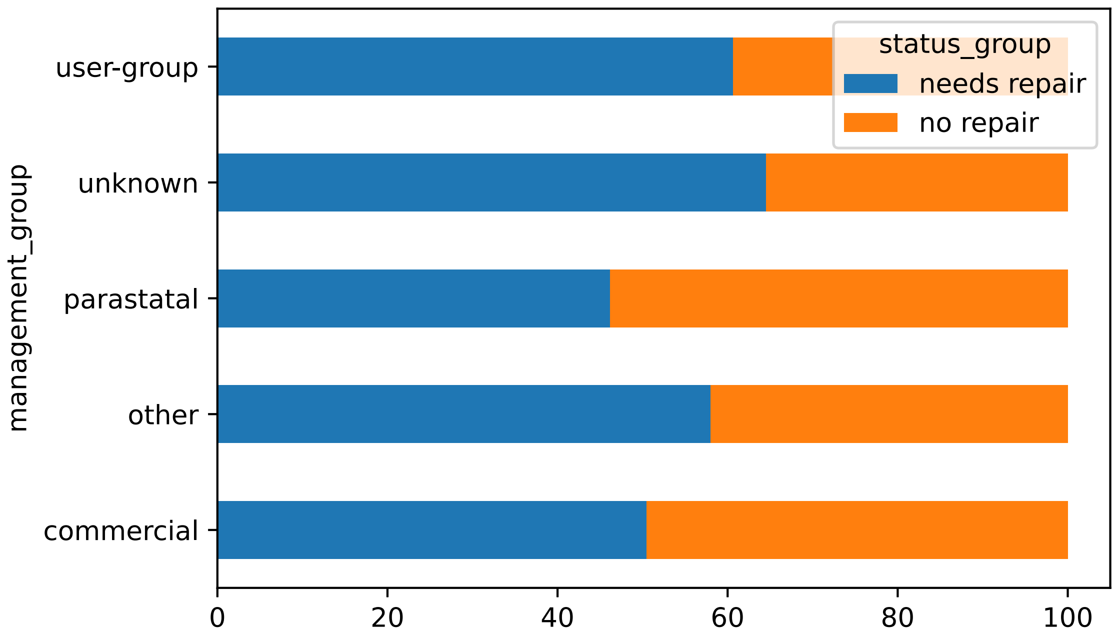
```python
for column in df_ne:
    pd.crosstab(df_ne[column], df_ne['status_group']
                            ).apply(lambda x: x/x.sum()*100, axis=1
                            ).plot(kind="barh",stacked=True)
```


status_group
needs repair
no repair
basin
Wami / Ruvu
Ruvuma / Southern Coast
Rufiji
Pangani
Lake Victoria
Lake Tanganyika
Lake Rukwa
Lake Nyasa
Internal
0
20
40
60
80
100

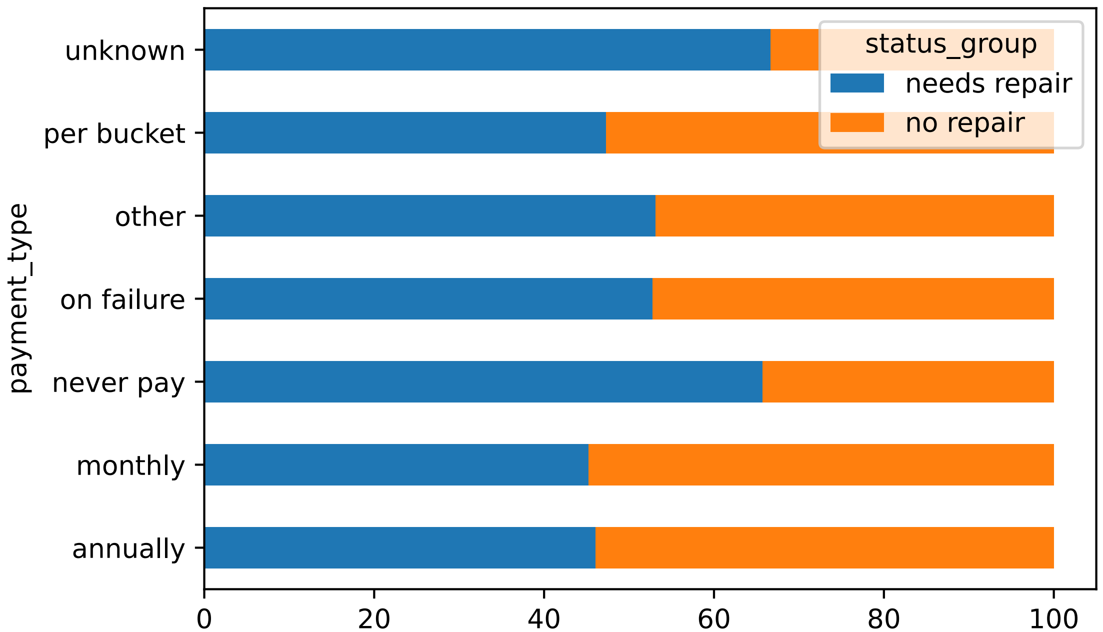

status_group
needs repair
no repair
region
Tanga
Tabora
Singida
Shinyanga
Ruvuma
Rukwa
Pwani
Mwanza
Mtwara
Morogoro
Mbeya
Mara
Manyara
Lindi
Kilimanjaro
Kigoma
Kagera
Iringa
Dodoma
Dar es Salaam
Arusha
0
20
40
60
80
100


lga
status_group
needs repair
no repair
0
20
40
60
80
100

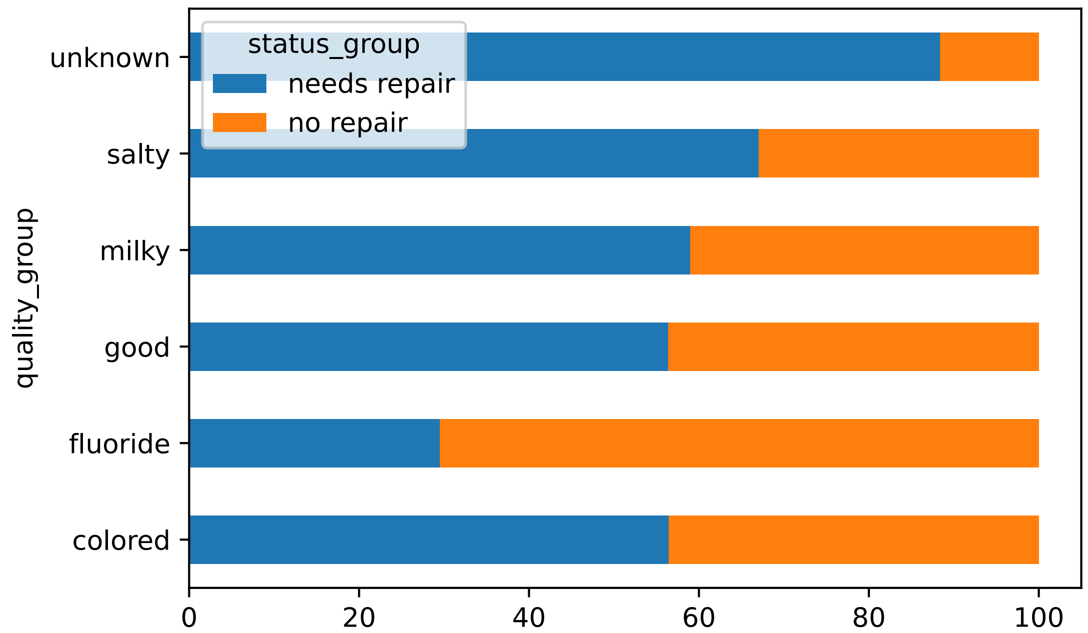

extraction_type_class
wind-powered
submersible
rope pump
other
motorpump
handpump
gravity
status_group
needs repair
no repair
0
20
40
60
80
100

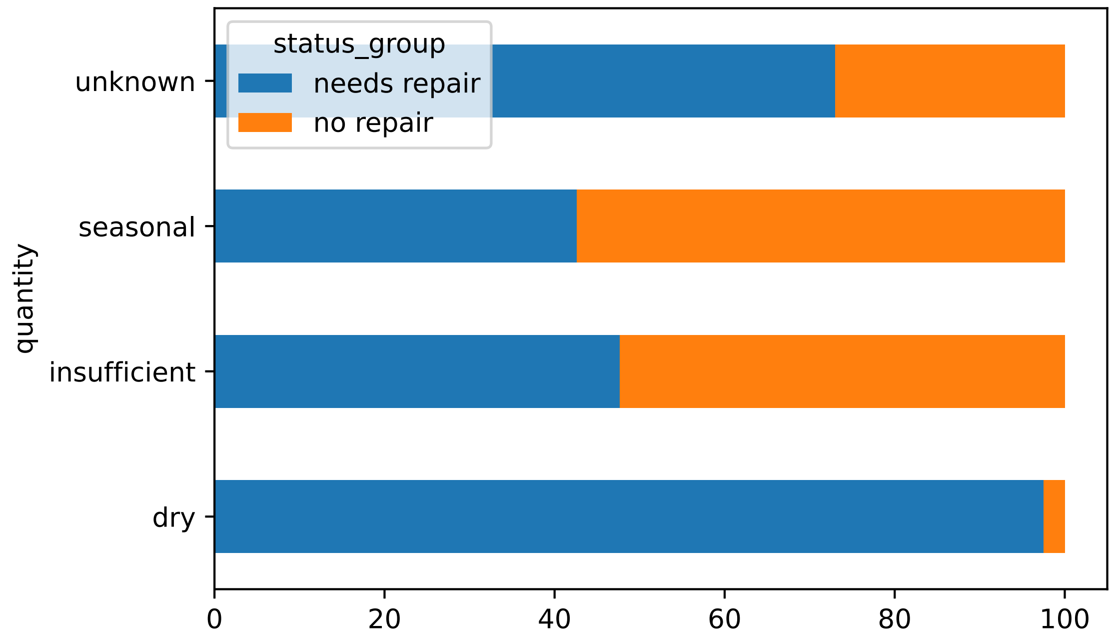


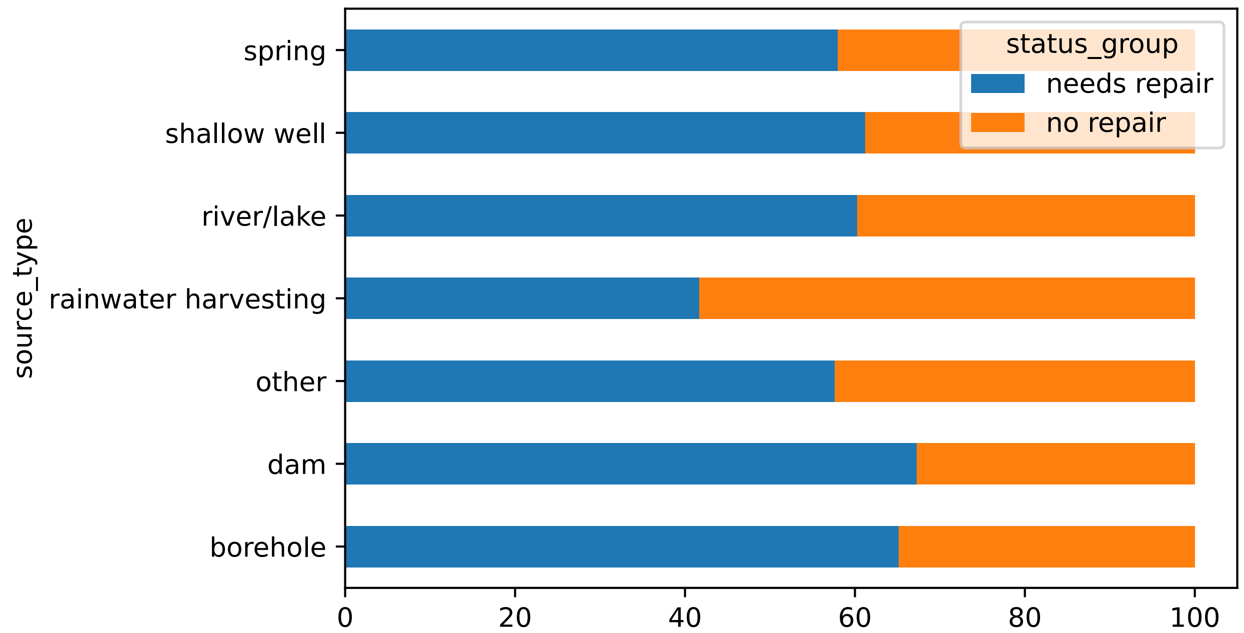
management_group
user-group
unknown
parastatal
other
commercial
status_group
needs repair
no repair
0
20
40
60
80
100



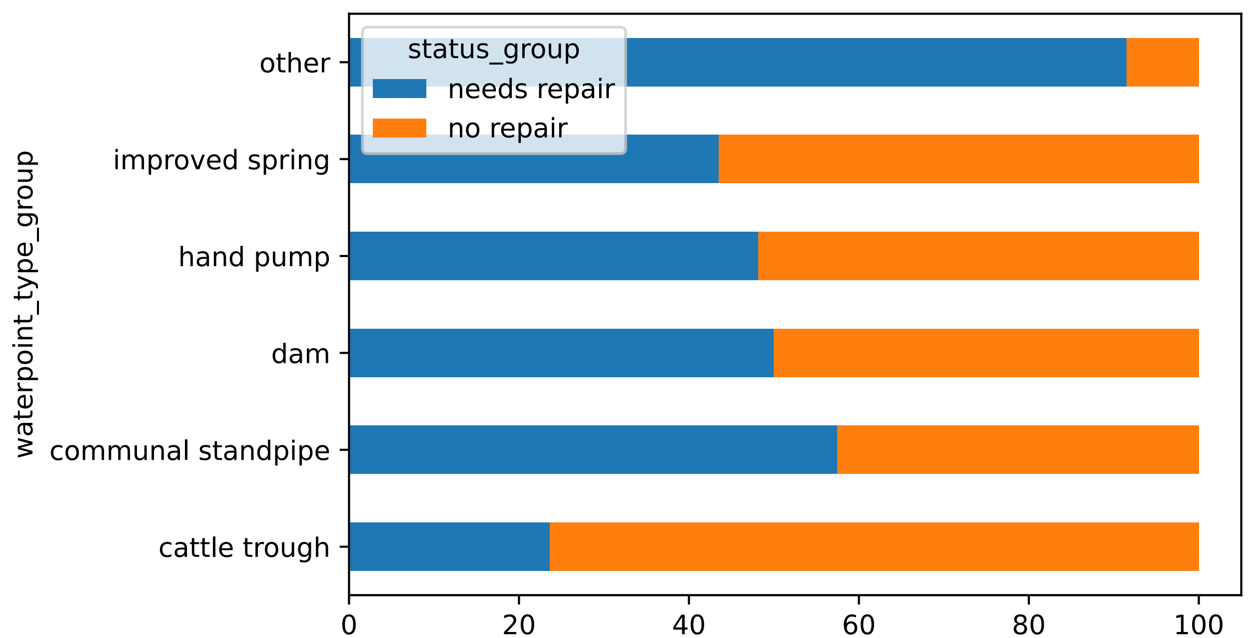
payment_type
unknown
per bucket
other
on failure
never pay
monthly
annually
status_group
needs repair
no repair
0
20
40
60
80
100


status_group
needs repair
no repair
quality_group
unknown
salty
milky
good
fluoride
colored
0
20
40
60
80
100

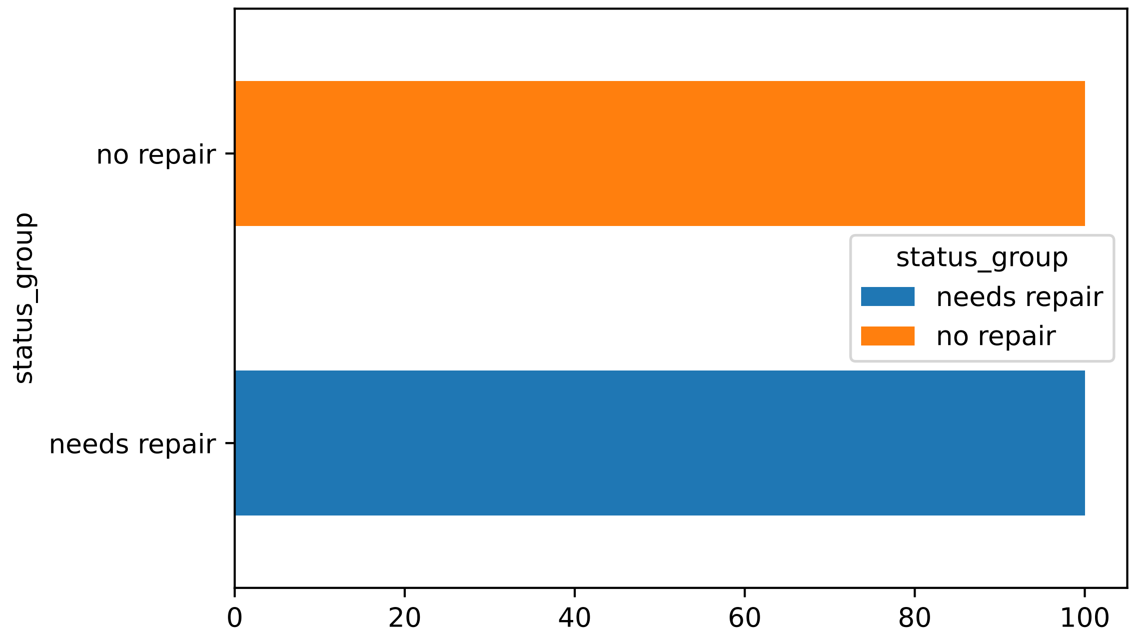

status_group
needs repair
no repair
quantity
unknown
seasonal
insufficient
dry
0
20
40
60
80
100



status_group
needs repair
no repair
source_type
spring
shallow well
river/lake
rainwater harvesting
other
dam
borehole
0
20
40
60
80
100



status_group
needs repair
no repair
waterpoint_type_group
other
improved spring
hand pump
dam
communal standpipe
cattle trough
0
20
40
60
80
100

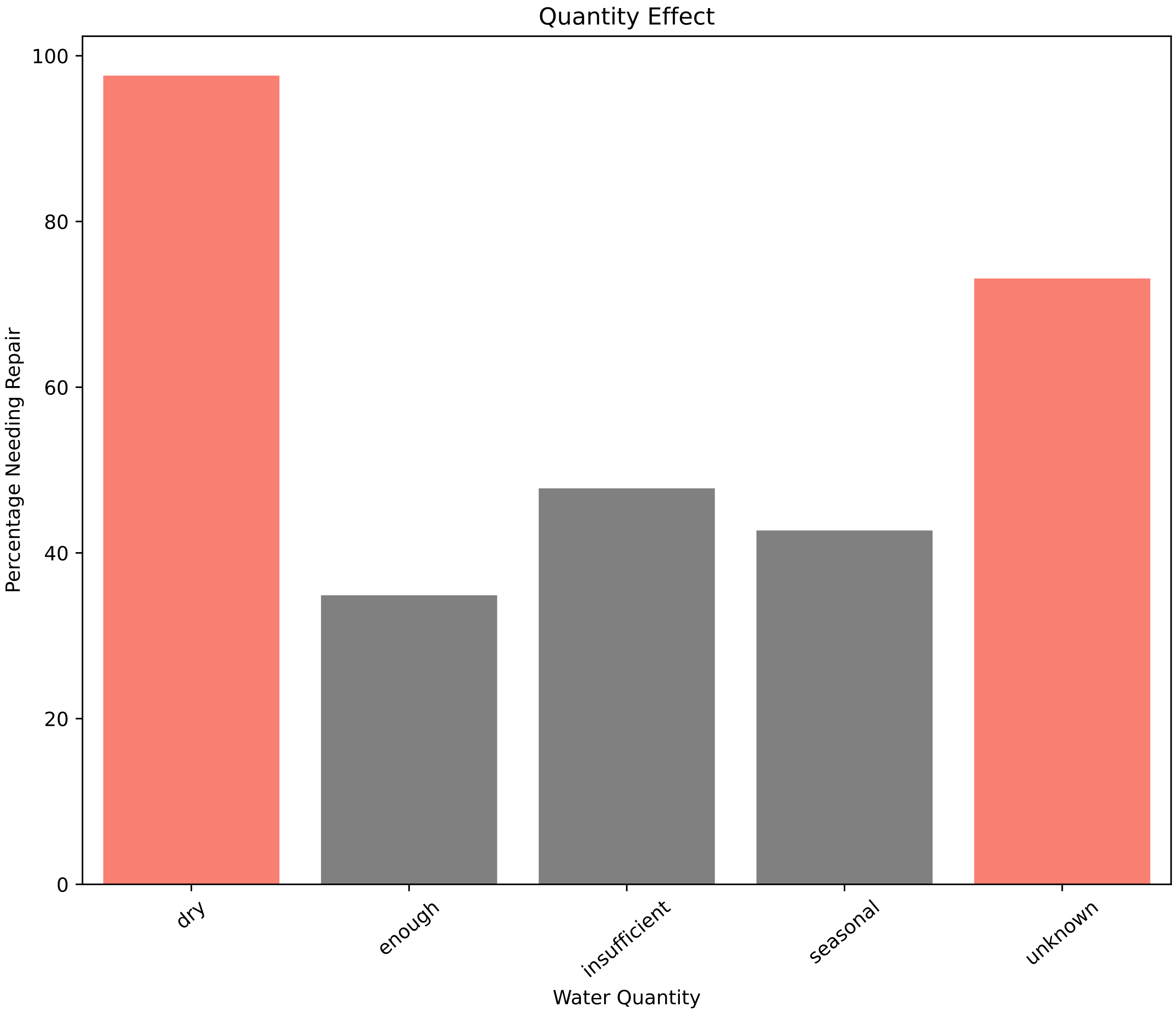


In [35]:
```
rep_q = df.groupby('quantity')['status_group'].value_counts(normalize=True).unstack()
```

In [36]:
```
# Quantity chart

rep_q = df.groupby('quantity')['status_group'].value_counts(normalize=True).unstack().reset_index()
rep_q['needs repair'] = rep_q['needs repair']*100

plt.figure(figsize=(10,8))
ax = sns.barplot(data=rep_q, x='quantity', y='needs repair', ci=False)

for bar in ax.patches:
    if bar.get_height() > 60:
        bar.set_color('salmon')
    else:
        bar.set_color('grey')

plt.xlabel('Water Quantity')
plt.ylabel('Percentage Needing Repair')
plt.title('Quantity Effect')
plt.xticks(np.arange(5), rotation=40)
```

Out[36]:
```
([<matplotlib.axis.XTick at 0x2183ae95970>,
  <matplotlib.axis.XTick at 0x2183ae95940>,
  <matplotlib.axis.XTick at 0x2183ae9c7f0>,
  <matplotlib.axis.XTick at 0x2183adcddf0>,
  <matplotlib.axis.XTick at 0x2183b09c340>],
 [Text(0, 0, 'dry'),
  Text(1, 0, 'enough'),
  Text(2, 0, 'insufficient'),
```

```
 Text(3, 0, 'seasonal'),
 Text(4, 0, 'unknown')])
```



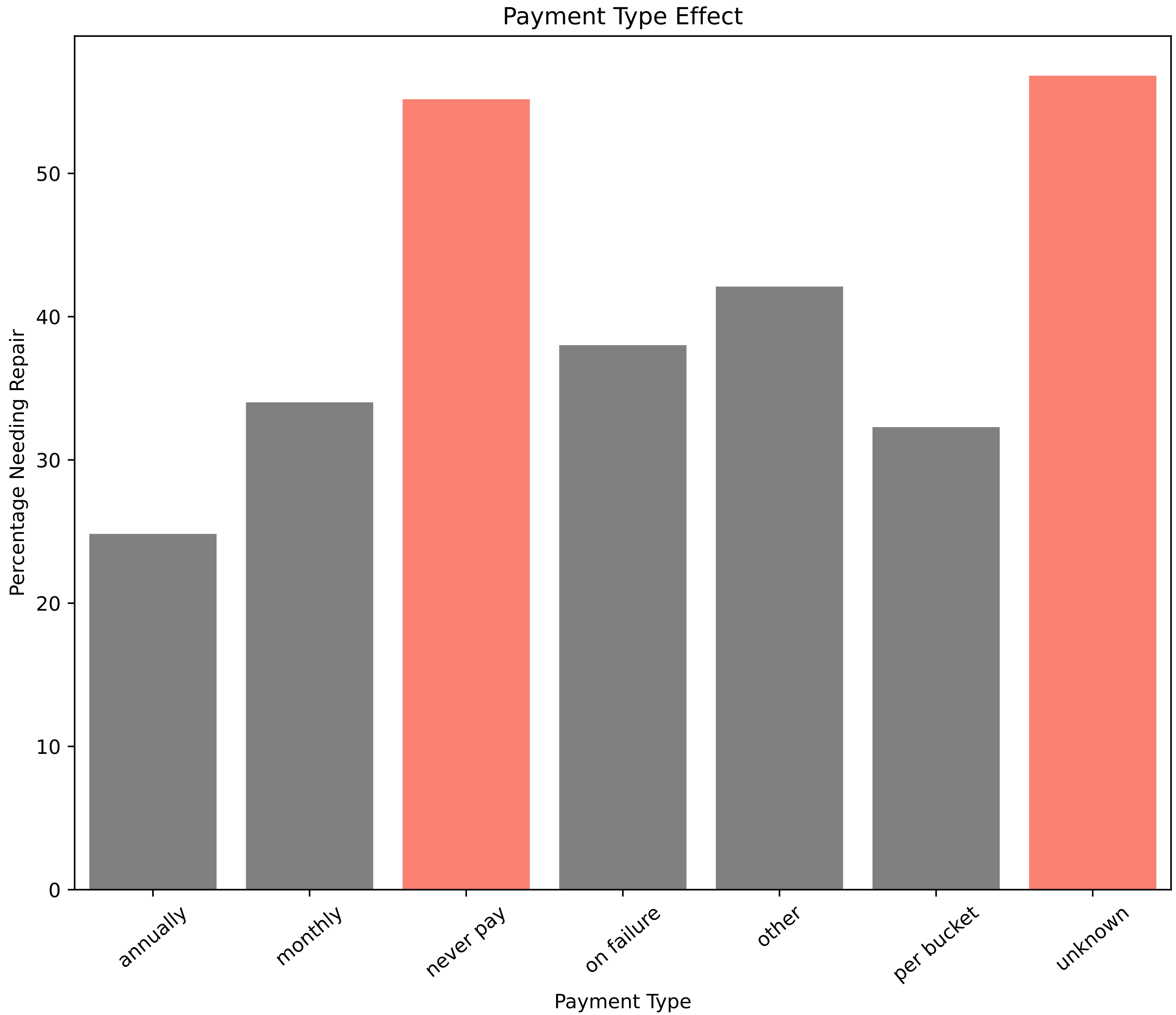
In [37]:

```
# Payment chart

rep_p = df.groupby('payment_type')['status_group'].value_counts(normalize=True).unstack().reset_index()
```

```python
rep_p['needs repair'] = rep_p['needs repair']*100

plt.figure(figsize=(10,8))
ax = sns.barplot(data=rep_p, x='payment_type', y='needs repair', ci=False)

for bar in ax.patches:
    if bar.get_height() > 50:
        bar.set_color('salmon')
    else:
        bar.set_color('grey')

plt.xlabel('Payment Type')
plt.ylabel('Percentage Needing Repair')
plt.title('Payment Type Effect')
plt.xticks(np.arange(7), rotation=40)
```

Out[37]:

```
([<matplotlib.axis.XTick at 0x2183ae258e0>,
  <matplotlib.axis.XTick at 0x2183ae258b0>,
  <matplotlib.axis.XTick at 0x2183b097f40>,
  <matplotlib.axis.XTick at 0x21839d308e0>,
  <matplotlib.axis.XTick at 0x21839d30df0>,
  <matplotlib.axis.XTick at 0x21839d23340>,
  <matplotlib.axis.XTick at 0x21839d23850>],
 [Text(0, 0, 'annually'),
  Text(1, 0, 'monthly'),
  Text(2, 0, 'never pay'),
  Text(3, 0, 'on failure'),
  Text(4, 0, 'other'),
  Text(5, 0, 'per bucket'),
  Text(6, 0, 'unknown')])
```

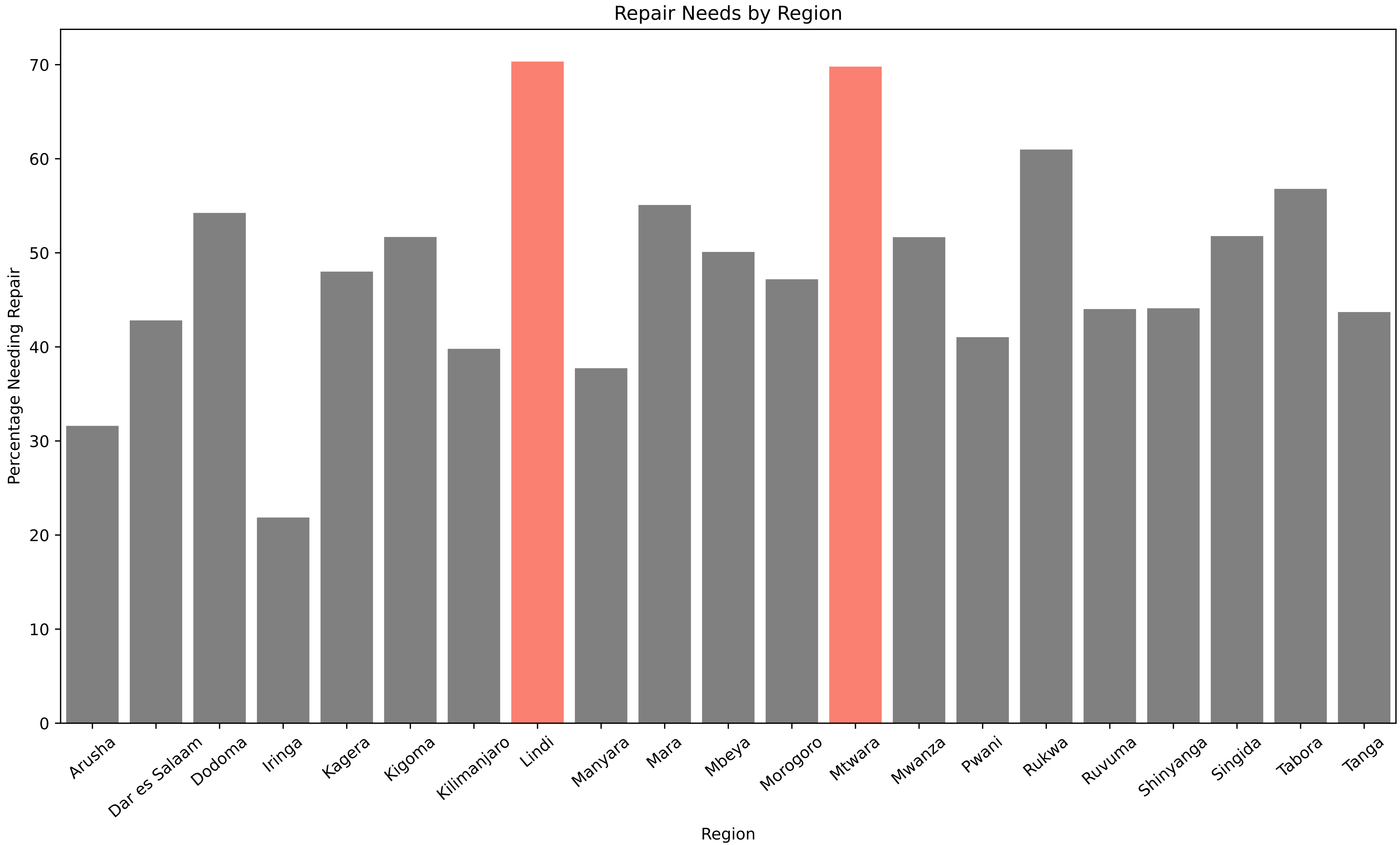


In [38]:
```
rep_r = df.groupby('region')['status_group'].value_counts(normalize=True).unstack().reset_index()
rep_r['needs repair'] = rep_r['needs repair']*100

plt.figure(figsize=(15,8))
ax = sns.barplot(data=rep_r, x='region', y='needs repair', ci=False)
```

```python
for bar in ax.patches:
    if bar.get_height() > 65:
        bar.set_color('salmon')
    else:
        bar.set_color('grey')

plt.xlabel('Region')
plt.ylabel('Percentage Needing Repair')
plt.title('Repair Needs by Region')
plt.xticks(rotation=40)
```

Out[38]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20]),
 [Text(0, 0, 'Arusha'),
  Text(1, 0, 'Dar es Salaam'),
  Text(2, 0, 'Dodoma'),
  Text(3, 0, 'Iringa'),
  Text(4, 0, 'Kagera'),
  Text(5, 0, 'Kigoma'),
  Text(6, 0, 'Kilimanjaro'),
  Text(7, 0, 'Lindi'),
  Text(8, 0, 'Manyara'),
  Text(9, 0, 'Mara'),
  Text(10, 0, 'Mbeya'),
  Text(11, 0, 'Morogoro'),
  Text(12, 0, 'Mtwara'),
  Text(13, 0, 'Mwanza'),
  Text(14, 0, 'Pwani'),
  Text(15, 0, 'Rukwa'),
  Text(16, 0, 'Ruvuma'),
  Text(17, 0, 'Shinyanga'),
  Text(18, 0, 'Singida'),
  Text(19, 0, 'Tabora'),
  Text(20, 0, 'Tanga')])
```



3. Prep for Modeling

In [39]:
```
df_cat = df_cat.drop('status_group', axis=1)
```

```
df_cat = pd.get_dummies(df_cat)
```

- We've got to one-hot encode the categoricals in order to do our models.
- Assigning numerical values to the categories would introduce bias

In [40]:
```
df_cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Columns: 187 entries, basin_Internal to waterpoint_type_group_other
dtypes: uint8(187)
memory usage: 11.0 MB
```

Number of ohe categores jumped to 187, but we have a lot of data points, so it should be fine

In [41]:
```
df = pd.concat([df_cont, df_cat], axis=1)
```

In [42]:
```
le = LabelEncoder()

tr_labels = le.fit_transform(tr_labels.status_group)
```

In [ ]:

In [43]:
```
X = df
y = tr_labels
```

In [44]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=11)
```

In [45]:
```
X_test.shape
```

Out[45]:
```
(14850, 189)
```

4. Models

4.1 Model 1

Decision Tree Classifier

In [46]:
```
tree = DecisionTreeClassifier(criterion='gini',
#                              max_features='log2',
#                              min_samples_leaf=2,
#                              max_depth=20,
                             class_weight='balanced')
clf_dt = tree.fit(X_train, y_train)
```

```python
# Test set predictions
pred = tree.predict(X_test)
# Confusion matrix and classification report

pred_tr = tree.predict(X_train)

print(confusion_matrix(y_test, pred))

print(classification_report(y_test, pred))

print("Training Accuracy for Decision Tree Classifier: {:.4}%".format(accuracy_score(y_train, pred_tr) * 100))
print("Testing Accuracy for Decision Tree Classifier: {:.4}%".format(accuracy_score(y_test, pred) * 100))
```

```
[[5180 1615]
 [1677 6378]]
              precision    recall  f1-score   support

           0       0.76      0.76      0.76      6795
           1       0.80      0.79      0.79      8055

    accuracy                           0.78     14850
   macro avg       0.78      0.78      0.78     14850
weighted avg       0.78      0.78      0.78     14850

Training Accuracy for Decision Tree Classifier: 99.4%
Testing Accuracy for Decision Tree Classifier: 77.83%
```

- Testing accuracy isn't bad, but we are definitely overfit.

In [47]:
```python
tree.feature_importances_
df.columns
feature_imp = pd.DataFrame({'feature': df.columns, 'importance': tree.feature_importances_*100})
feature_imp.sort_values(by=['importance'], ascending=False).head(20)
```

Out[47]:

	feature	importance
0	0	26.155969
1	1	25.613491
171	quantity_dry	12.059091
188	waterpoint_type_group_other	6.908221
14	region_Iringa	1.908849
160	payment_type_never pay	1.305752
172	quantity_enough	0.850720
151	extraction_type_class_submersible	0.839355
180	source_type_river/lake	0.730567

	feature	importance
157	management_group_user-group	0.704486
173	quantity_insufficient	0.701207
148	extraction_type_class_motorpump	0.650503
181	source_type_shallow well	0.645853
13	region_Dodoma	0.581934
182	source_type_spring	0.574858
16	region_Kigoma	0.554834
3	basin_Lake Nyasa	0.522248
153	management_group_commercial	0.512721
184	waterpoint_type_group_communal standpipe	0.498405
146	extraction_type_class_gravity	0.489796

- Latitude and Longitude are being overrepresented here because they are continuous
- Dry quantity and never pay show up as issues.

In [45]:

Out[45]:

	feature	importance
3	lga	12.163934
10	source_type	11.366511
6	payment_type	10.771261
2	district_code	10.177237
4	extraction_type_class	10.063785
9	quantity	9.341607
1	region_code	9.285020
0	region	8.750916
5	management_group	4.486133
12	waterpoint_type_group	3.955747
8	quality_group	3.837119

	feature	importance
11	source_class	3.492356
7	water_quality	2.308375

- The above is for the hash trick being kept for reference

4.2 Model 2

Random Forest Classifier

4.2.1 No changes to hyperparameters

In [48]:

```
clf = RandomForestClassifier().fit(X_train, y_train)

pred = clf.predict(X_test)

# Test set predictions
pred_tr = clf.predict(X_train)
# Confusion matrix and classification report

print("Training Accuracy for Random Forest Classifier: {:.4}%".format(accuracy_score(y_train, pred_tr)* 100))

print("Testing Accuracy for Random Forest Classifier: {:.4}%".format(accuracy_score(y_test, pred)* 100))

print(confusion_matrix(y_test, pred))

print(classification_report(y_test, pred))
```

```
Training Accuracy for Random Forest Classifier: 99.41%
Testing Accuracy for Random Forest Classifier: 80.18%
[[5187 1608]
 [1335 6720]]
              precision    recall  f1-score   support

           0       0.80      0.76      0.78      6795
           1       0.81      0.83      0.82      8055

    accuracy                           0.80     14850
   macro avg       0.80      0.80      0.80     14850
weighted avg       0.80      0.80      0.80     14850
```

- The accuracy improved, but we are still overfit.

4.2.2. Manual tweaks to hyperparameters

In [49]:
```python
clf = RandomForestClassifier( n_estimators=200,
                            max_samples=0.25,
                            max_depth=20,
                            class_weight='balanced'
                            ).fit(X_train, y_train)

pred = clf.predict(X_test)

# Test set predictions
pred_tr = clf.predict(X_train)
# Confusion matrix and classification report

print("Training Accuracy for Random Forest Classifier: {:.4}%".format(accuracy_score(y_train, pred_tr)* 100))

print("Testing Accuracy for Random Forest Classifier: {:.4}%".format(accuracy_score(y_test, pred)* 100))

print(confusion_matrix(y_test, pred))

print(classification_report(y_test, pred))
```

```
Training Accuracy for Random Forest Classifier: 84.6%
Testing Accuracy for Random Forest Classifier: 80.26%
[[4782 2013]
 [ 919 7136]]
              precision    recall  f1-score   support

           0       0.84      0.70      0.77      6795
           1       0.78      0.89      0.83      8055

    accuracy                           0.80     14850
   macro avg       0.81      0.79      0.80     14850
weighted avg       0.81      0.80      0.80     14850
```

- Overfitting issue mostly fixed. Testing accuracy went up.
- Precision of 0.84 for needs repair isn't bad.

In [50]:
```python
feature_imp = pd.DataFrame({'feature': df.columns, 'importance': clf.feature_importances_*100})
feature_imp.sort_values(by=['importance'], ascending=False).head(20)
```

Out[50]:

	feature	importance
1	1	14.478446
0	0	14.039000
171	quantity_dry	11.390208
188	waterpoint_type_group_other	4.899773
172	quantity_enough	4.573172

	feature	importance
149	extraction_type_class_other	3.462667
160	payment_type_never pay	2.560499
173	quantity_insufficient	1.612517
147	extraction_type_class_handpump	1.501113
163	payment_type_per bucket	1.396543
14	region_Iringa	1.231623
184	waterpoint_type_group_communal standpipe	1.177427
186	waterpoint_type_group_hand pump	1.104277
182	source_type_spring	1.064123
157	management_group_user-group	1.052528
181	source_type_shallow well	1.031616
146	extraction_type_class_gravity	0.990114
167	quality_group_good	0.947095
164	payment_type_unknown	0.908150
170	quality_group_unknown	0.878841

Based on these, let's try to see what's important.

- Quantity is very important, especially dry and enough.
- Only use 1 geographic column. Region, especially Kigoma and Iringa shows up here.
    - I still like lga more just because of the discrepancies seen in the graph.
    - This also fits our business problem most.
- Extraction Type: Other and Gravity
- Waterpoint Type: Other and communal standpipe
- Payment Type: Never pay, per bucket, monthly, unknown
- Source Type: Borehole, shallow well

4.2.3 RFC with Grid Search

In [51]:
```
rfg = RandomForestClassifier()

param_grid ={'bootstrap': [True],
    'max_depth': [10, 20, 30, 40, None],
    'min_samples_leaf': [2, 4],
```

```
    'min_samples_split': [2, 5, 10],
    'n_estimators': [100, 200, 400],
    'class_weight': ['balanced']
    }

rf_grid = GridSearchCV(estimator = rfg, param_grid = param_grid,
                          cv = 3, n_jobs = -1, verbose = 2)
```

In [52]:

```
#rf_grid.fit(X_train, y_train)

#rf_grid.best_params_
```

- The parameters below were given by the grid search.
- I've commented out the fit just because it takes 15 minutes each time.

In [53]:

```
rfg = RandomForestClassifier( n_estimators=200,
                            max_samples=0.25,
                            min_samples_leaf= 2,
                            min_samples_split=2,
                            max_depth=40,
                            class_weight='balanced'
                            ).fit(X_train, y_train)

pred = rfg.predict(X_test)

# Test set predictions
pred_tr = rfg.predict(X_train)
# Confusion matrix and classification report

print("Training Accuracy for Random Forest Classifier: {:.4}%".format(accuracy_score(y_train, pred_tr)* 100))

print("Testing Accuracy for Random Forest Classifier: {:.4}%".format(accuracy_score(y_test, pred)* 100))

print(confusion_matrix(y_test, pred))

print(classification_report(y_test, pred))
```

```
Training Accuracy for Random Forest Classifier: 83.34%
Testing Accuracy for Random Forest Classifier: 80.18%
[[5008 1787]
 [1157 6898]]
              precision    recall  f1-score   support

           0       0.81      0.74      0.77      6795
           1       0.79      0.86      0.82      8055

    accuracy                           0.80     14850
   macro avg       0.80      0.80      0.80     14850
weighted avg       0.80      0.80      0.80     14850
```

- This is very similar to the previous model with a slightly worse accuracy.
- Slight overfit is still there
- Precision went down to 81 for the needs repair
- Choosing between the previous 2 models is tough, so we will wait for the CV scores.

4.3 Gradient Boosting

In [54]:

```
xgb_clf = xgboost.XGBClassifier()
xgb_clf.fit(X_train, y_train)
pred = xgb_clf.predict(X_test)
pred_tr = xgb_clf.predict(X_train)



print("Training Accuracy for Gradient Boost: {:.4}%".format(accuracy_score(y_train, pred_tr)* 100))

print("Testing Accuracy for Gradient Boost: {:.4}%".format(accuracy_score(y_test, pred)* 100))

print(confusion_matrix(y_test, pred))

print(classification_report(y_test, pred))
```

```
Training Accuracy for Gradient Boost: 82.35%
Testing Accuracy for Gradient Boost: 79.64%
[[4737 2058]
 [ 965 7090]]
              precision    recall  f1-score   support

           0       0.83      0.70      0.76      6795
           1       0.78      0.88      0.82      8055

    accuracy                           0.80     14850
   macro avg       0.80      0.79      0.79     14850
weighted avg       0.80      0.80      0.79     14850
```

- I had high hopes for this, but we're getting more success with RFC

5. Model Selection

In [55]:

```
cv_model_1  =cross_val_score(tree, X, y, cv=5, estimator='accuracy').mean()
cv_model_22 =cross_val_score(clf, X, y, cv=5, estimator='accuracy').mean()
cv_model_23 =cross_val_score(rfg, X, y, cv=5, estimator='accuracy').mean()
cv_model_3  =cross_val_score(xgb_clf, X, y, cv=5, estimator='accuracy').mean()
```

In [56]:
```
print(f'Cross Value for Decision Tree: {cv_model_1*100:.1f}%')
print(f'Cross Value for Random Forest Mine: {cv_model_22*100:.1f}%')
print(f'Cross Value for Random Forest GridSearch: {cv_model_23*100:.1f}%')
print(f'Cross Value for Xgboost: {cv_model_3*100:.1f}%')
```

```
Cross Value for Decision Tree: 77.7%
Cross Value for Random Forest Mine: 80.5%
Cross Value for Random Forest GridSearch: 80.2%
Cross Value for Xgboost: 79.6%
```

- Based on these, I will go with Model 2.2 which is the Random Forest with my hyperparameters.
- The accuracies are close, but I like the slightly higher precision for Model 2.2

6. Conclusion

6.1 Results

- Our best model was correct in guessing the status of the waterpoint about 80.5% of the time. While this is not ideal, I am happy with the results based on the time allotted for this project as well as shortcomings in the dataset.
- The precision of our model in finding waterpoints in need of repair was 0.84. This means that our model correctly labeled 84% of the waterpoints in need of repair.
- The recall of our model was 0.71 which was quite lower than our precision score. In layman's terms, if we sent someone to a location where this model indicated a need for repair, the waterpoint would be in need of repair 71% of the time.
- There is a delicate balance between precision and recall where increasing one decreases the other. In this case, where lack of water can mean the difference between life or death, having a higher sensitivity(precision) is of more benefit. In those 29% of cases where the waterpoint is still funcitoning when someone goes to check on it, it would advisable to run a further inspection to see if the waterpoint will need repair soon.

6.2 Next Steps

- I would like to do something about the 0 values for latitude and longitude. Taking the mean lat/long for that particular LGA or Ward and assigining it to the 0 value makes most sense to me.
- Figure out how to separate the urban areas from the rural areas.
- The construction dates would be useful if we had the values for all waterpoints in order to calculate age, which is obviously a very important factor. Another feature that would be of great value would be records about maintainance/repairs.