Initial Water Well exploratory

In [47]:
```
import matplotlib
import itertools
import numpy as np
import pandas as pd
from numbers import Number
import sqlite3
import sqldf
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import statsmodels.api as sm
warnings.filterwarnings('ignore')

from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, recall_score, precision_score, f
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import roc_auc_score, RocCurveDisplay
from sklearn.model_selection import cross_validate
```

Import Data and Merge Datasets

In [2]:
```
labels_df = pd.read_csv("Pump_it_Up_Data_Mining_the_Water_Table_-_Training_s

values_df = pd.read_csv("Pump_it_Up_Data_Mining_the_Water_Table_-_Training_s

merged_df = labels_df.merge(values_df, on='id')

test_df = pd.read_csv("Pump_it_Up_Data_Mining_the_Water_Table_-_Test_set_val

pd.set_option('display.max_columns', None)
merged_df.head()
```

Out[2]:

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

In [3]:

```
query = """
SELECT management, COUNT(*) as count
FROM merged_df
GROUP BY management
"""

sqldf.run(query)
```

Out[3]:

	management	count
0	company	685
1	other	844
2	other - school	99
3	parastatal	1768
4	private operator	1971
5	trust	78
6	unknown	561
7	vwc	40507
8	water authority	904
9	water board	2933
10	wua	2535
11	wug	6515

In [99]:

```
query = """
SELECT status_group, COUNT(*) as count
FROM merged_df
GROUP BY status_group
"""

sqldf.run(query)
```

Out[99]:

	status_group	count
0	functional	32259
1	functional needs repair	4317
2	non functional	22824

In [100…

```
#merged_df.info()
#merged_df.info()
```

Some Initial Cleaning

remove a column with lots of Nulls, then drop rows with Nulls

In [5]:
```
merged_df_cleaning = merged_df.drop('scheme_name', axis=1)
merged_df_cleaning = merged_df_cleaning.dropna()
test_df_cleaning = test_df.drop('scheme_name', axis=1)
test_df_cleaning = test_df.dropna()
merged_df_cleaning_binary = merged_df[merged_df['status_group'] != 'functior
merged_df_cleaning_binary.head()
#test_df_cleaning.info()
```

Out[5]:

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

Exploratory Data Analysis

In [6]:
```
query = """
SELECT status_group, COUNT(*) as count
FROM merged_df_cleaning_binary
GROUP BY status_group
"""

sqldf.run(query)
```

Out[6]:

	status_group	count
0	functional	32259
1	non functional	22824

In [7]:
```
query = """
SELECT status_group, COUNT(*) as count
FROM merged_df
GROUP BY status_group
"""

sqldf.run(query)
```

Out[7]:

	status_group	count
0	functional	32259
1	functional needs repair	4317
2	non functional	22824

In [8]:
```
query = """
SELECT status_group, water_quality, COUNT(*) as count
FROM merged_df
GROUP BY status_group, water_quality
"""

sqldf.run(query)
```

Out[8]:

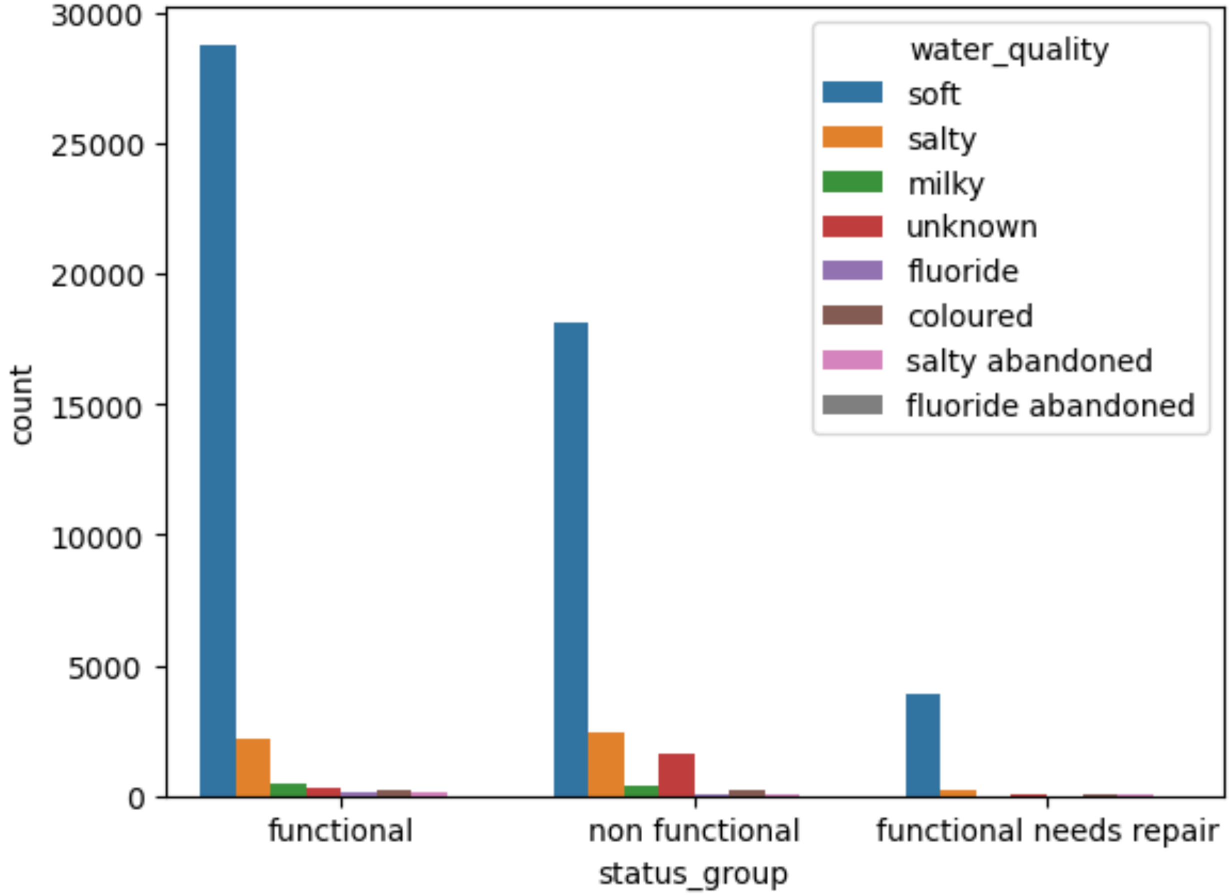
	status_group	water_quality	count
0	functional	coloured	246
1	functional	fluoride	151
2	functional	fluoride abandoned	6
3	functional	milky	438
4	functional	salty	2220
5	functional	salty abandoned	174
6	functional	soft	28760
7	functional	unknown	264
8	functional needs repair	coloured	54
9	functional needs repair	fluoride	13
10	functional needs repair	milky	14
11	functional needs repair	salty	225
12	functional needs repair	salty abandoned	72
13	functional needs repair	soft	3904
14	functional needs repair	unknown	35
15	non functional	coloured	190
16	non functional	fluoride	36
17	non functional	fluoride abandoned	11
18	non functional	milky	352
19	non functional	salty	2411
20	non functional	salty abandoned	93
21	non functional	soft	18154
22	non functional	unknown	1577

In [9]:

```
sns.countplot(merged_df, x="status_group", hue="water_quality")
```

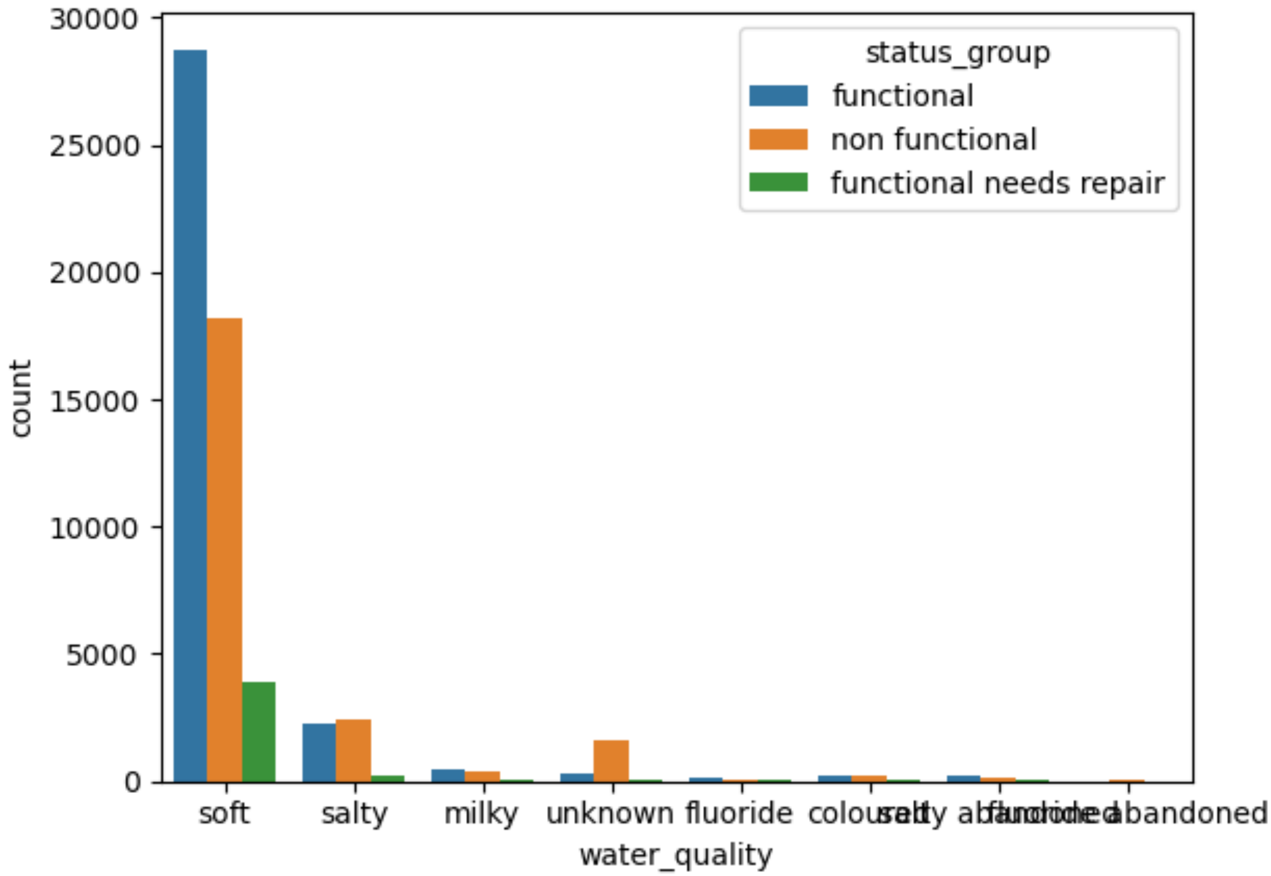
Out[9]:

```
<Axes: xlabel='status_group', ylabel='count'>
```



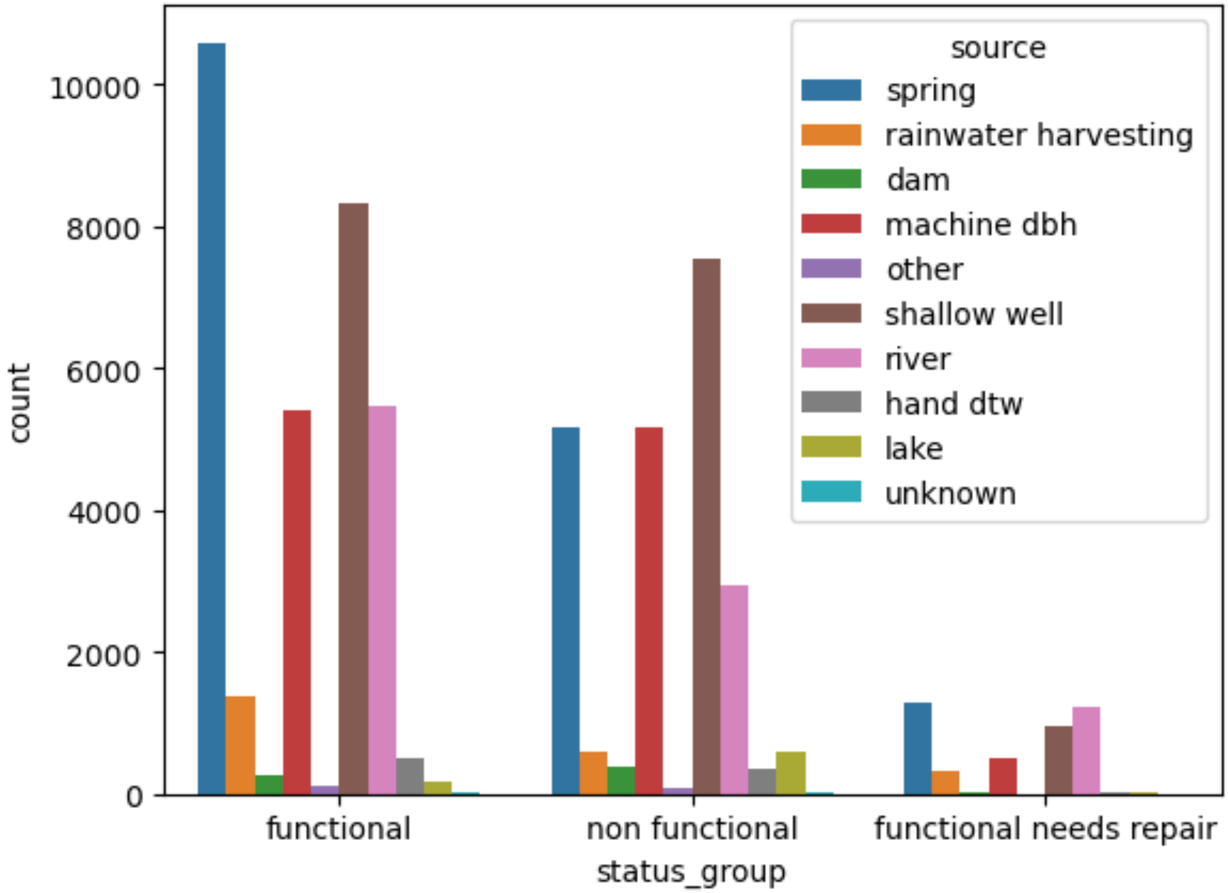
In [10]:
```
sns.countplot(merged_df, x="water_quality", hue="status_group")
```

Out[10]: <Axes: xlabel='water_quality', ylabel='count'>



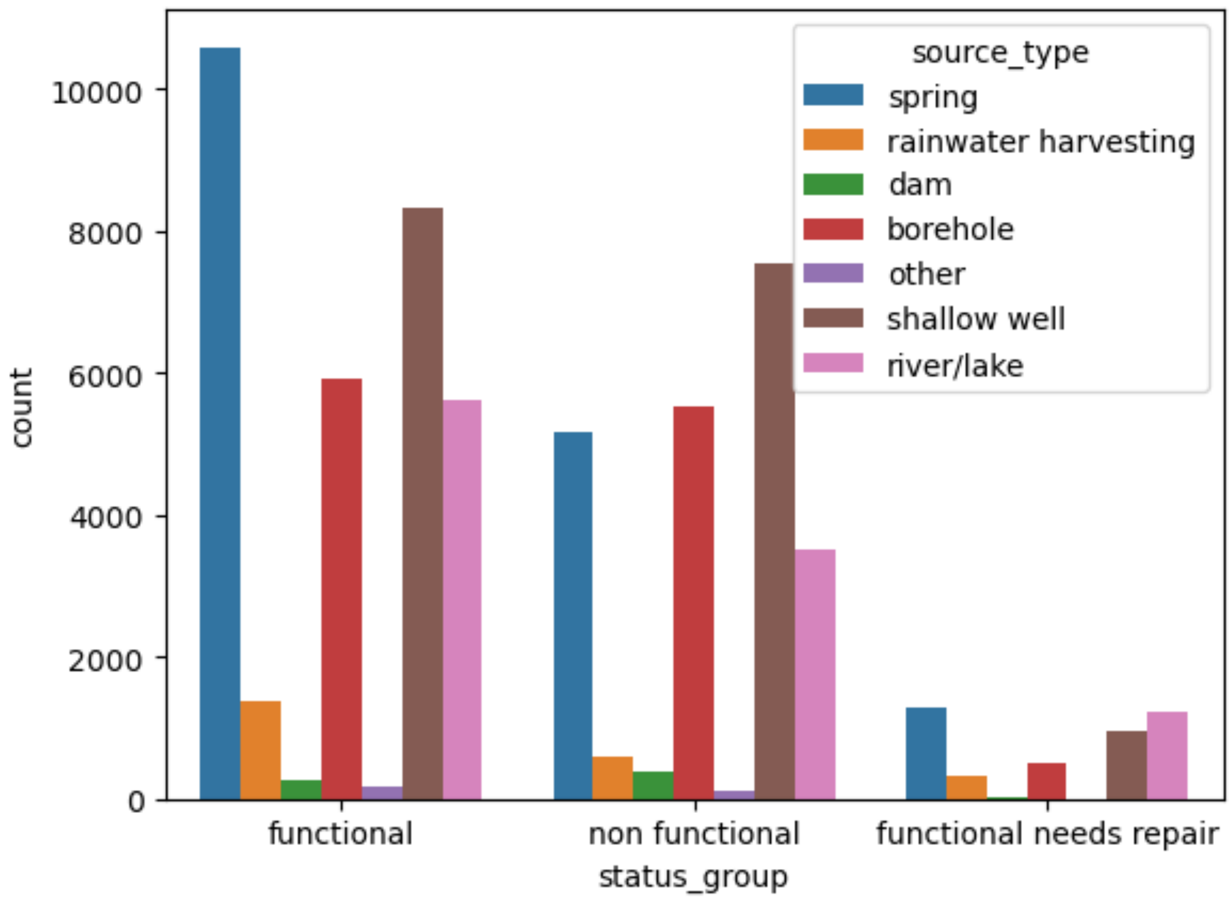
In [11]:
```
sns.countplot(merged_df, x="status_group", hue="source")
```

Out[11]: <Axes: xlabel='status_group', ylabel='count'>

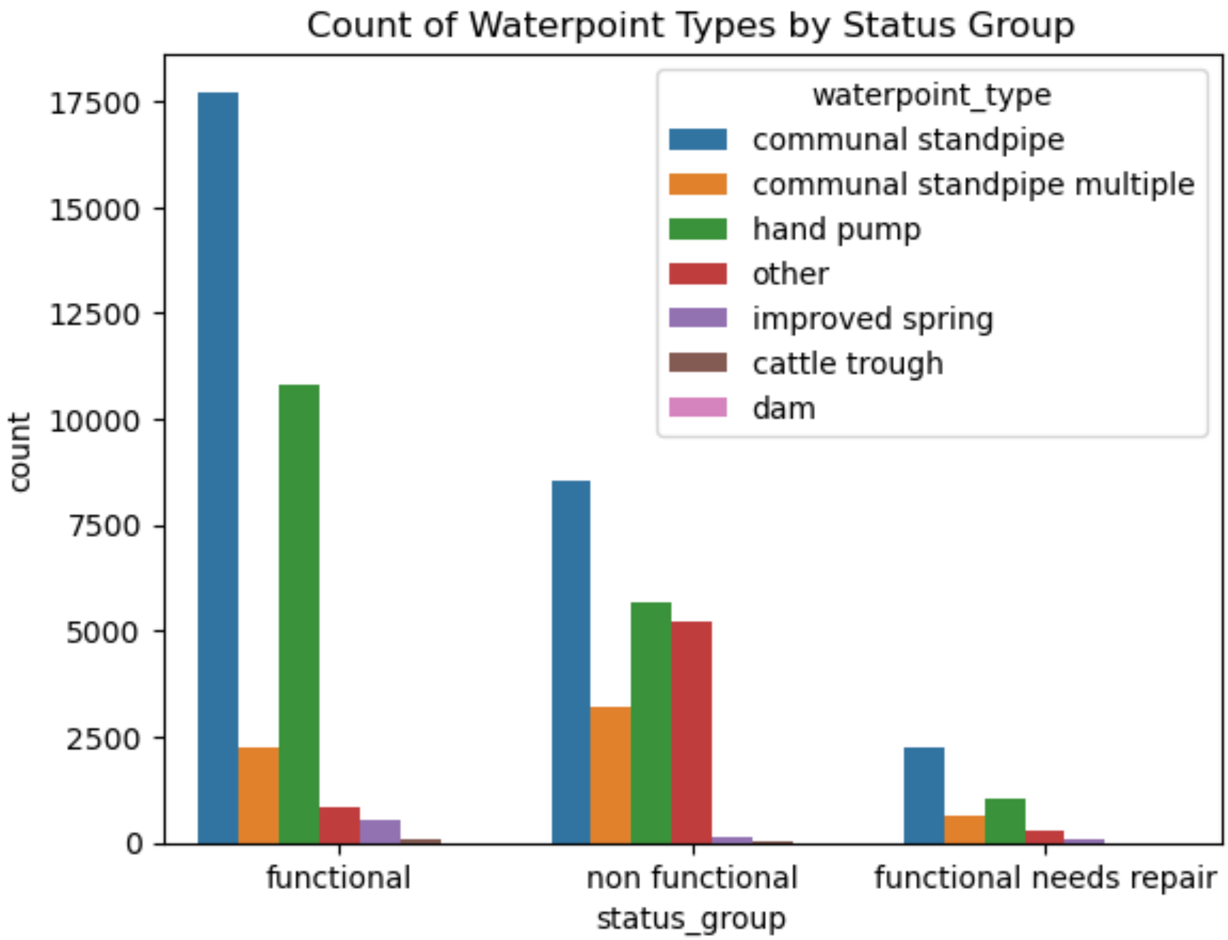


In [12]:
```
sns.countplot(merged_df, x="status_group", hue="source_type")
```

Out[12]:
```
<Axes: xlabel='status_group', ylabel='count'>
```

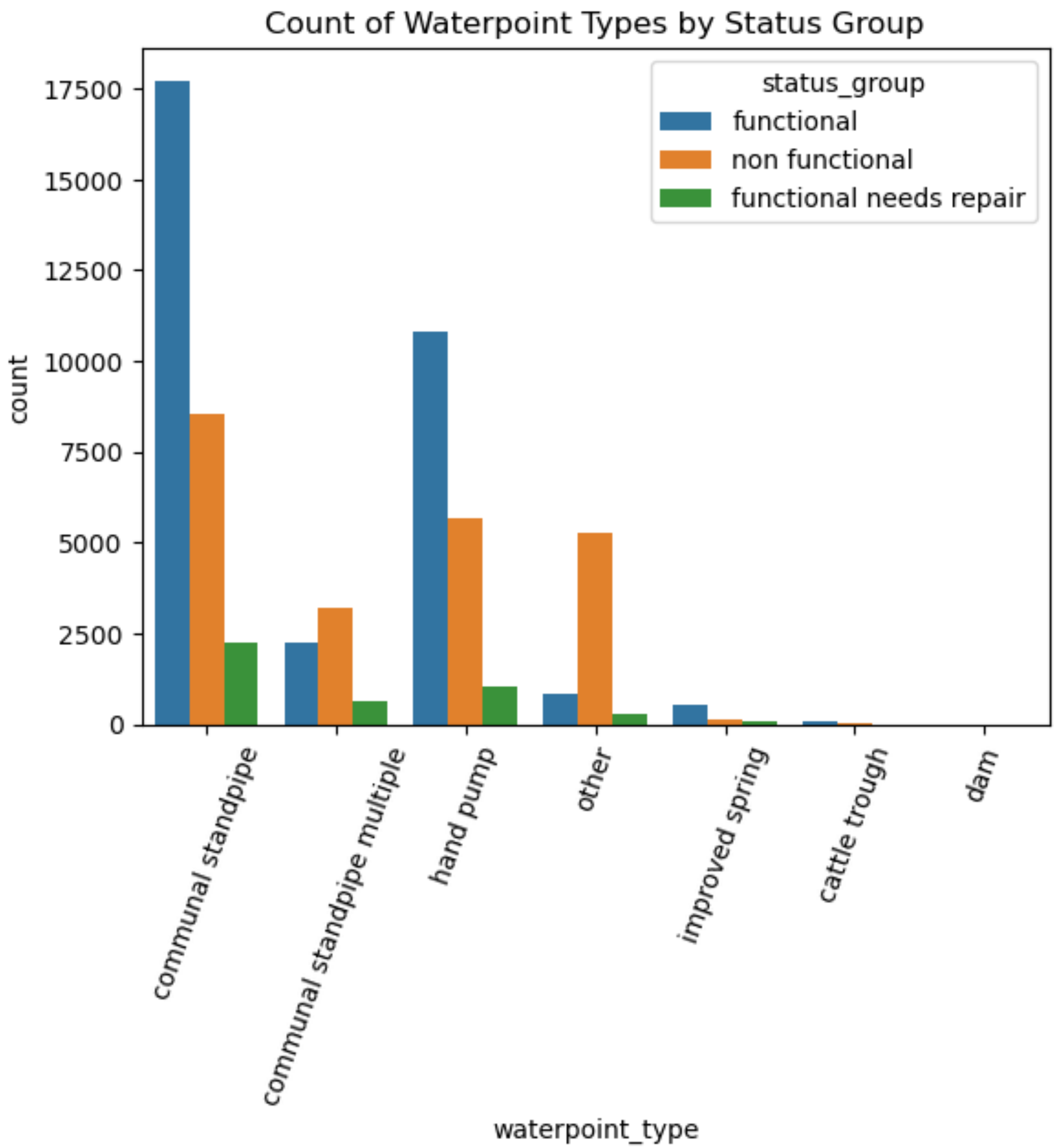


In [13]:
```
sns.countplot(merged_df, x="status_group", hue="waterpoint_type")
plt.title("Count of Waterpoint Types by Status Group")
plt.show()
```



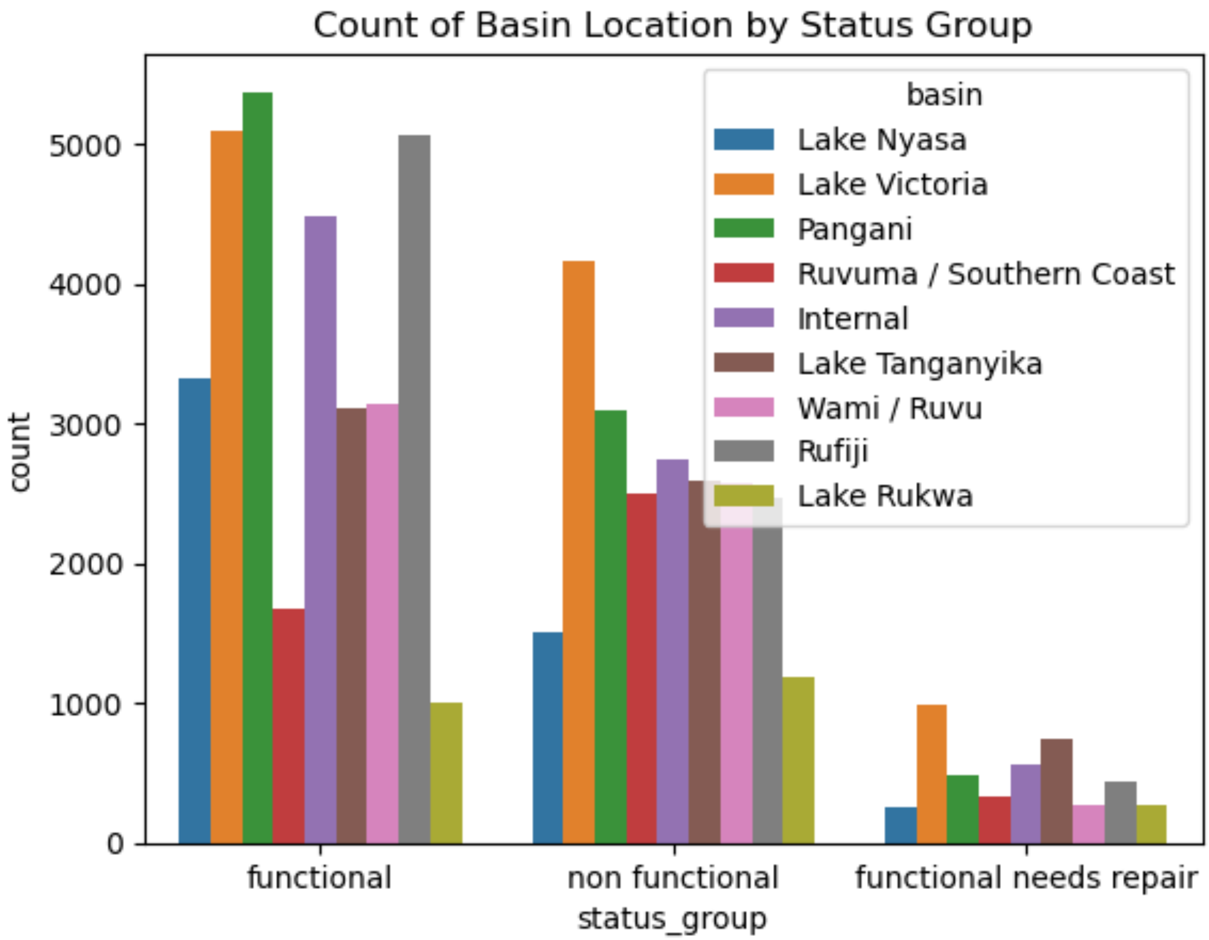
In [108…

```
sns.countplot(merged_df, x="waterpoint_type", hue="status_group")
plt.title("Count of Waterpoint Types by Status Group")
plt.xticks(rotation=70)
plt.show()
```



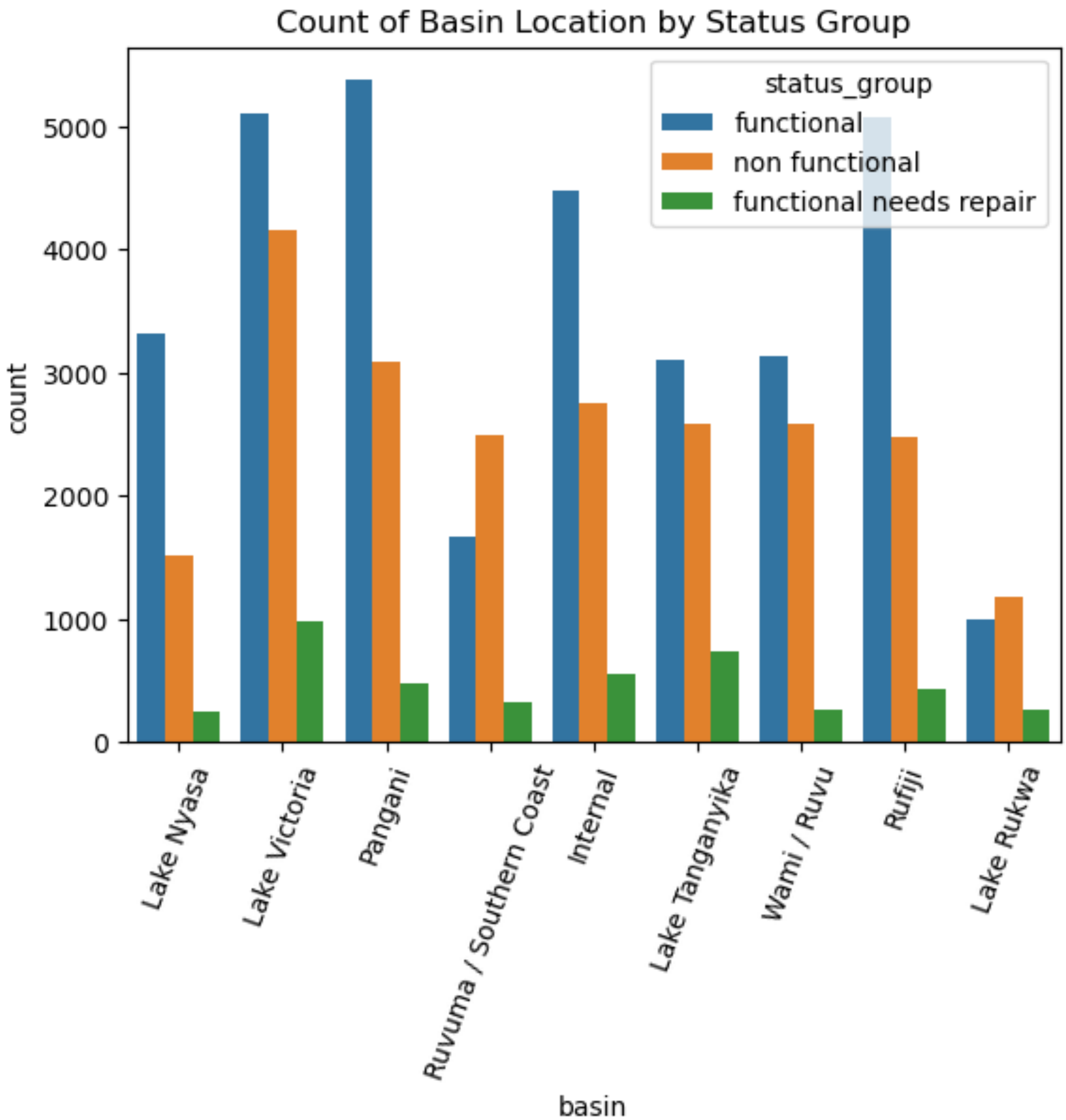
In [ ]:

In [14]:
```
sns.countplot(merged_df, x="status_group", hue="basin")
plt.title("Count of Basin Location by Status Group")
plt.show()
```



In [106…

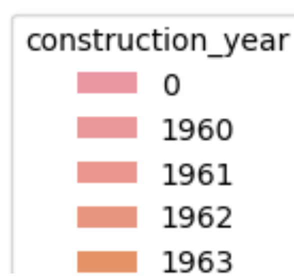
```
sns.countplot(merged_df, x="basin", hue="status_group")
plt.title("Count of Basin Location by Status Group")
plt.xticks(rotation=70)
plt.show()
```

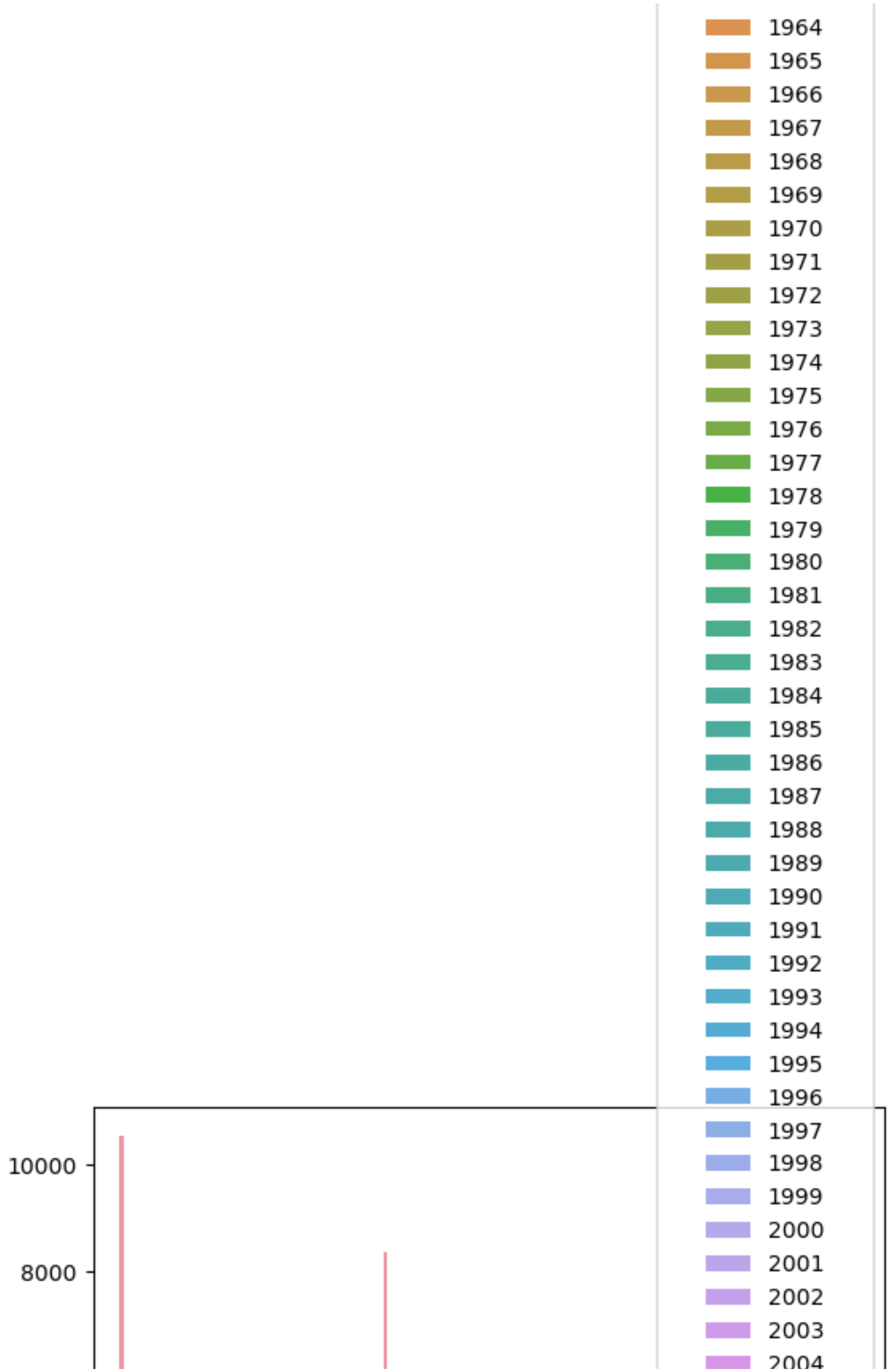


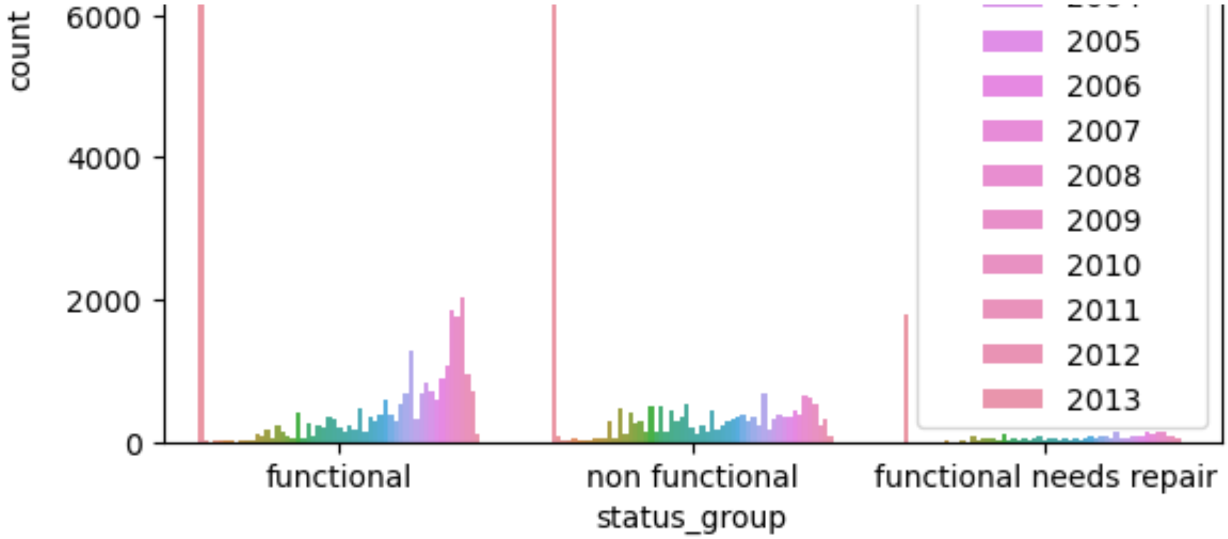
!! Basin might be useful

In [15]:
```
sns.countplot(merged_df, x="status_group", hue="construction_year")
```

Out[15]: <Axes: xlabel='status_group', ylabel='count'>



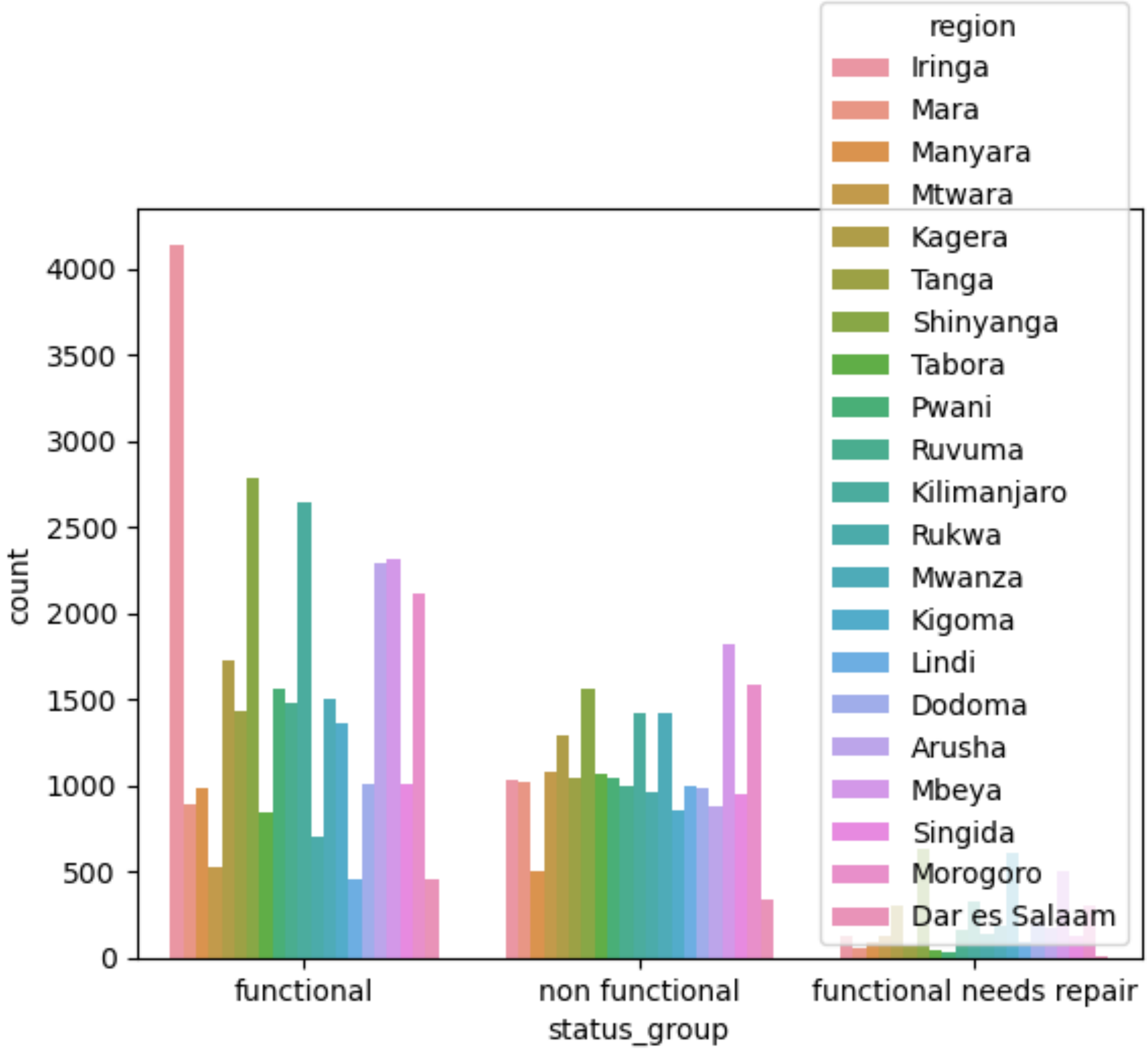

1964
1965
1966
1967
1968
1969
1970
1971
1972
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
10000
8000



okay, so no surprise - recently constructed wells seem more likely to be functional. This is a useful column

In [16]:
```
sns.countplot(merged_df, x="status_group", hue="region")
```

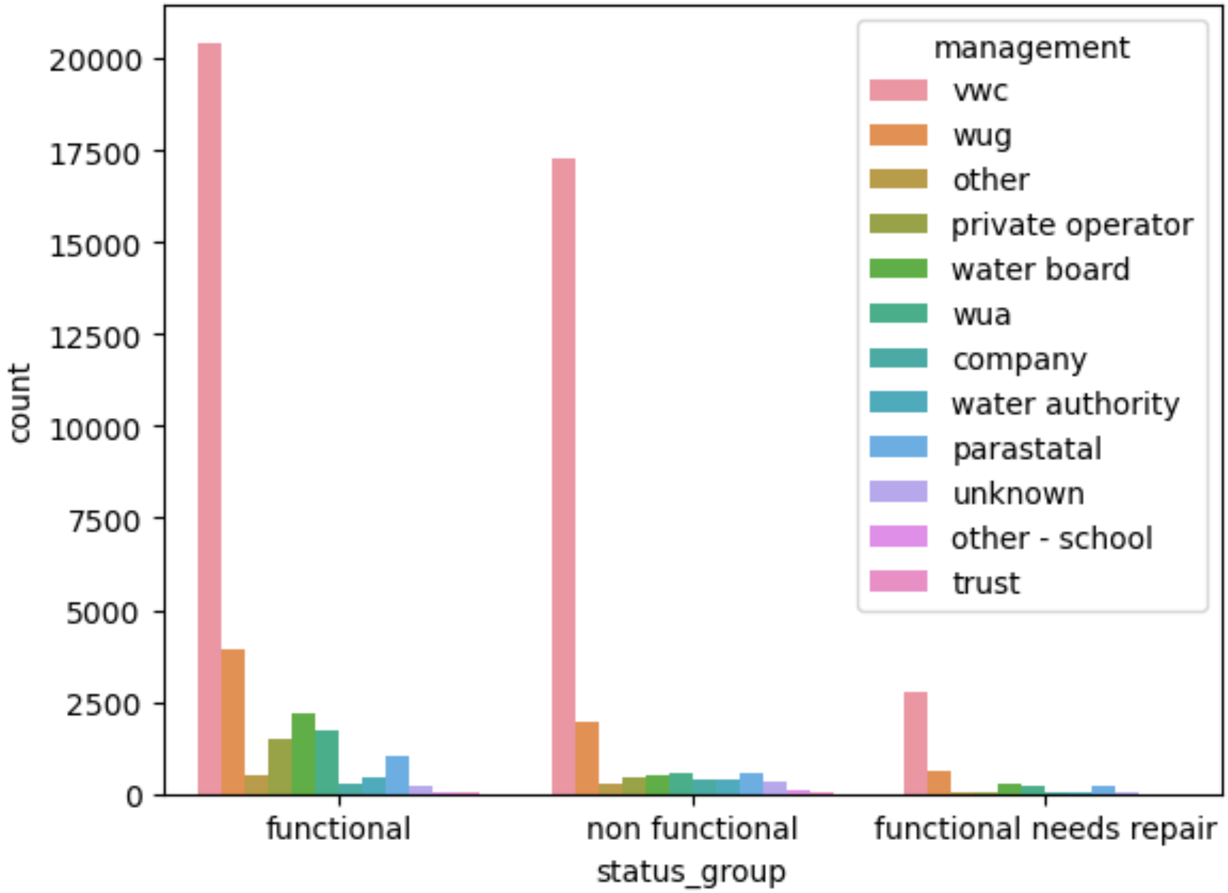
Out[16]: <Axes: xlabel='status_group', ylabel='count'>



region could be useful

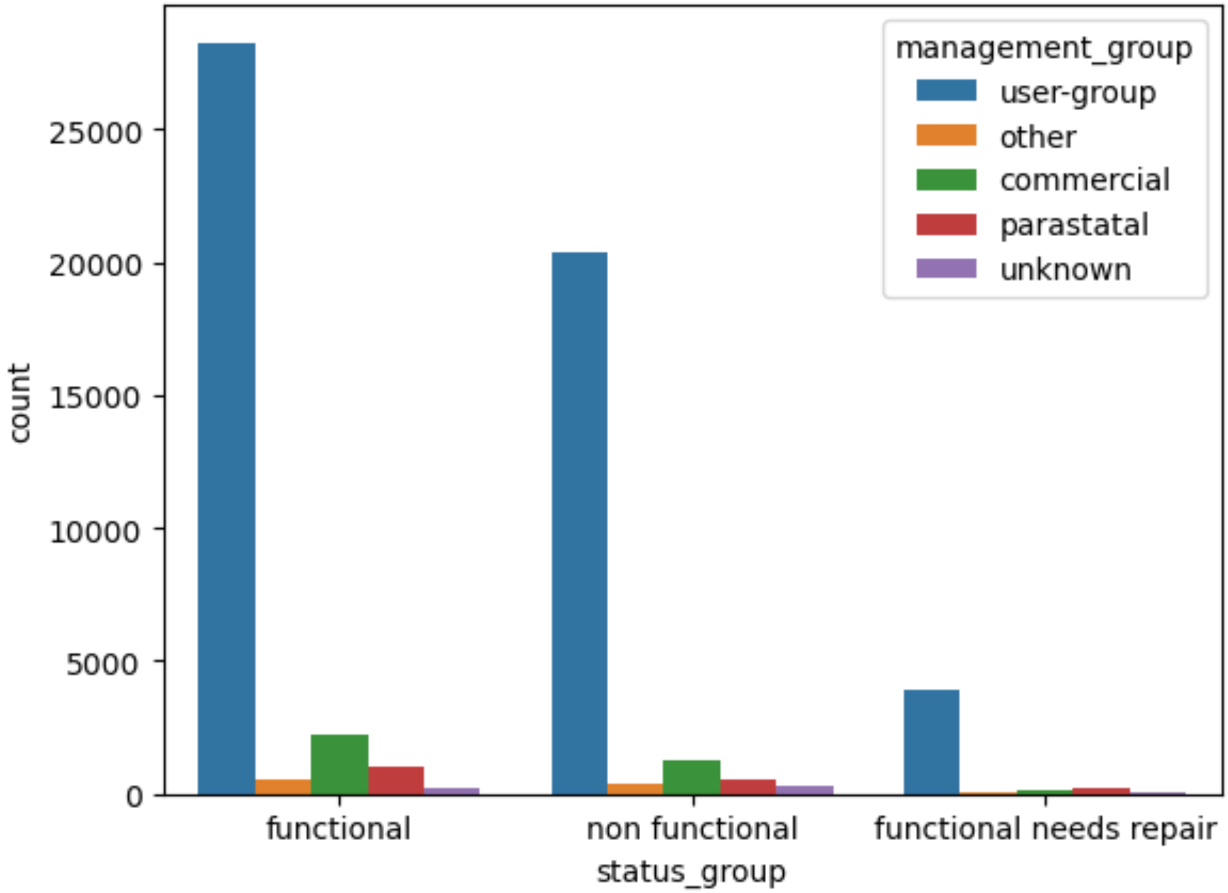
In [17]:
```
sns.countplot(merged_df, x="status_group", hue="management")
```

Out[17]:
```
<Axes: xlabel='status_group', ylabel='count'>
```



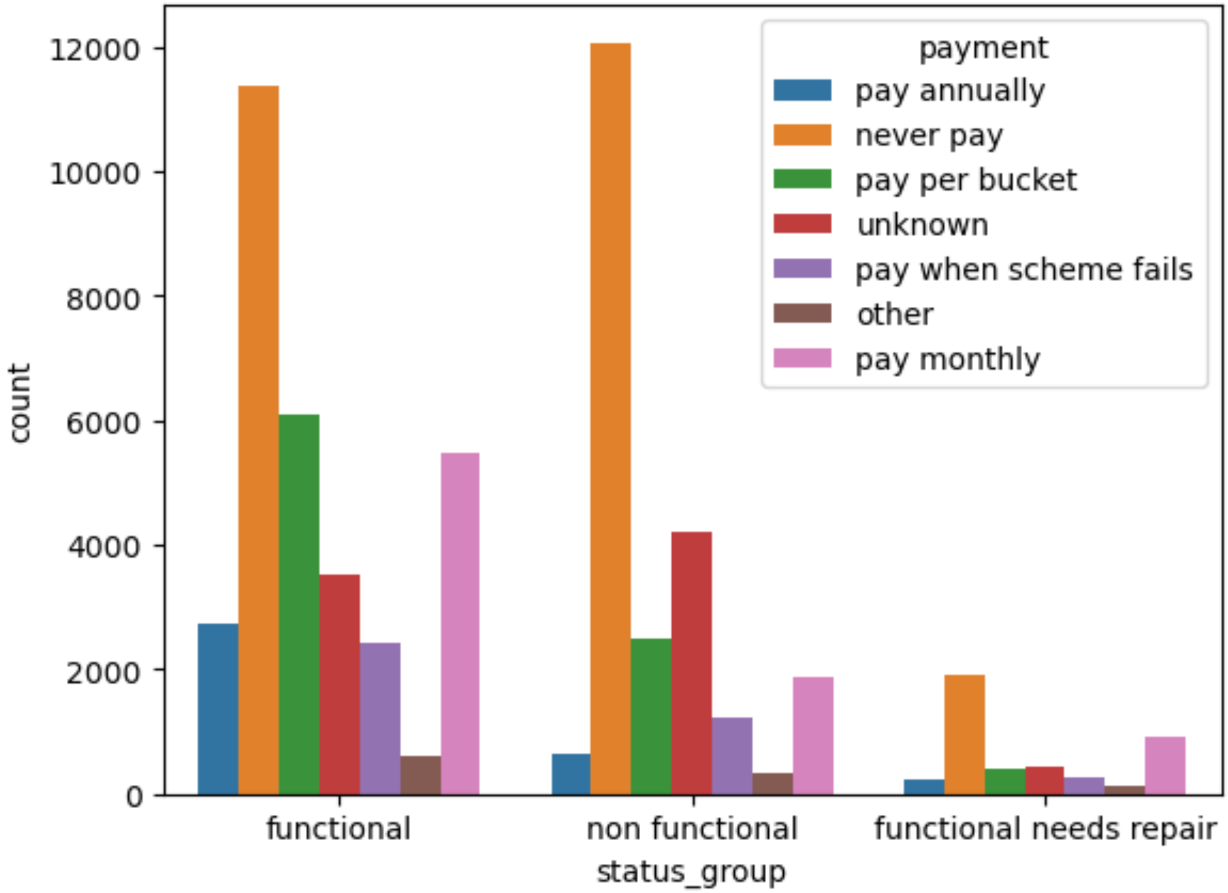
In [18]:
```
sns.countplot(merged_df, x="status_group", hue="management_group")
```

Out[18]: <Axes: xlabel='status_group', ylabel='count'>



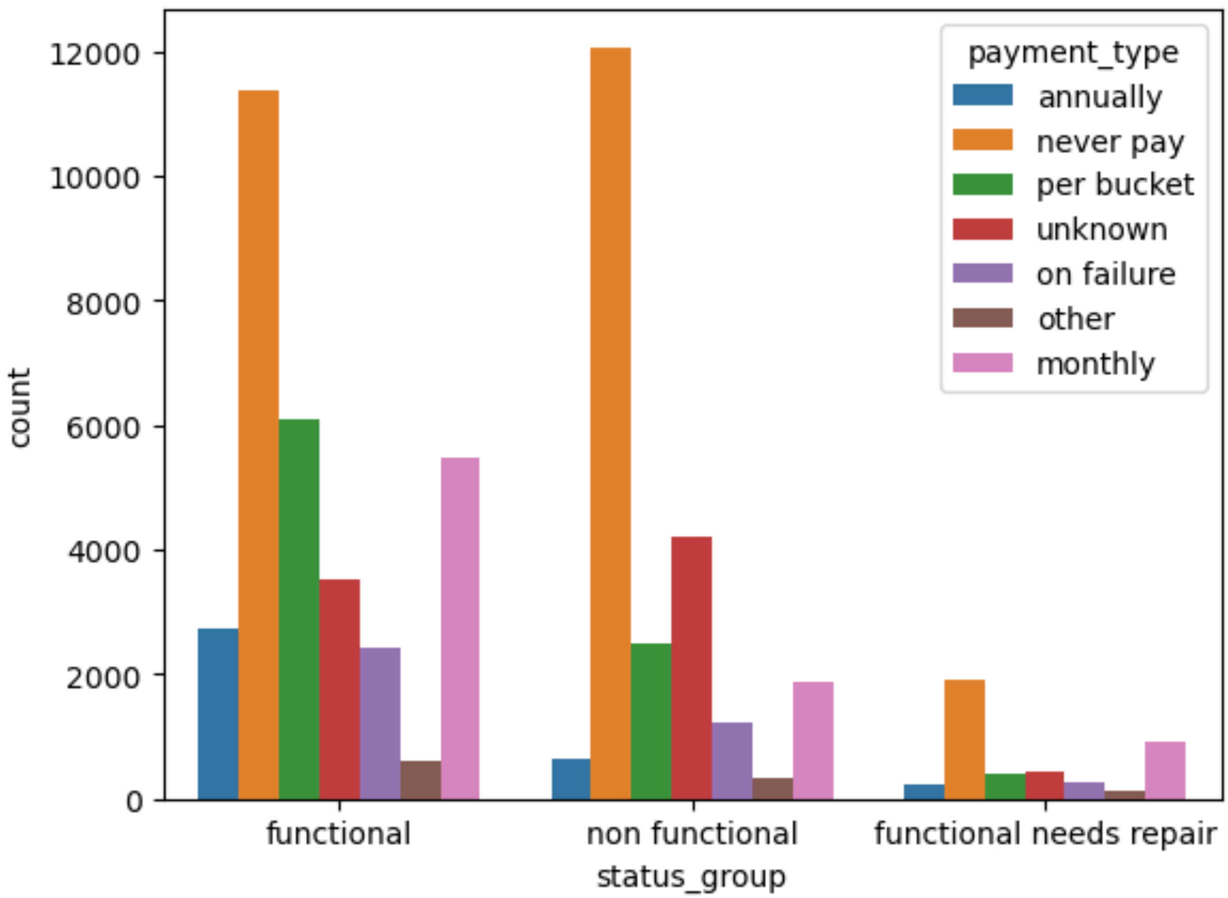
In [19]:
```
sns.countplot(merged_df, x="status_group", hue="payment")
```

Out[19]:
```
<Axes: xlabel='status_group', ylabel='count'>
```



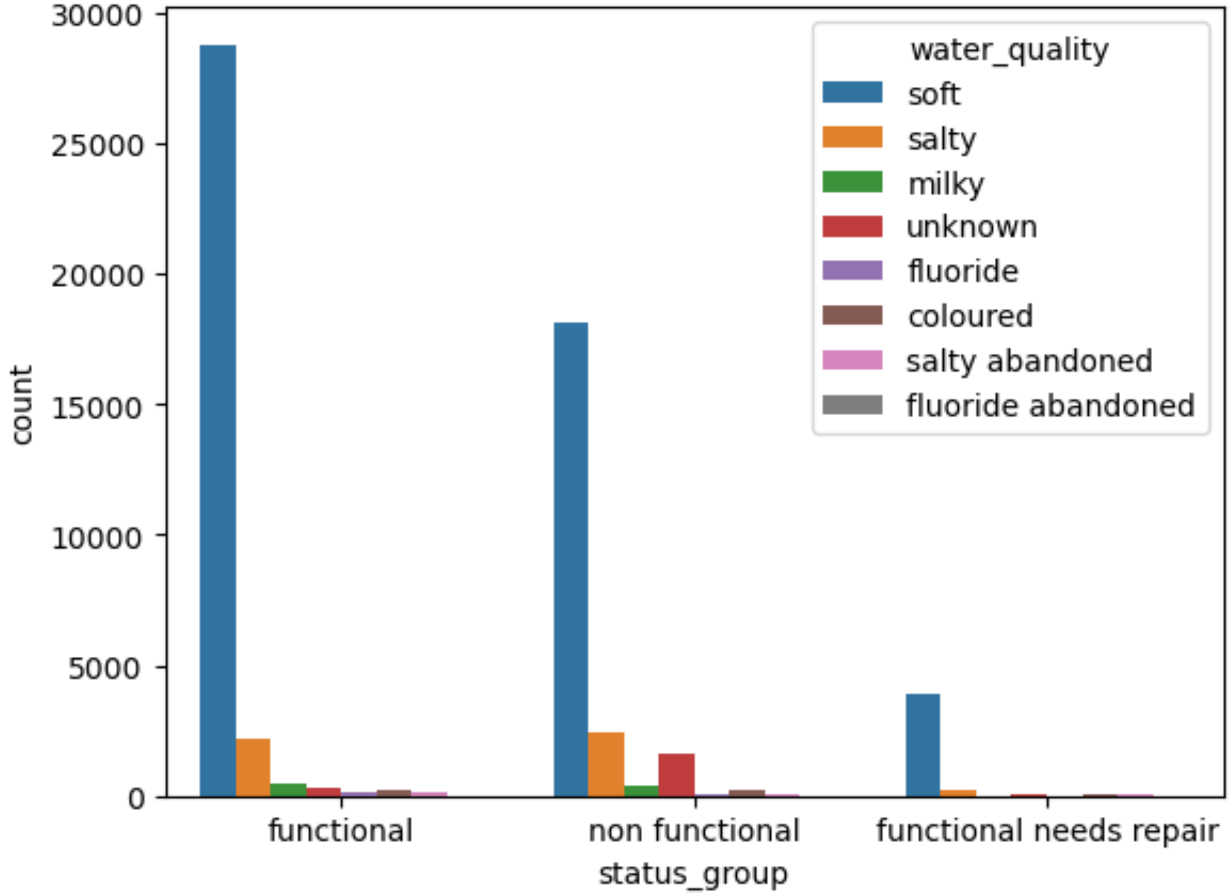
In [20]:
```
sns.countplot(merged_df, x="status_group", hue="payment_type")
```

Out[20]:
```
<Axes: xlabel='status_group', ylabel='count'>
```



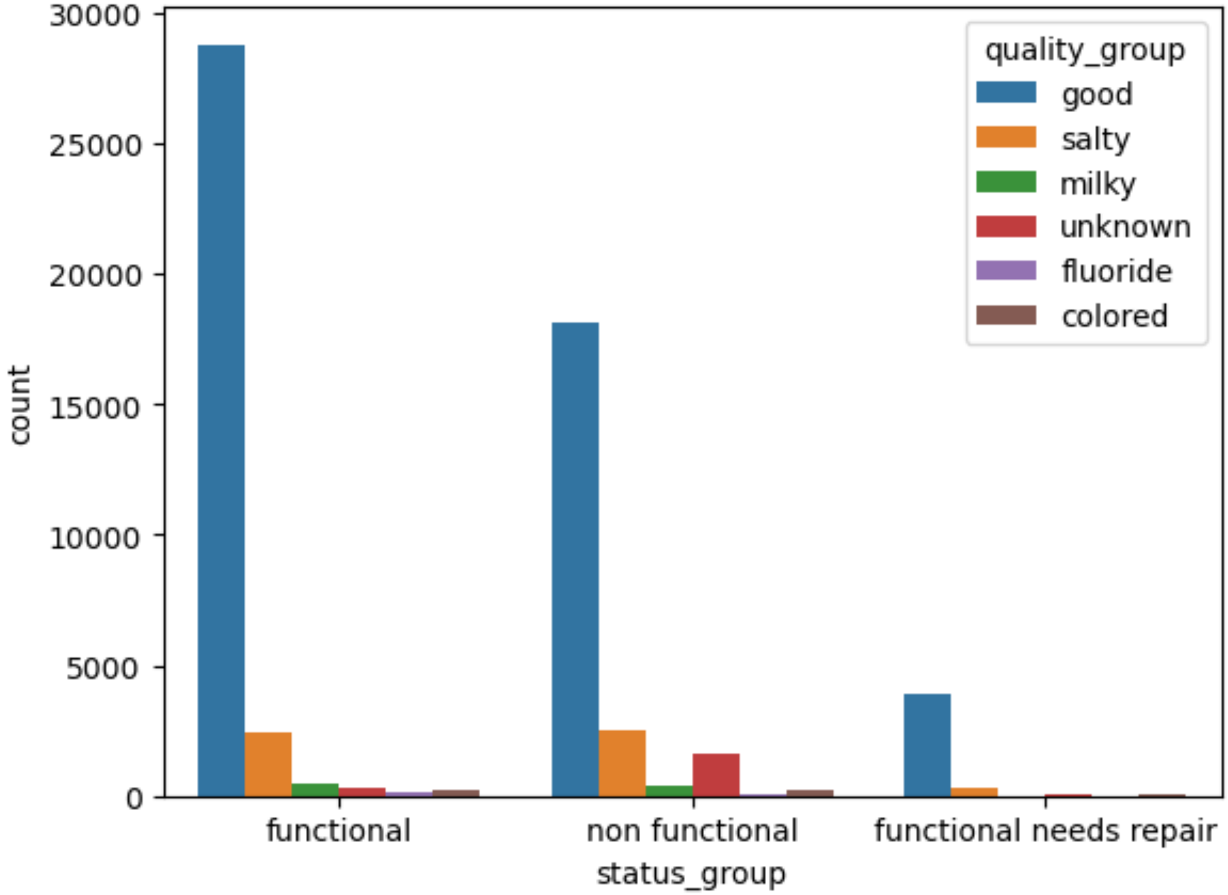
In [21]:
```
sns.countplot(merged_df, x="status_group", hue="water_quality")
```

Out[21]:
```
<Axes: xlabel='status_group', ylabel='count'>
```



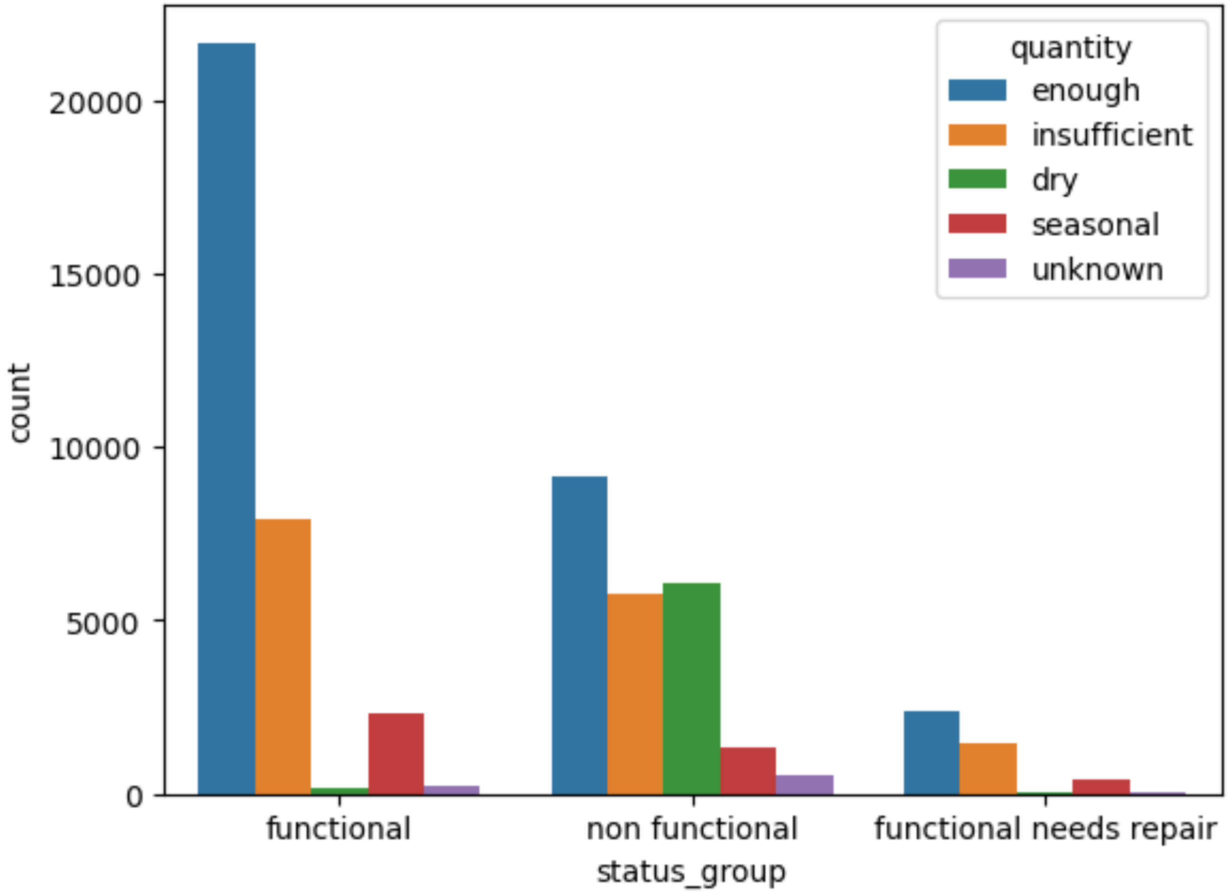
In [22]:
```
sns.countplot(merged_df, x="status_group", hue="quality_group")
```

Out[22]: <Axes: xlabel='status_group', ylabel='count'>



In [23]:
```
sns.countplot(merged_df, x="status_group", hue="quantity")
```

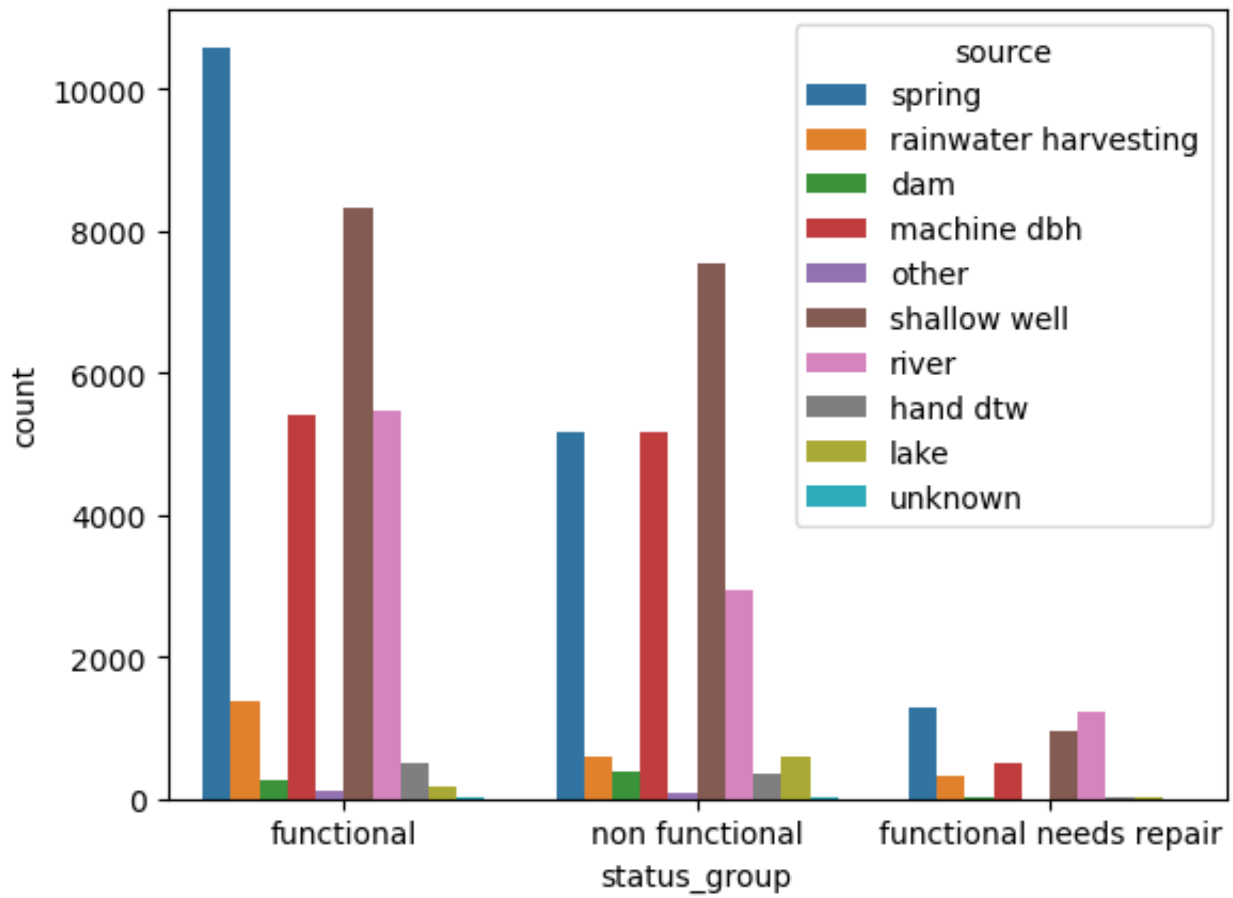
Out[23]: <Axes: xlabel='status_group', ylabel='count'>



looks like there could be some useful differences here!

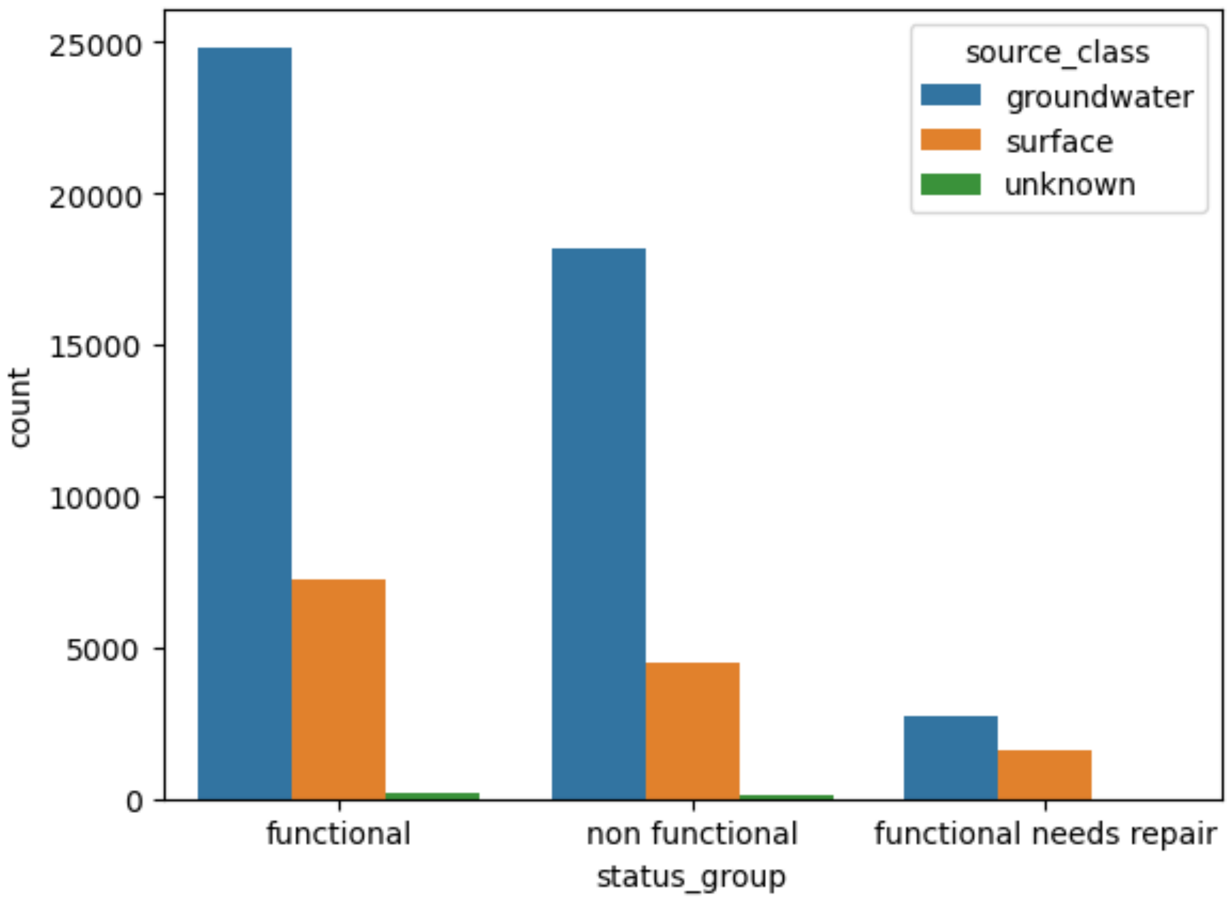
In [24]:
```
sns.countplot(merged_df, x="status_group", hue="source")
```

Out[24]: <Axes: xlabel='status_group', ylabel='count'>



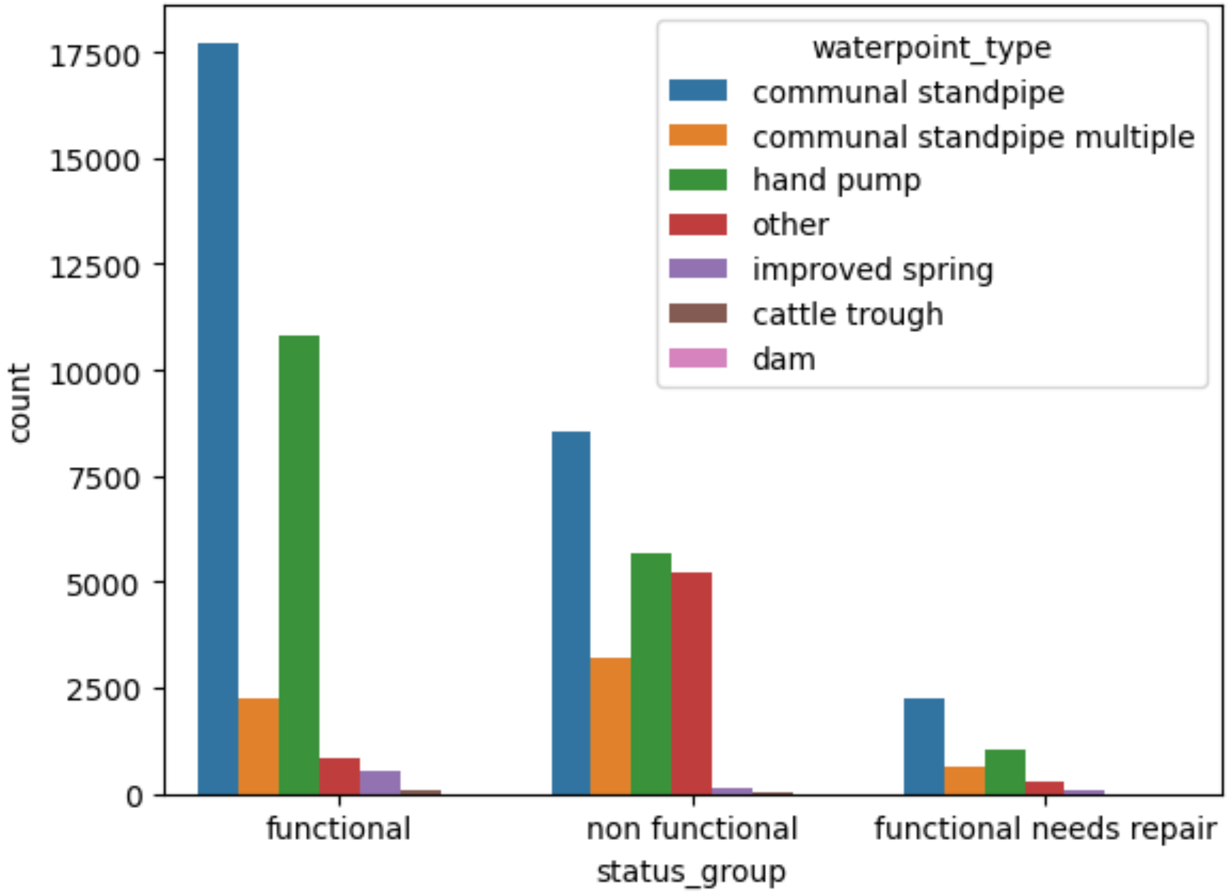
In [25]:
```
sns.countplot(merged_df, x="status_group", hue="source_class")
```

Out[25]: <Axes: xlabel='status_group', ylabel='count'>



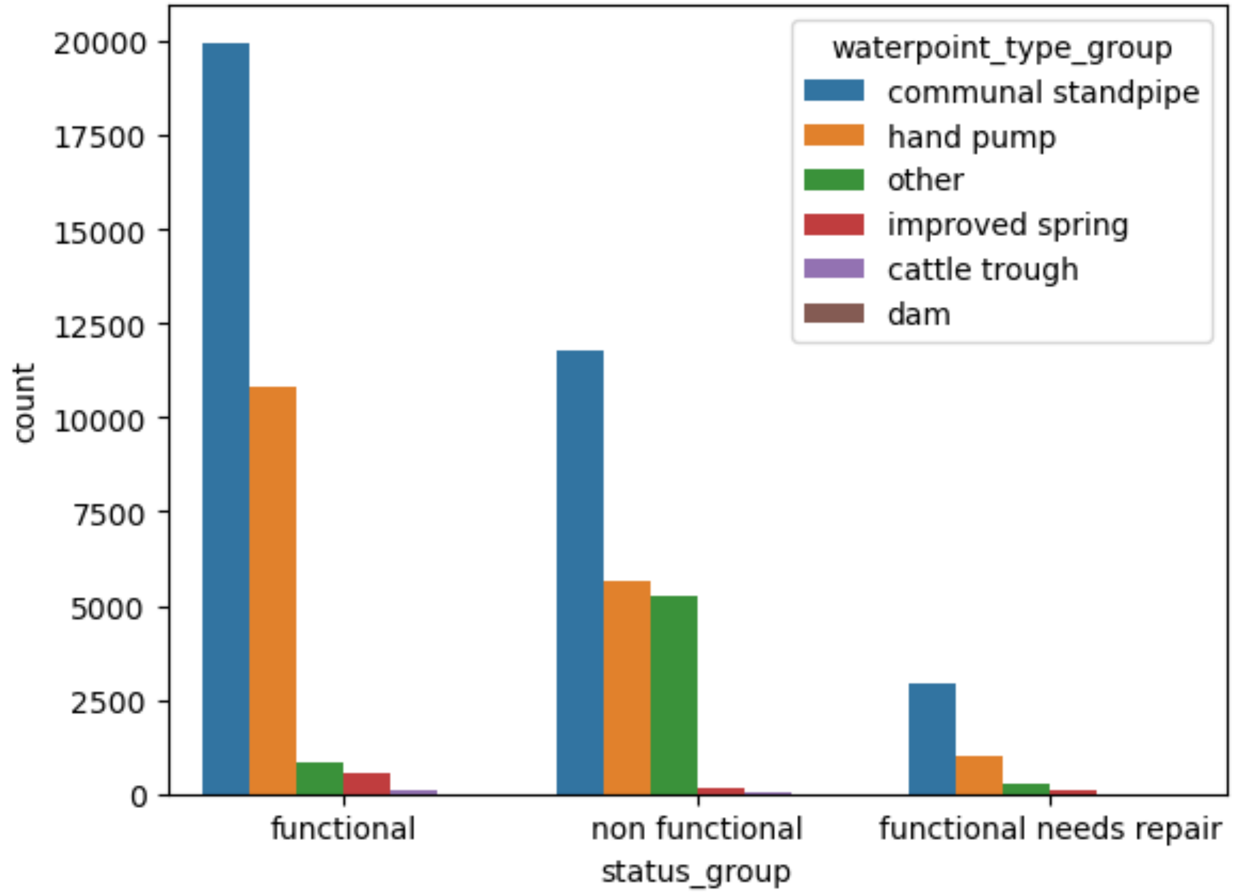
In [26]:
```
sns.countplot(merged_df, x="status_group", hue="waterpoint_type")
```

Out[26]: <Axes: xlabel='status_group', ylabel='count'>



In [27]:
```
sns.countplot(merged_df, x="status_group", hue="waterpoint_type_group")
```

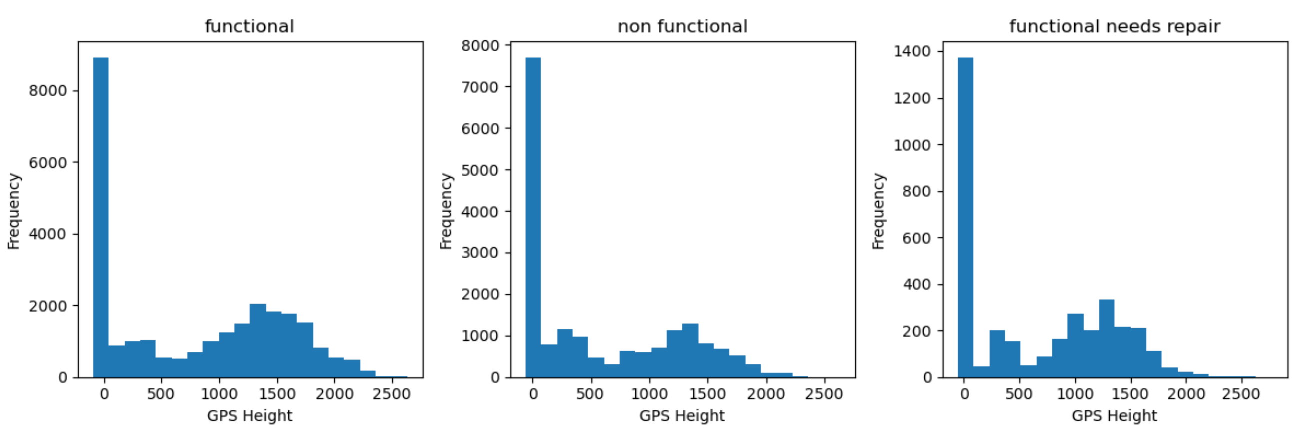
Out[27]: <Axes: xlabel='status_group', ylabel='count'>



In [28]:
```
fig, axs = plt.subplots(1, len(merged_df_cleaning['status_group'].unique()),

for i, category in enumerate(merged_df_cleaning['status_group'].unique()):
    data = merged_df_cleaning[merged_df_cleaning['status_group'] == category
    axs[i].hist(data, bins=20)
    axs[i].set_title(category)
    axs[i].set_xlabel('GPS Height')
    axs[i].set_ylabel('Frequency')

plt.tight_layout()
plt.show()
```



In [29]:
```
from mpl_toolkits.basemap import Basemap

# Create a Basemap instance
map = Basemap(llcrnrlon=merged_df_cleaning['longitude'].min(), llcrnrlat=mer
              urcrnrlon=merged_df_cleaning['longitude'].max(), urcrnrlat=mer
              projection='merc', resolution='l')

# Create a figure and axes
fig, ax = plt.subplots(figsize=(12, 8))

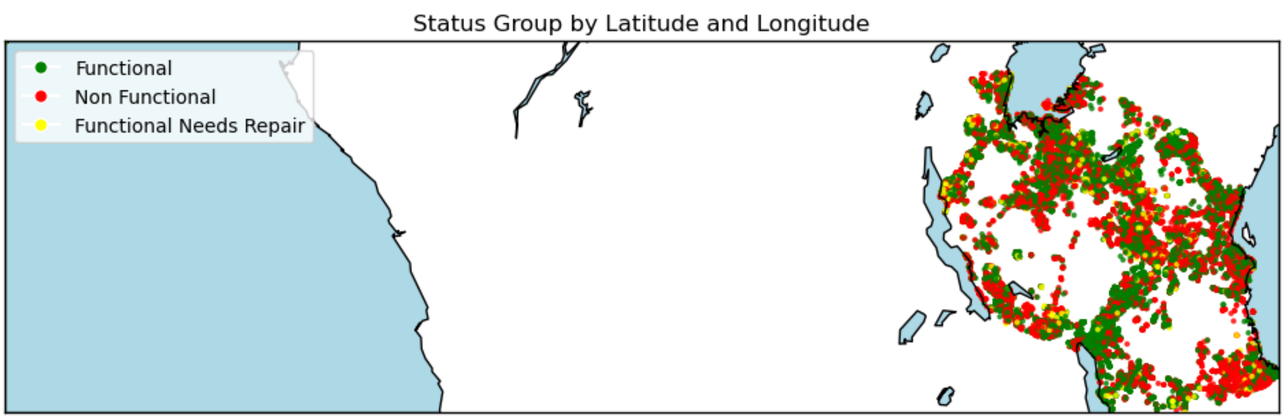
# Draw the map boundaries and coastlines
map.drawmapboundary(fill_color='lightblue')
map.fillcontinents(color='white', lake_color='lightblue')
map.drawcoastlines()

# Plot the data points on the map
x, y = map(merged_df_cleaning['longitude'].values, merged_df_cleaning['latit
scatter = map.scatter(x, y, c=merged_df_cleaning['status_group'].map({'funct
                      s=4, alpha=0.7)

# Create a legend
legend_elements = [plt.Line2D([0], [0], marker='o', color='w', markerfacecol
                   plt.Line2D([0], [0], marker='o', color='w', markerfacecol
                   plt.Line2D([0], [0], marker='o', color='w', markerfacecol
ax.legend(handles=legend_elements, loc='upper left')

# Set plot title
ax.set_title('Status Group by Latitude and Longitude')

# Show the plot
plt.show()
```



Build a First Model / Baseline Model

In [30]:
```
# Preprocess the data
```

```
# Drop unnecessary columns
first_model_df = merged_df_cleaning[['construction_year', 'basin', 'region',
# Handle missing values
first_model_df.dropna(inplace=True)
# Split the data into features (X) and target variable (y)
X = first_model_df[['construction_year', 'basin', 'region', 'payment', 'paym
y = first_model_df['status_group']

# Encode categorical variables
X_encoded = pd.get_dummies(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=

# Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)

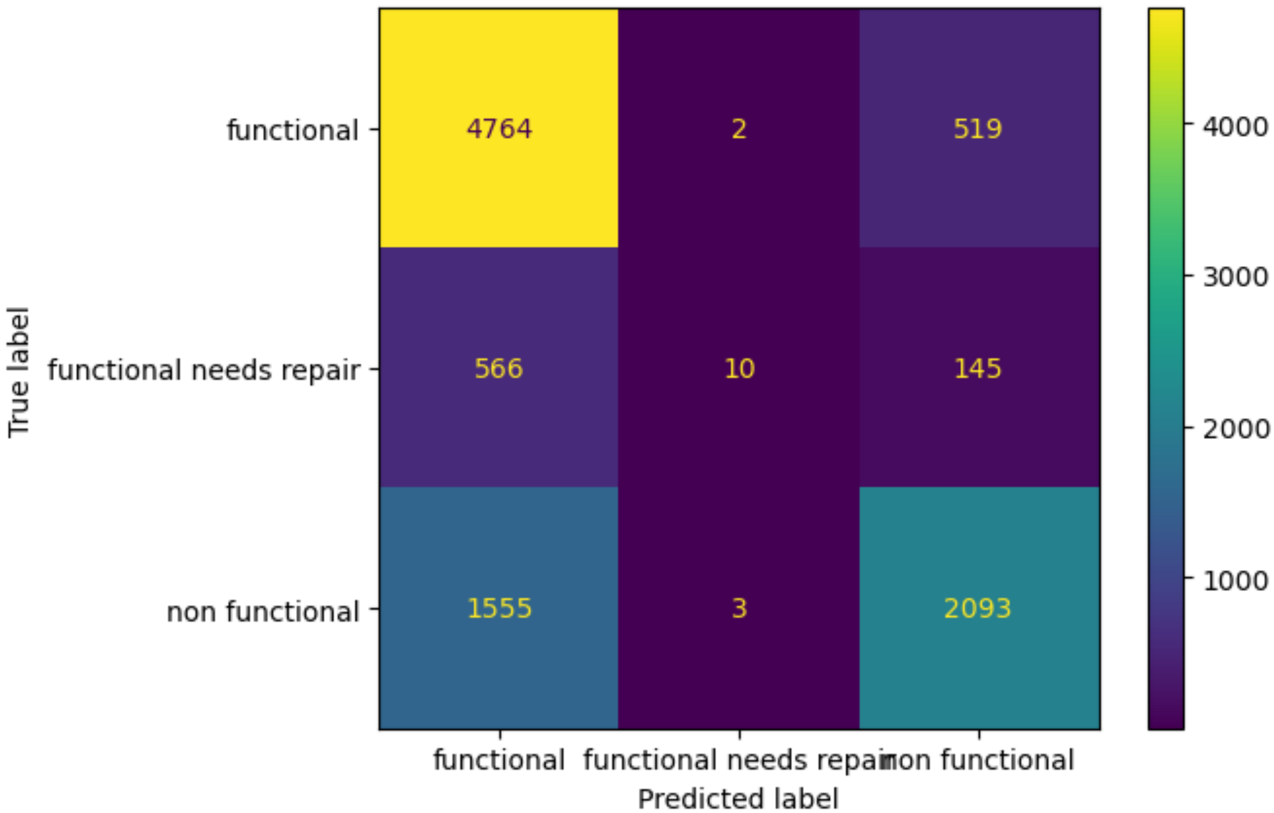
# Make predictions on the testing set
y_pred = model.predict(X_test)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7110904007455732
```

In [31]:
```
ConfusionMatrixDisplay.from_estimator(model, X_test, y_test)
```

Out[31]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x17d4a26
70>
```



In [32]:
```
y_pred_proba = model.predict_proba(X_test)
#Compute the ROC curve for each class using the roc_curve function:
#python
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(num_classes):
fpr[i], tpr[i], _ = roc_curve(y_test[:, i], y_pred_proba[:, i])
roc_auc[i] = auc(fpr[i], tpr[i])
Plot the ROC curve for each class using RocCurveDisplay:
```python
plt.figure(figsize=(8, 6))
for i in range(numclasses):
rocdisplay = RocCurveDisplay(fpr=fpr[i], tpr=tpr[i], rocauc=rocauc[i], estim
rocdisplay.plot()
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```
```

```
  Cell In[32], line 8
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i], y_pred_proba[:, i])
    ^
IndentationError: expected an indented block
```

Switching Model to Binanry

In [33]:
```
# Preprocess the data
# Drop unnecessary columns
binary_model_df = merged_df_cleaning_binary[['construction_year', 'basin', '
# Handle missing values
binary_model_df.dropna(inplace=True)
# Split the data into features (X) and target variable (y)
X = binary_model_df[['construction_year', 'basin', 'region', 'payment', 'pay
y = binary_model_df['status_group']

# Encode categorical variables
X_encoded = pd.get_dummies(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=

# Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)

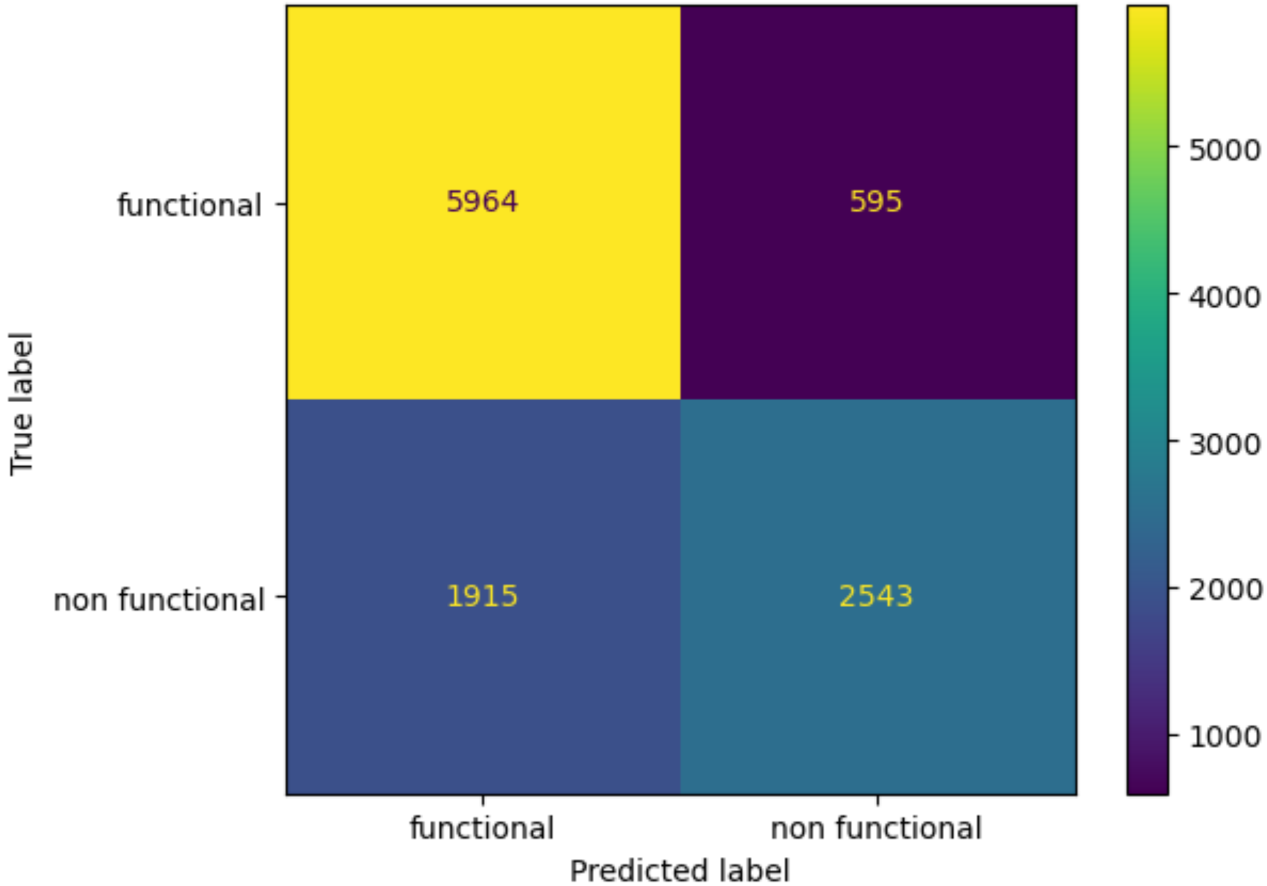
# Make predictions on the testing set
y_pred = model.predict(X_test)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7721702822910048
```

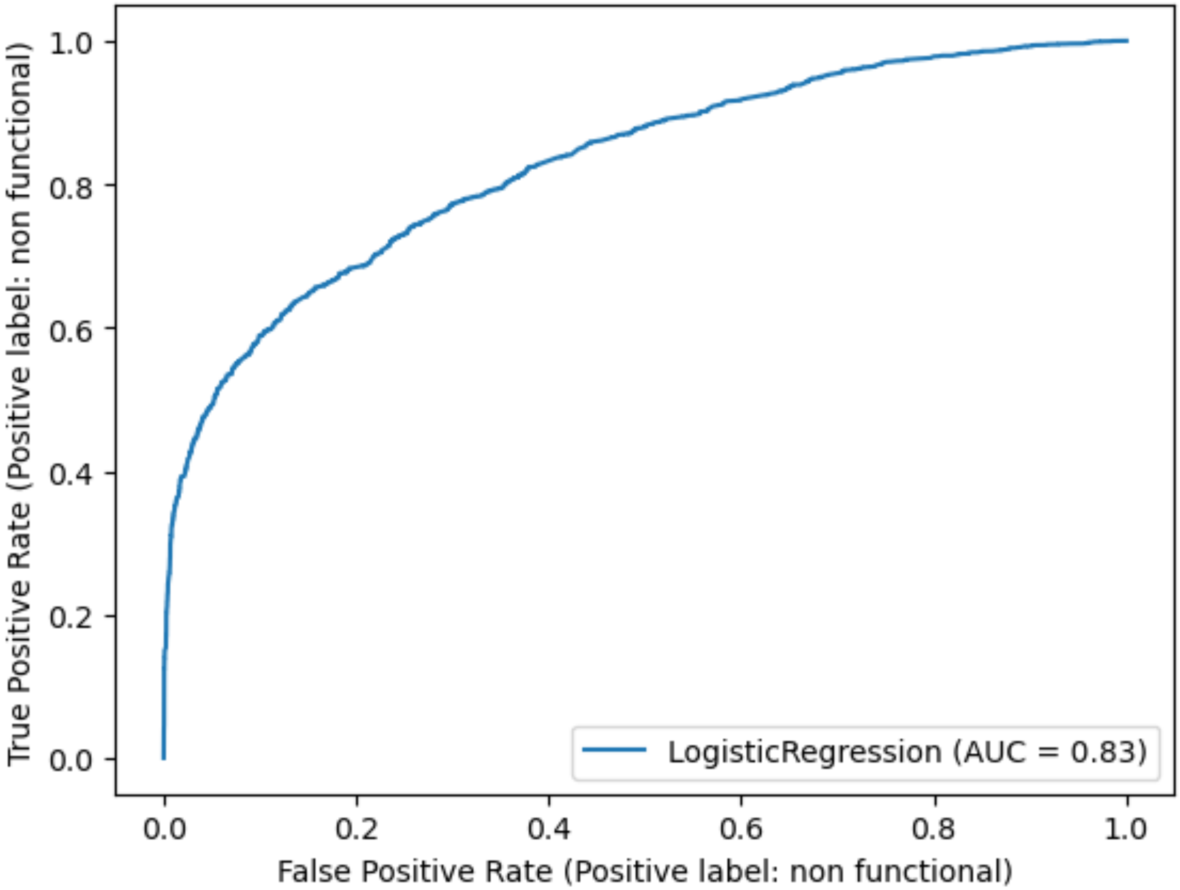
In [34]:
```
ConfusionMatrixDisplay.from_estimator(model, X_test, y_test)
```

Out[34]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x28aa42d
c0>
```



In [35]:
```
RocCurveDisplay.from_estimator(model, X_test, y_test)
```

Out[35]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x287460fa0>



Eliminating Construction Year

In [36]:
```
# Preprocess the data
# Drop unnecessary columns
binary_model_df = merged_df_cleaning_binary[['construction_year', 'basin', '
# Handle missing values
binary_model_df.dropna(inplace=True)
# Split the data into features (X) and target variable (y)
X = binary_model_df[['basin', 'region', 'payment', 'payment_type', 'quantity
y = binary_model_df['status_group']

# Encode categorical variables
X_encoded = pd.get_dummies(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=

# Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Make predictions on the testing set
```

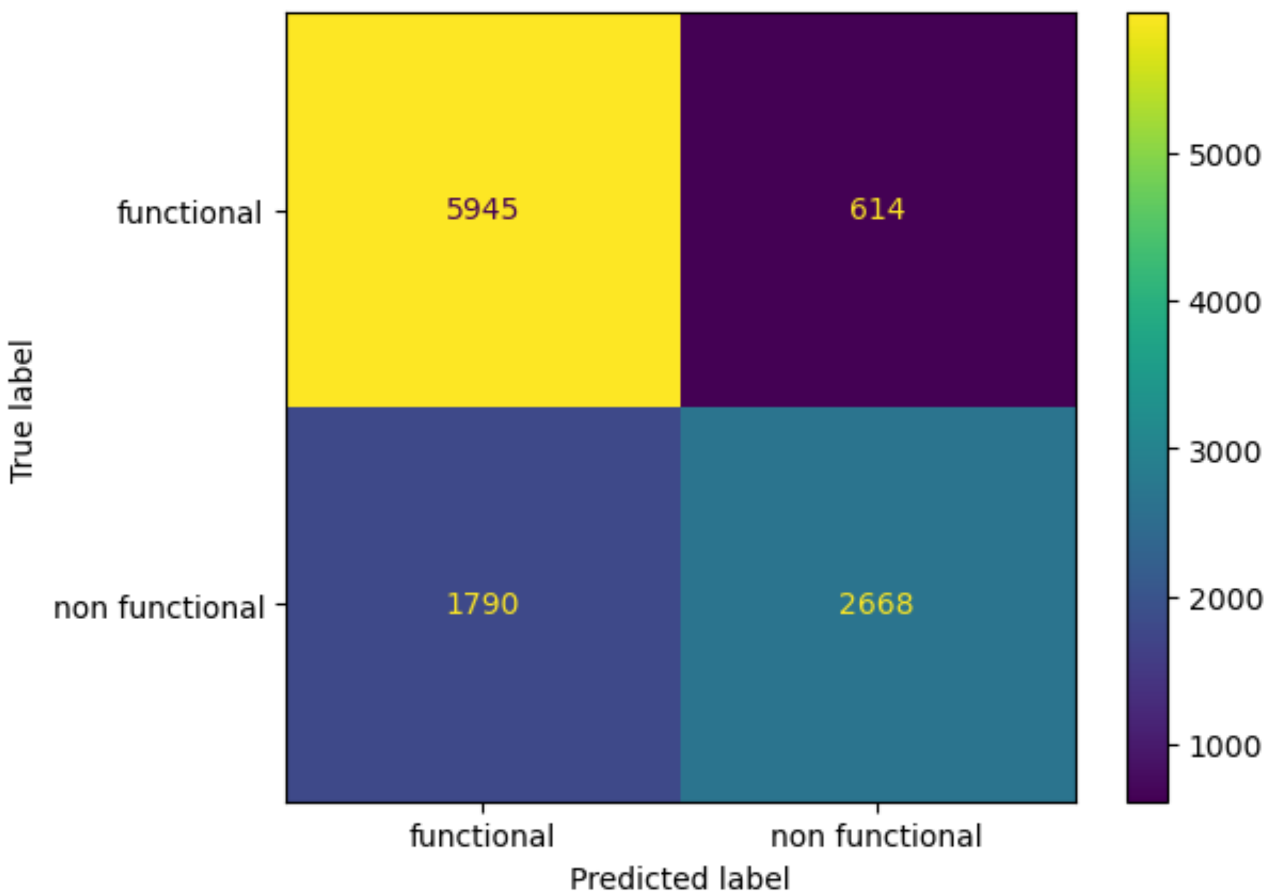
```
y_pred = model.predict(X_test)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7817917763456477
```

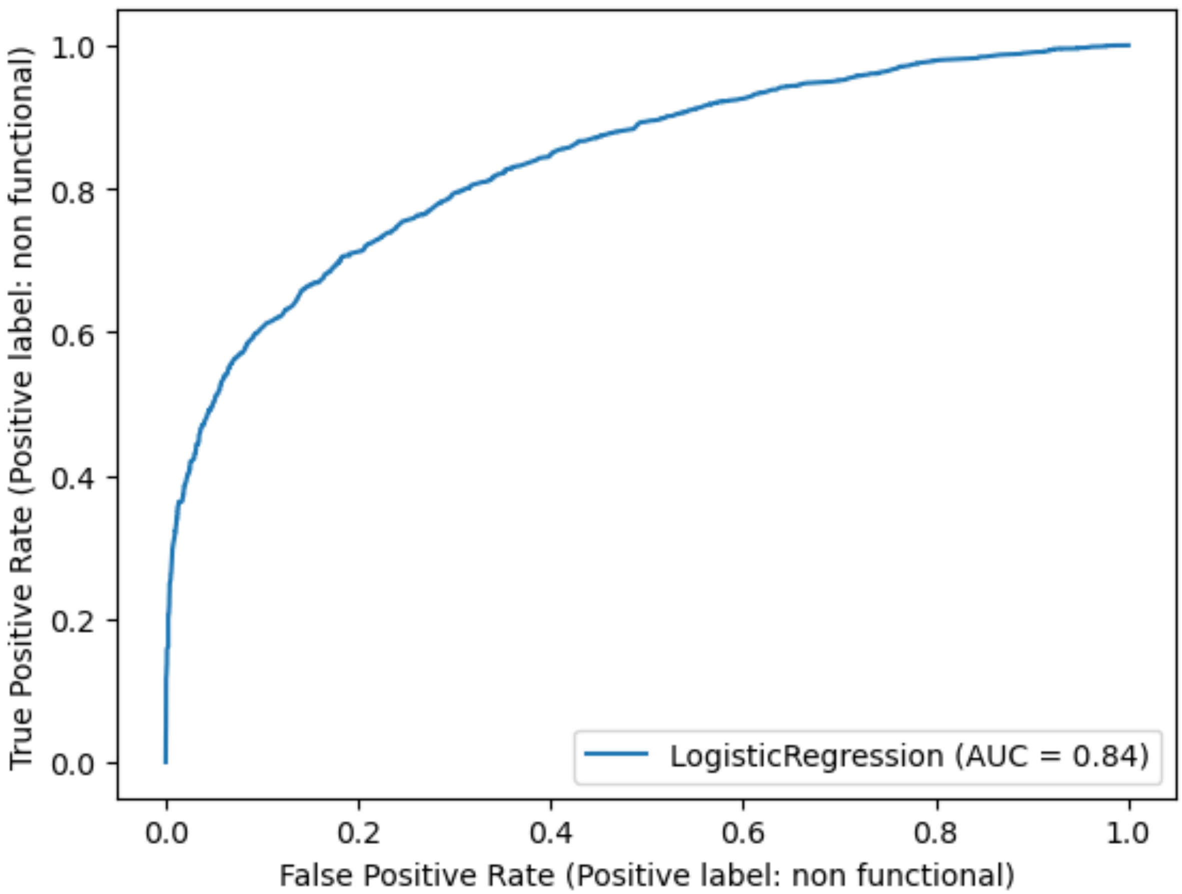
In [37]:
```
ConfusionMatrixDisplay.from_estimator(model, X_test, y_test)
```

Out[37]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x287b7ecd0>



In [38]:
```
RocCurveDisplay.from_estimator(model, X_test, y_test)
```

Out[38]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x28ac1ad00>



Adding Back In ConstYR as Years Old

In [39]:
```
# Preprocess the data
# Drop unnecessary columns
binary_model_df = merged_df_cleaning_binary[['construction_year', 'basin', '
binary_model_df['Years_Old'] = (binary_model_df['construction_year'].max() +
# Handle missing values
binary_model_df.dropna(inplace=True)
# Split the data into features (X) and target variable (y)
X = binary_model_df[['Years_Old', 'basin', 'region', 'payment', 'payment_typ
y = binary_model_df['status_group']

# Encode categorical variables
X_encoded = pd.get_dummies(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=

# Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)
```

```
# Make predictions on the testing set
y_pred = model.predict(X_test)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

Accuracy: 0.7590995733865844

Scaling Data to accomodate Years Old

In [50]:
```
# Preprocess the data
# Drop unnecessary columns
binary_model_df = merged_df_cleaning_binary[['construction_year', 'basin', '
binary_model_df['Years_Old'] = (binary_model_df['construction_year'].max() +
# Handle missing values
binary_model_df.dropna(inplace=True)
# Split the data into features (X) and target variable (y)
X = binary_model_df[['Years_Old', 'basin', 'region', 'payment', 'payment_typ
y = binary_model_df['status_group']

# Encode categorical variables
X_encoded = pd.get_dummies(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=

scaler = preprocessing.MinMaxScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)  # Use transform instead of fit

# Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train_scaled, y_train)

# Make predictions on the testing set
y_pred = model.predict(X_test_scaled)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

Accuracy: 0.7817917763456477

Same exact Acc Score as when I drop Construction entirely! Either somthing fishy is going on, or construction year is useless. But thinking about it, wouldn't construction year have at least some predictive relevance?

Dropping Construction Year again, Toying with dropping other categories

In [93]:
```
# Preprocess the data
# Drop unnecessary columns
binary_model_df = merged_df_cleaning_binary[['construction_year', 'basin', '
# Handle missing values
binary_model_df.dropna(inplace=True)
# Split the data into features (X) and target variable (y)
X = binary_model_df[['basin', 'region', 'payment_type', 'quantity', 'waterpo
y = binary_model_df['status_group']

# Encode categorical variables
X_encoded = pd.get_dummies(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=

# Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Make predictions on the testing set
y_pred = model.predict(X_test)

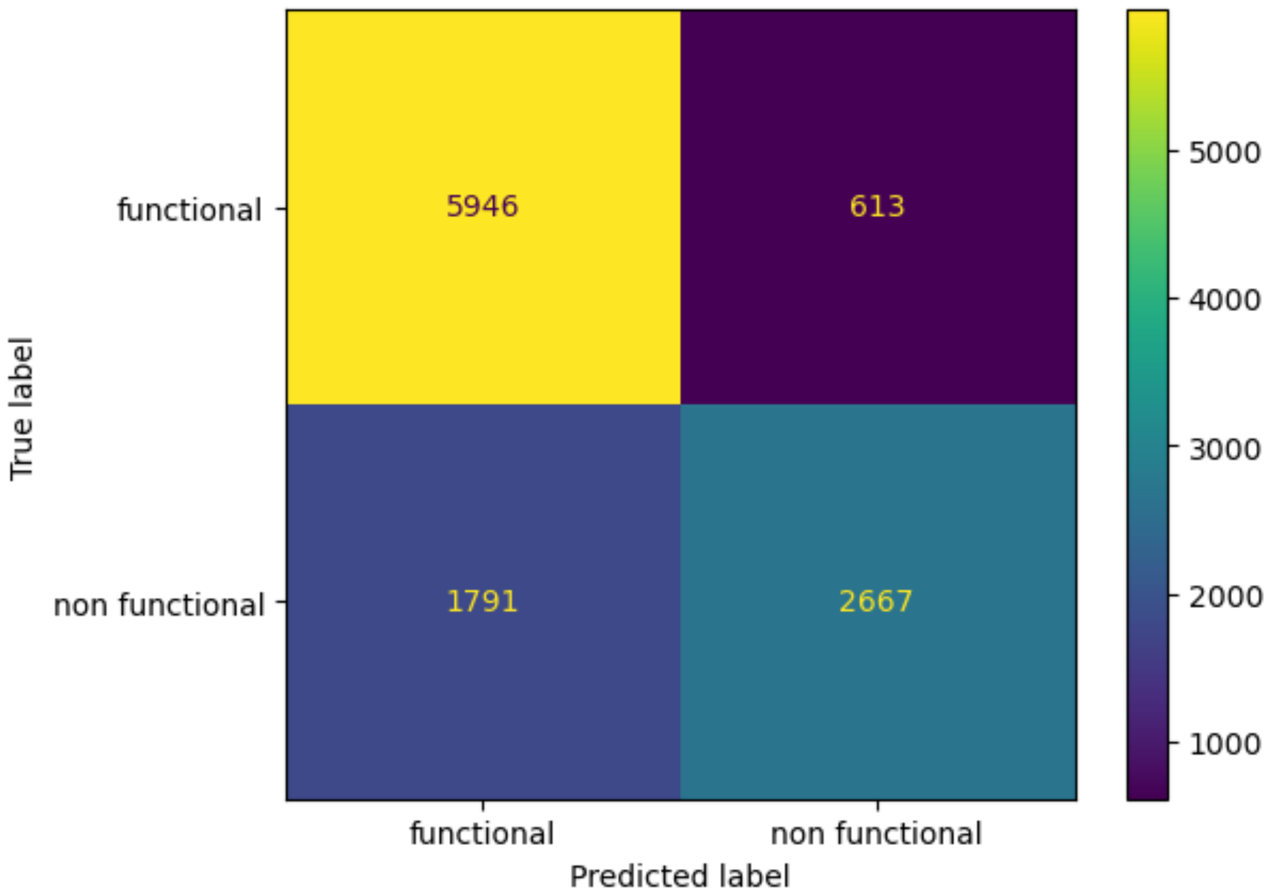
# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

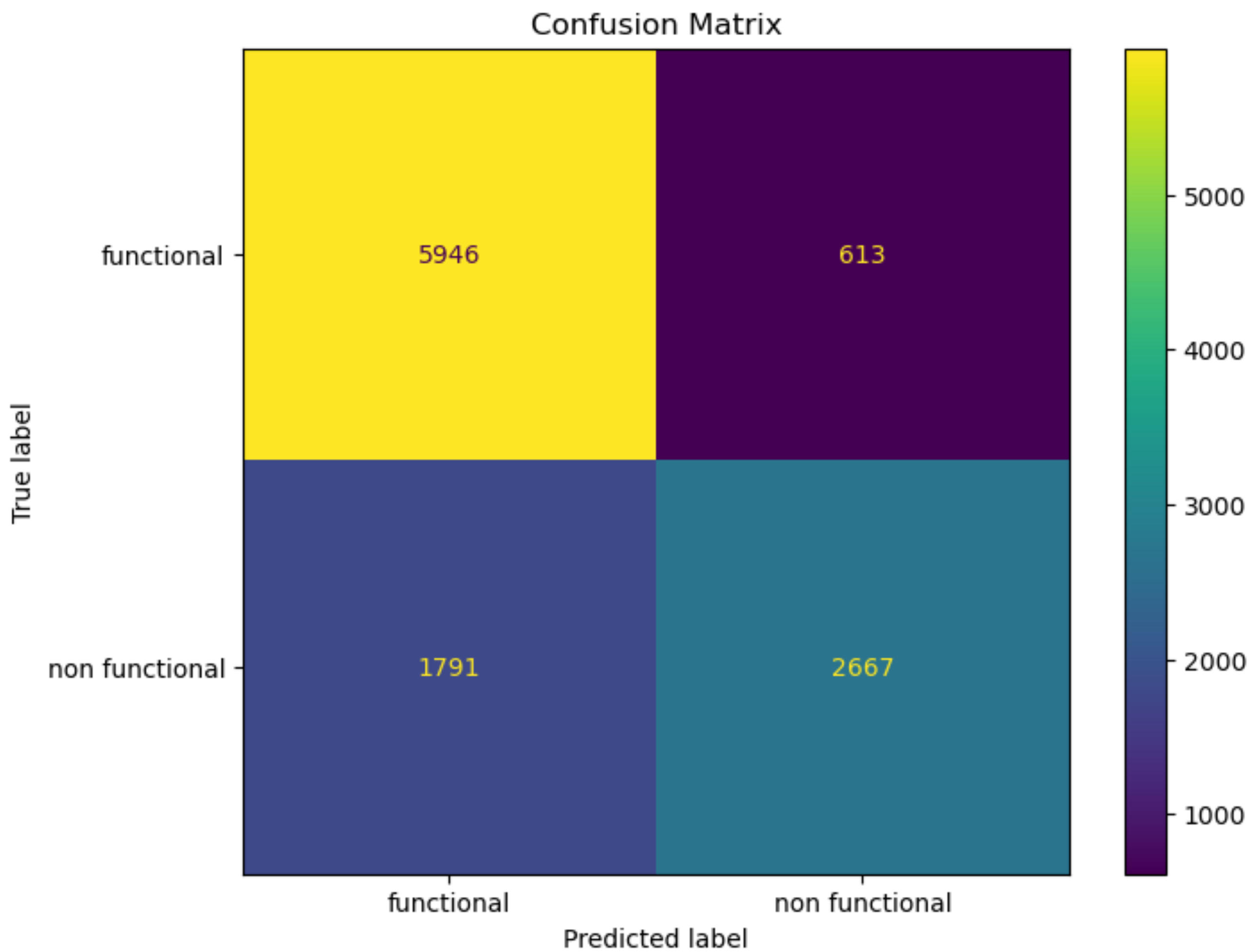
```
Accuracy: 0.7817917763456477
```

In [94]:
```
model.coef_
```

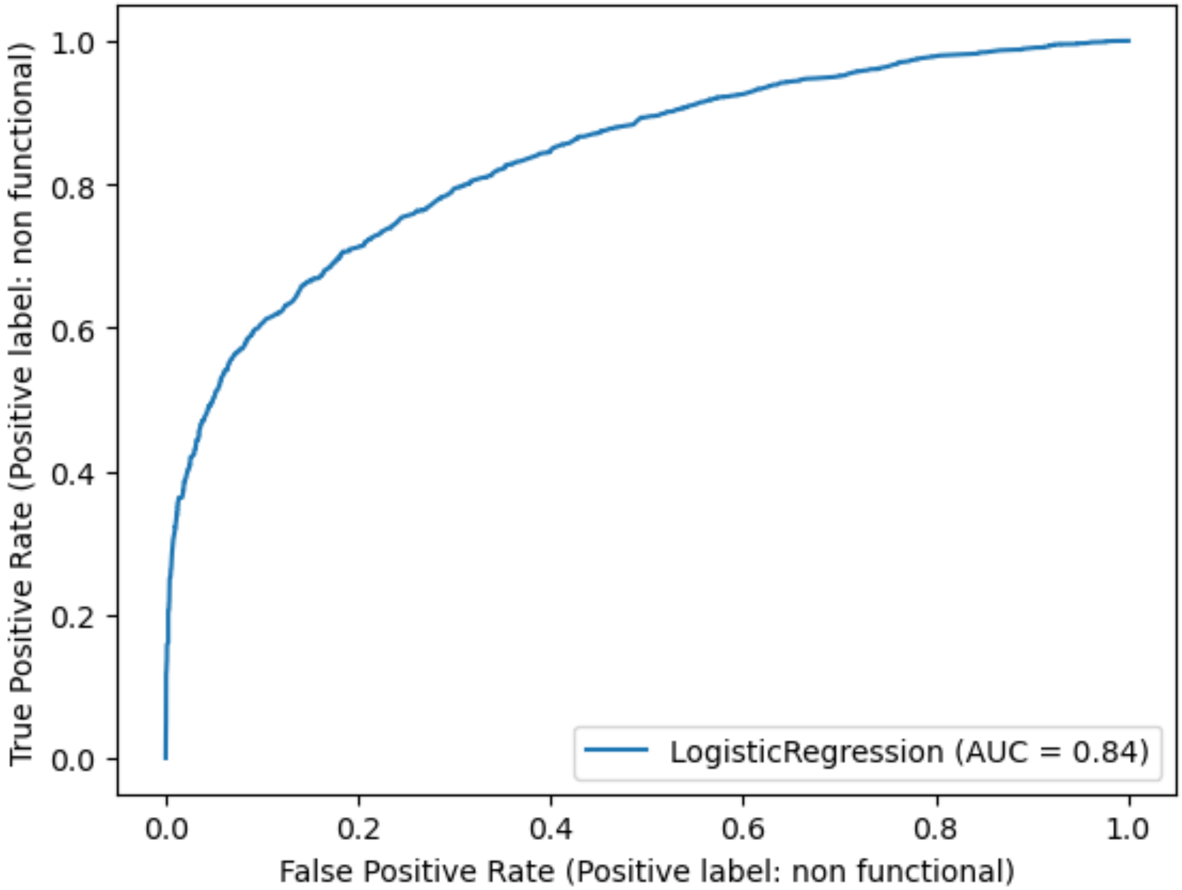
Out[94]:
```
array([[ 3.95587729e-01, -1.30329475e+00,  9.12314807e-02,
        -4.47136928e-05,  1.67477081e-01,  6.71848330e-01,
        -9.71457638e-02, -8.30704055e-02,  1.68640018e-01,
        -1.07379863e+00,  4.95867791e-01, -4.75099797e-01,
        -3.10693490e-01, -1.95084729e-01,  3.01615277e-01,
        -5.73844031e-01,  7.83467675e-01, -9.53746707e-01,
         6.64621995e-01,  7.67485376e-01,  2.84204759e-01,
         4.58708605e-01, -3.29604900e-01,  5.48973704e-01,
         8.89007616e-01,  2.80381799e-01, -6.22733492e-01,
        -5.36198457e-01,  2.28528600e-01, -6.20829954e-01,
        -5.84760977e-01, -3.82854021e-01,  5.64824399e-01,
        -4.95617207e-02,  2.87911157e-01, -3.77822132e-01,
         5.53492302e-01,  3.31404761e+00, -1.36306527e+00,
        -8.94333347e-01, -1.25446196e+00,  2.09041967e-01,
        -2.78789718e-01, -2.27360087e-01,  9.00007328e-01,
        -6.51617224e-01, -3.65787253e-01, -1.41334092e+00,
         2.04811688e+00,  1.65044979e+00, -8.82720620e-01,
         6.54856500e-01, -1.17785016e-01, -9.38616033e-01,
        -5.48413912e-01, -2.24422324e-01,  3.54894956e-01,
         5.56424563e-01, -2.82257139e-01, -1.36409480e-01,
        -7.47722814e-02]])
```

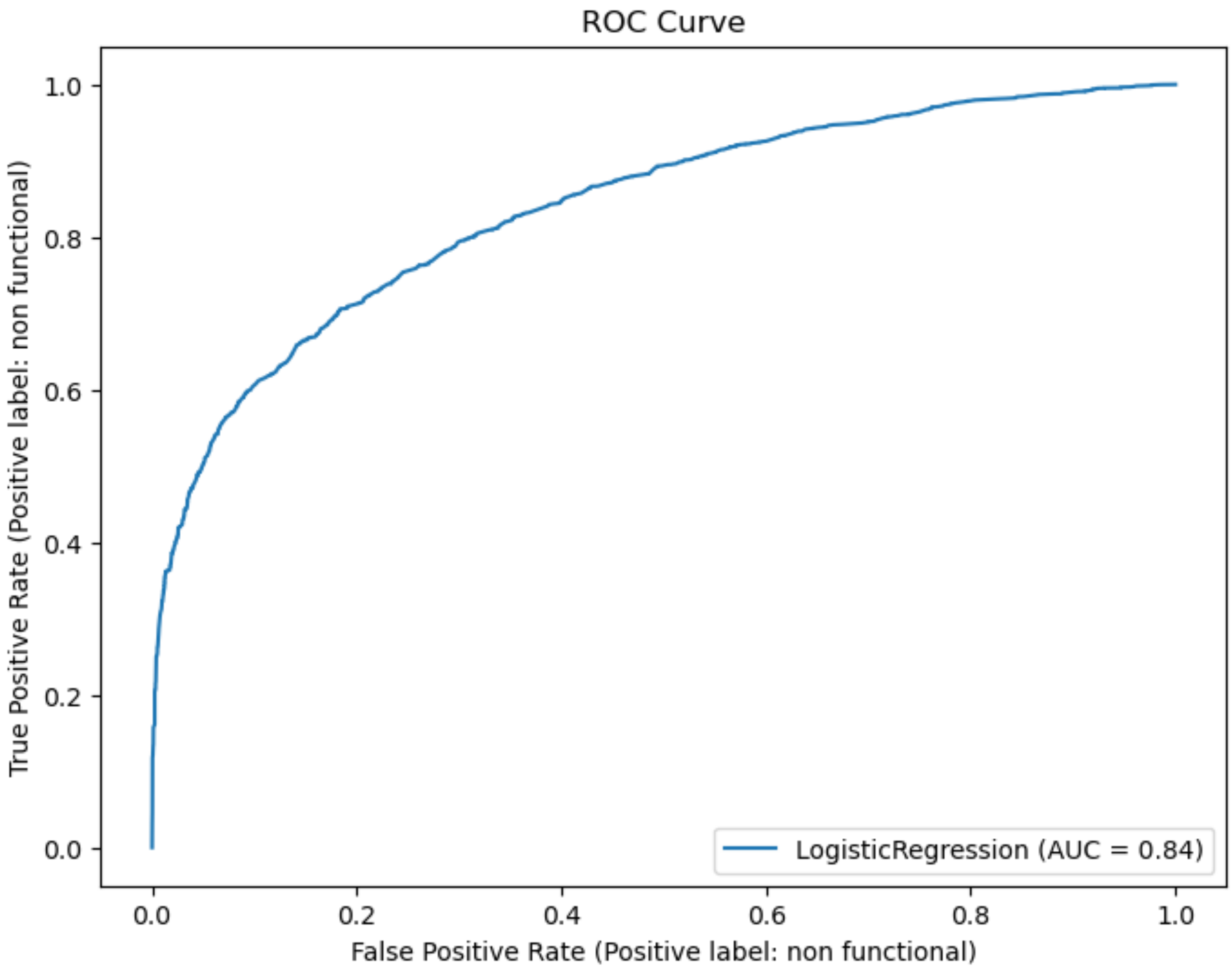
In [96]:
```
disp = ConfusionMatrixDisplay.from_estimator(model, X_test, y_test)
fig, ax = plt.subplots(figsize=(8, 6))
disp.plot(ax=ax)
ax.set_title("Confusion Matrix")
plt.show()
```


functional
non functional
True label
5946
613
1791
2667
functional
non functional
Predicted label
5000
4000
3000
2000
1000



In [97]:
```
disp = RocCurveDisplay.from_estimator(model, X_test, y_test)
fig, ax = plt.subplots(figsize=(8, 6))
disp.plot(ax=ax)
ax.set_title("ROC Curve")
plt.show()
```


1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: non functional)
LogisticRegression (AUC = 0.84)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: non functional)



Reverting to Scaled Model to Allow for Hyperparameterization on C

We didn't end up using this as our final model. Final Linear Regression model is the one above this

In [83]:
```
# Preprocess the data
# Drop unnecessary columns
binary_model_df = merged_df_cleaning_binary[['construction_year', 'basin', '
binary_model_df['Years_Old'] = (binary_model_df['construction_year'].max() +
# Handle missing values
binary_model_df.dropna(inplace=True)
# Split the data into features (X) and target variable (y)
X = binary_model_df[['Years_Old', 'basin', 'region', 'payment', 'payment_typ
y = binary_model_df['status_group']

# Encode categorical variables
X_encoded = pd.get_dummies(X)
```

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=

scaler = preprocessing.MinMaxScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)  # Use transform instead of fit

# Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train_scaled, y_train)

# Make predictions on the testing set
y_pred = model.predict(X_test_scaled)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7817917763456477
```

In [84]:
```
print(X_encoded.dtypes)
```

```
Years_Old                         int64
basin_Internal                     bool
basin_Lake Nyasa                   bool
basin_Lake Rukwa                   bool
basin_Lake Tanganyika              bool
                                  ...
management_vwc                     bool
management_water authority         bool
management_water board             bool
management_wua                     bool
management_wug                     bool
Length: 69, dtype: object
```

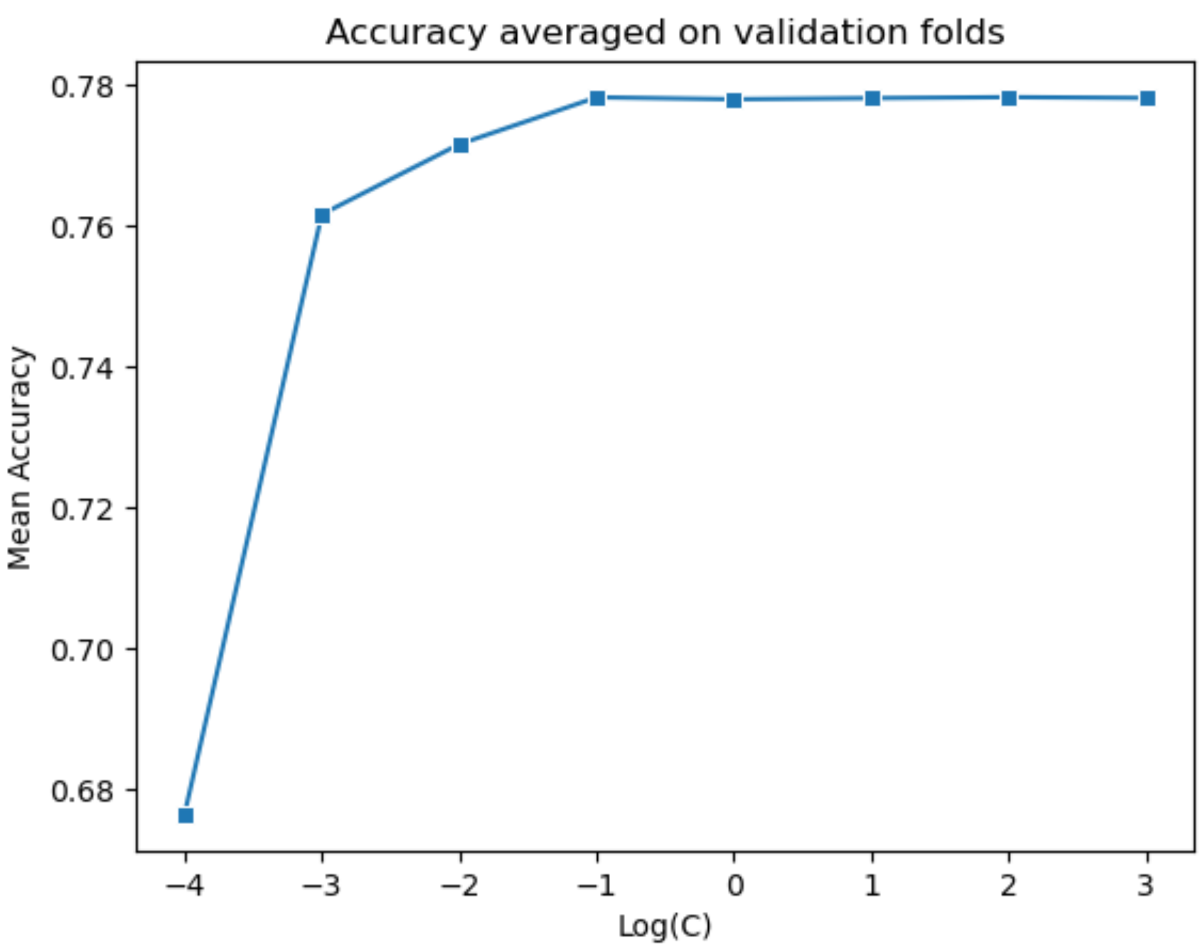
In [85]:
```
C_list = [1e-4, 1e-3, 1e-2, 1e-1, 1, 10, 100, 1e3]
cv_scores = []
cv_scores_std = []

for c in C_list:
    logreg = LogisticRegression(C=c)
    cv_loop_results = cross_validate(
        estimator=logreg,
        X=X_train_scaled,
        y=y_train,
        cv=8
    )
    cv_scores.append(np.mean(cv_loop_results['test_score']))
    cv_scores_std.append(np.std(cv_loop_results['test_score']))
```

In [86]:
```
cv_scores
```

Out[86]:
```
[0.6763263072653412,
 0.7616528016213779,
 0.7716149857043857,
 0.778286897139203,
 0.7780146813302007,
 0.7781735617678762,
 0.7783096902698206,
 0.7781962189553688]
```

In [87]:
```
fig, ax = plt.subplots()
sns.lineplot(x = np.log10(C_list), y = cv_scores, marker = 's', ax = ax)
ax.set_xlabel('Log(C)')
ax.set_ylabel('Mean Accuracy')
ax.set_title('Accuracy averaged on validation folds')
plt.show()
```



In [88]:
```
# Preprocess the data
# Drop unnecessary columns
binary_model_df = merged_df_cleaning_binary[['construction_year', 'basin', '
binary_model_df['Years_Old'] = (binary_model_df['construction_year'].max() +
```

```
# Handle missing values
binary_model_df.dropna(inplace=True)
# Split the data into features (X) and target variable (y)
X = binary_model_df[['Years_Old', 'basin', 'region', 'payment', 'payment_typ
y = binary_model_df['status_group']

# Encode categorical variables
X_encoded = pd.get_dummies(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=

scaler = preprocessing.MinMaxScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)  # Use transform instead of fit

# Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train_scaled, y_train)

# Make predictions on the testing set
y_pred = model.predict(X_test_scaled)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7817917763456477
```

In [110…

```
#disp = ConfusionMatrixDisplay.from_estimator(model, X_test, y_test)
#fig, ax = plt.subplots(figsize=(8, 6))
#disp.plot(ax=ax)
#ax.set_title("Confusion Matrix")
#plt.show()
```

In [109…

```
#RocCurveDisplay.from_estimator(model, X_test, y_test)
#fig, ax = plt.subplots(figsize=(8, 6))
#disp.plot(ax=ax)
#ax.set_title("ROC Curve")
#plt.show()
```

In [ ]: