Taarifa Report

Hubert Luo and Amanda Wu

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Contents

Introduction

This report analyzes the status of wells in Tanzania, with 59,400 wells in the Taarifa dataset from the DrivenData competition and 72,909 wells from the Taarifa API, resulting in a total of 132,309 wells. We also took a brief look at alternative data collected on the distance of each well to the nearest road. Each of the wells had a status (functional, non-functional, or functional but in need of repair) as well as various attributes, such as the extraction type or source of the well. A data dictionary describing each of the attributes is listed below. Note that not all of these attributes are present in both datasets.

Data Dictionary

- 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
- 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
- NEAR_DIST - Distance to nearest road

Data Summary

Categorical Variables

We first summarize some of the categorical variables, specifically water quantity, extraction type, waterpoint type, payment type, source, water quality, management type, and well status in the tables below. Note the last attribute in each row, specified (other), includes wells of known attribute that do not fall into one of the attributes listed above.

quantity	extraction_type	waterpoint_type	payment
dry :13307	gravity :59729	unknown :72909	annually : 8136
enough :74259	nira/tanira:18244	communal standpipe :28522	monthly :18636
insufficient:33841	other :14407	hand pump :17488	never pay :55750
seasonal : 9130	submersible:12575	other : 6380	on failure: 8743
unknown : 1772	swn 80 : 8250	communal standpipe multiple: 6103	other : 2393
NA	mono : 5759	improved spring : 784	per bucket:19615
NA	(Other) :13345	(Other) : 123	unknown :19036

source_type	quality_group	management_group	status_group
spring :37778	colored : 1092	user-group :52490	functional :72531
shallow well :37735	fluoride: 484	vwc :49112	functional needs repair: 9469
borehole :26119	good :113224	wug : 8103	non functional :50309
river/lake :13056	milky : 1801	parastatal : 4006	NA
river/lake/river/lake:10377	salty : 11500	water board: 3776	NA
rainwater harvesting : 5128	unknown : 4208	commercial : 3638	NA
(Other) : 2116	NA	(Other) :11184	NA

We then analyzed the continuous data in the tables and graphs below, focusing on population and construction year. From the summary below, we see that the data is heavily right skewed, with a long right tail as the majority of wells have surrounding populations of less than 1,000 while some have populations that far exceed 1,000 and reach as high as 30,500. The standard deviation is also extremely large at 562.83 even though 75% of the data is less than or equal to 325, demonstrating the large effect the extremely high population values have on our data.

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     1.0    40.0   150.0   282.5   325.0 30500.0
```

Summary of Well Status

We then took a closer look at well status. As mentioned in the introduction, each of the wells has 3 possible statuses, as summarized below. 38.02% of wells are non-functional, while 7.16% are functional and in need of repair and the rest (54.82%) are functional without being in need of repair

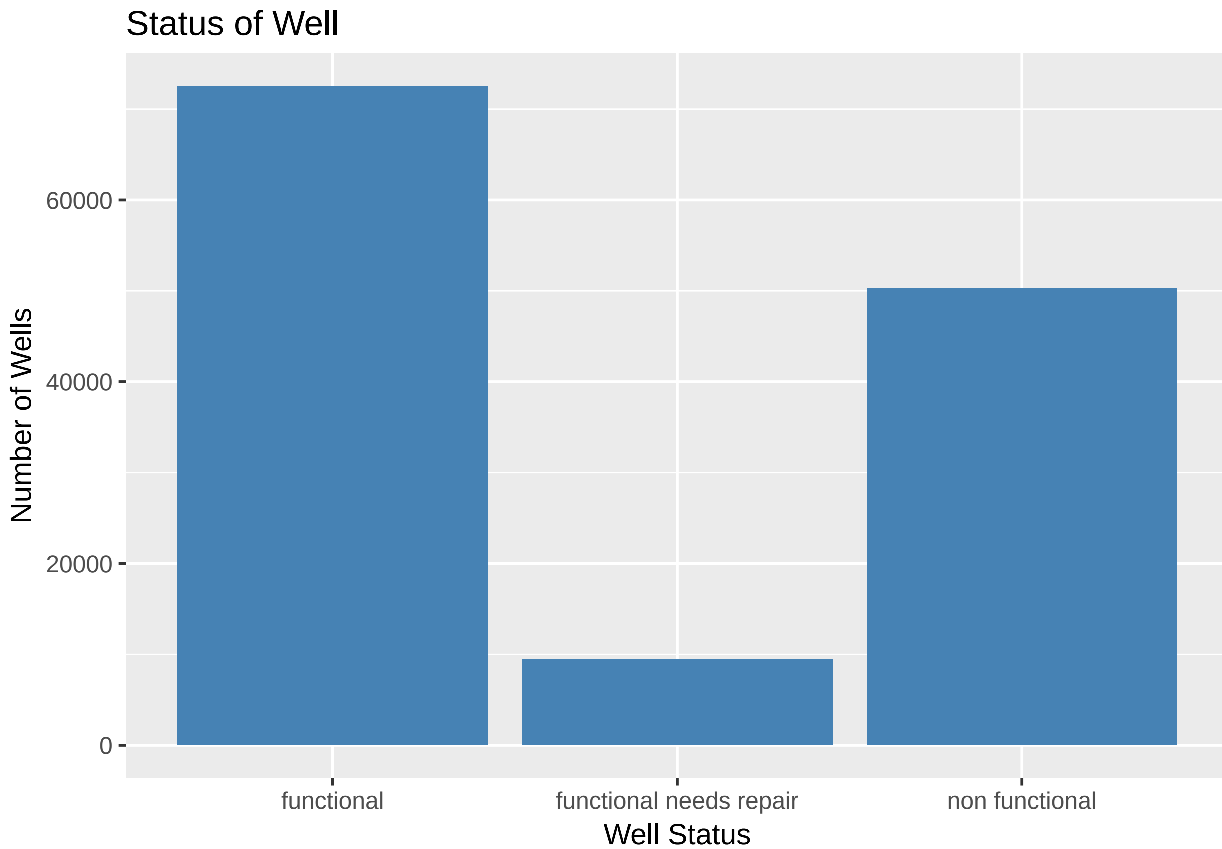


Table 3: Overall Distribution of Wells by Status

Well Status	Percentage of Wells
functional	54.82
functional needs repair	7.16
non functional	38.02

Continuous Variables

As a result, when binning our data for future analysis we decided to organize the population observations in to 10 bins of size 100, ranging from 0 to 1,000 and putting all the populations exceeding 1,000 into the final bin of 900 to 1,000 in order to reduce the disproportionately large affect these extreme values played in our analysis. The final summary counts and a histogram are displayed below.

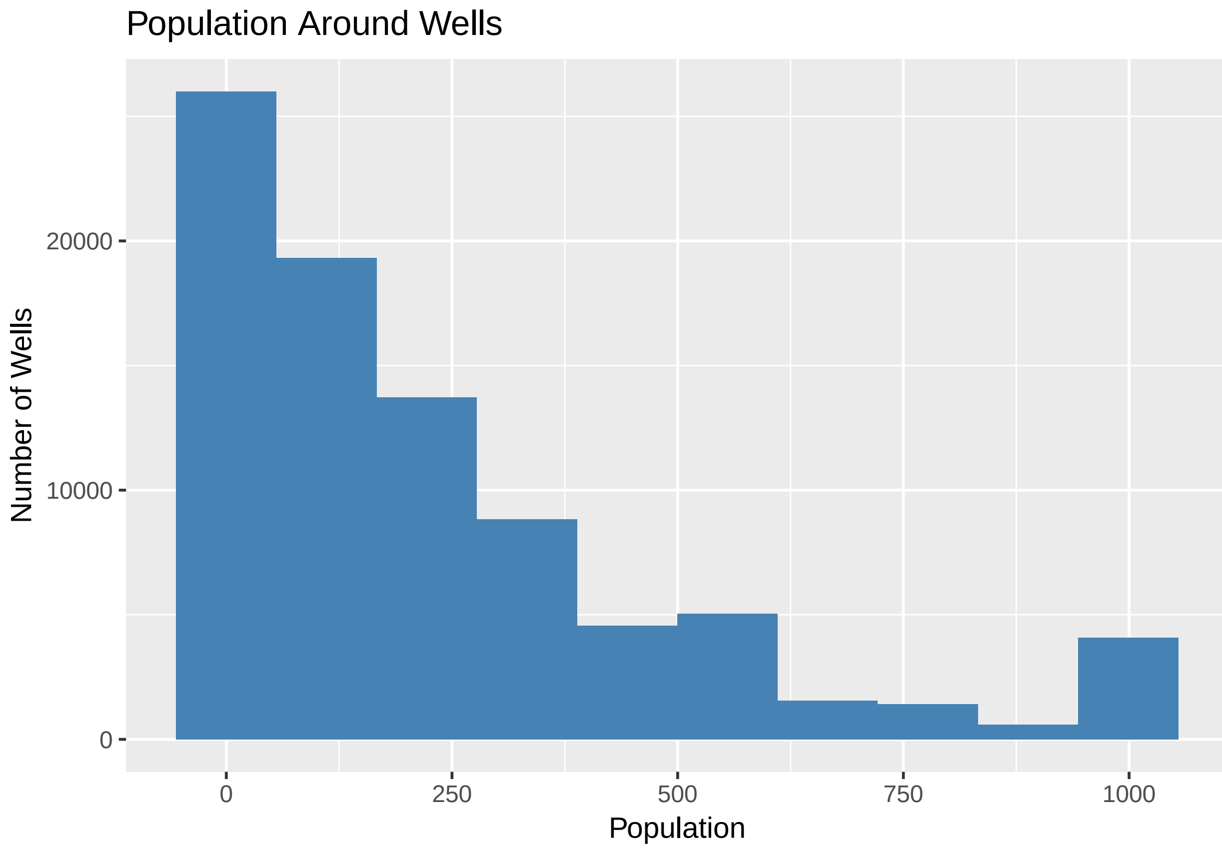
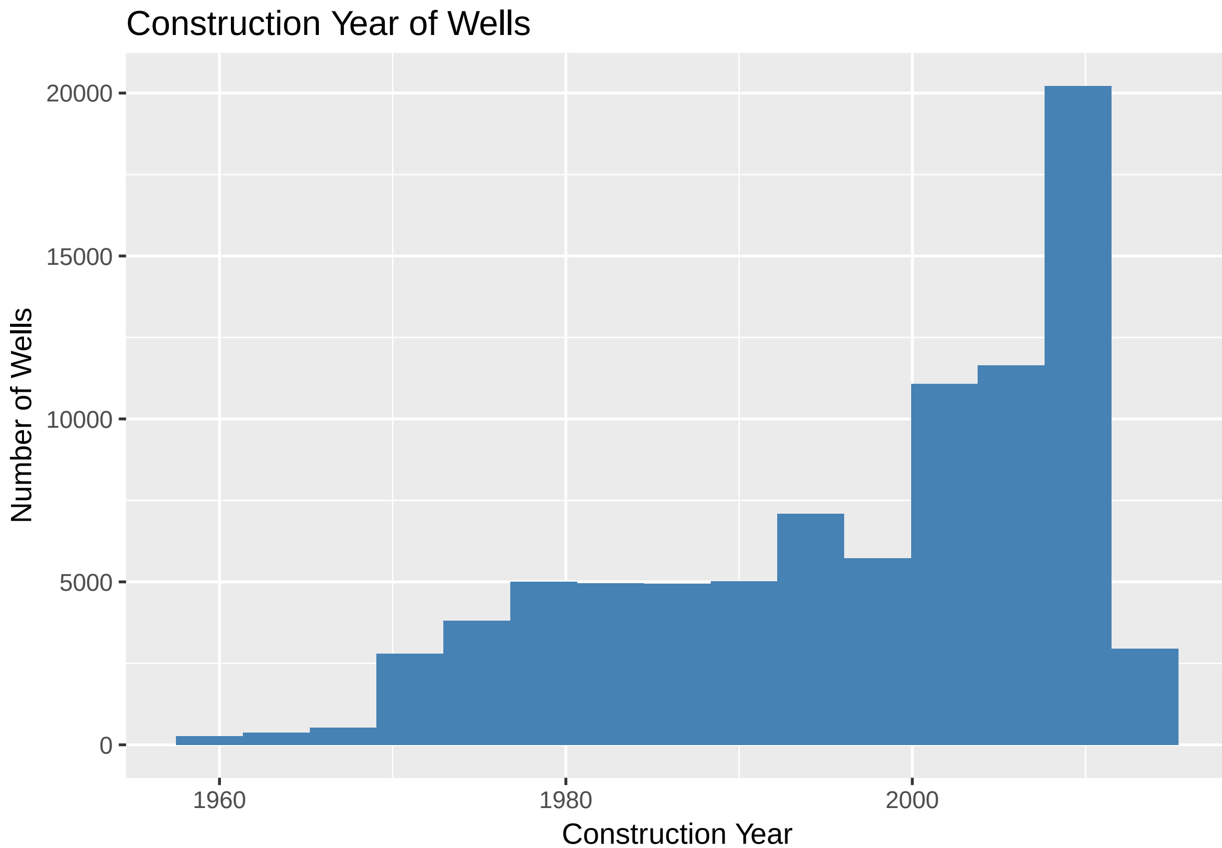


Table 4: Population Around Wells

	Number of Wells
(0,100]	35638
(100,200]	15278
(200,300]	11990
(300,400]	6876
(400,500]	4942
(500,600]	2710
(600,700]	1512
(700,800]	1383
(800,900]	666
(900,1e+03]	4123

We then analyzed the construction year of wells, with a summary and histogram displayed below. The wells ranged from being constructed in 1960 to 2014, with a median of 2000.

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1960    1988    2000    1997    2008    2014
```



Finally, we looked at the distance to the nearest road. The data is extremeley right-skewed, as the mean of 106,936 exceeds even that of the 75th percentile of 7,879. As a result, we capped the distances at 50,000 and assigned all distances greater than 50,000 a value of 50,000. Note that the distances were calculated for the competition dataset so the median was assigned to the remaining values.

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0     471    2553  106936    7879 3337890
```

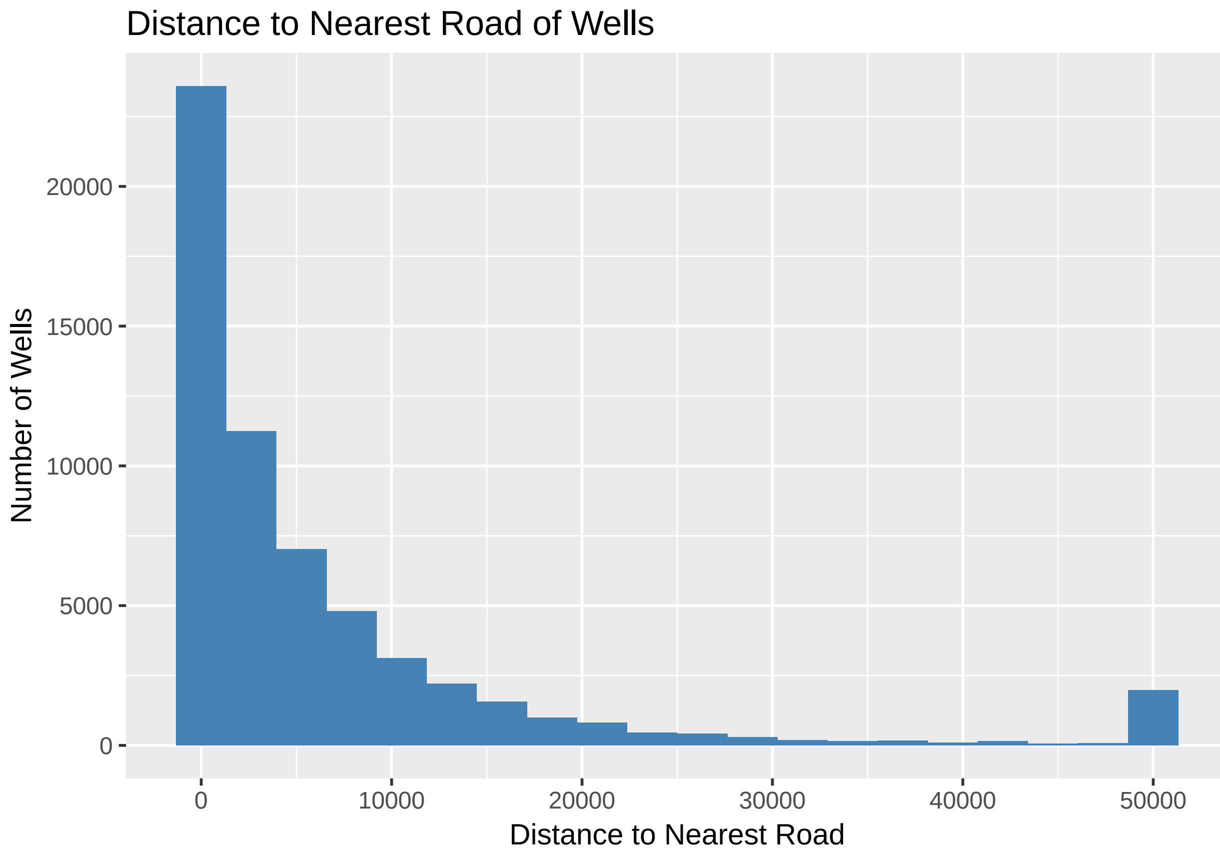


Table 5: Distance to Nearest Road for Wells

	Number of Wells
(0,2.5e+03]	29468
(2.5e+03,5e+03]	8569
(5e+03,7.5e+03]	5765
(7.5e+03,1e+04]	3895
(1e+04,1.25e+04]	2722
(1.25e+04,1.5e+04]	1920
(1.5e+04,1.75e+04]	1384
(1.75e+04,2e+04]	900
(2e+04,2.25e+04]	757
(2.25e+04,2.5e+04]	422
(2.5e+04,2.75e+04]	388
(2.75e+04,3e+04]	305
(3e+04,3.25e+04]	163
(3.25e+04,3.5e+04]	149
(3.5e+04,3.75e+04]	164
(3.75e+04,4e+04]	123
(4e+04,4.25e+04]	108
(4.25e+04,4.5e+04]	132
(4.5e+04,4.75e+04]	56
(4.75e+04,5e+04]	2010

Missing Data

Most of our unkown categorical data is missing at random so keeping these values in our dataset should not create bias. However, water quality, water quantity and extraction types all have large number of missing values as well as higher than average unfunctioning well percentages of 84.03% 71.39%, and 80.6%. Thus, there is evidence that missing values associated with these 3 categories need to be investigated futhur or handled through classification later.

A table summary of the percentage of missing data for each variable is listed below. Note that waterpoint type for all of the data from the Taarifa API was missing so it had the highest percentage of missing values at 55.1%. Population and construction year had missing values around 35% of the time, while the rest of the variables were below 15%. Source, management, and water quantity had the lowest percentages of missing values, with all below 1.5%. In addition, only 65.3% of the wells in the combined dataset had a reported construction year and only 64.3% had a population, with the rest being reported as '0' in the data.

For missing continuous data such as population or year, we replaced the missing values with the median, as the large number of outliers for population especially meant that the median was more meaningful for our data.

Table 6: Percentage of Missing Values

	Percentage
quantity	1.34
extraction_type	10.89
waterpoint_type	55.11
construction_year	34.67
payment	14.39
source	0.00
population	35.67
quality	3.18
management	0.95

Comparing Datasets

38.42% of the wells in the Taarifa contest dataset were non-functional, compared to 37.7% in the Taarifa API dataset. We then compared some of the variables between the two datasets below.

Table 7: Comparison of Proportion of Wells by Quantity between Datasets

Quantity	Contest	API	Difference (Contest-API)
dry	10.52	9.68	0.84
unknown	1.33	1.35	-0.02
seasonal	6.82	6.97	-0.15
insufficient	25.47	25.66	-0.19
enough	55.87	56.33	-0.46

Table 8: Comparison of Proportion of Wells by Payment between Datasets

Payment	Contest	API	Difference (Contest-API)
never pay	42.67	41.70	0.97

Payment	Contest	API	Difference (Contest-API)
per bucket	15.13	14.58	0.55
annually	6.13	6.16	-0.03
on failure	6.59	6.62	-0.03
other	1.77	1.84	-0.07
monthly	13.97	14.18	-0.21
unknown	13.73	14.92	-1.19

Table 9: Comparison of Proportion of Wells by Source between Datasets

Source	Contest	API	Difference (Contest-API)
borehole	20.12	19.44	0.68
spring	28.65	28.47	0.18
other	0.47	0.48	-0.01
rainwater harvesting	3.86	3.89	-0.03
dam	1.10	1.14	-0.04
shallow well	28.32	28.68	-0.36
river/lake	17.47	17.91	-0.44

Table 10: Comparison of Proportion of Wells by Water Quality between Datasets

Water Quality	Contest	API	Difference (Contest-API)
salty	8.75	8.65	0.10
fluoride	0.37	0.37	0.00
colored	0.82	0.83	-0.01
milky	1.35	1.37	-0.02
good	85.55	85.59	-0.04
unknown	3.16	3.20	-0.04
	NA	0.00	NA

Feature Selection

We first narrowed down the list of features to only include those that appeared in both datasets and were also meaningful for future analysis on different datasets. For example, we dropped region and latitude/longitude as any conclusions provided by these factors from Tanzania were not broadly applicable to different situations. An exception was made for waterpoint type - we decided to investiagate it as a feature even though it wasn't in both datasets as previous analysis by Topor et. al had identified it as an important predictive feature.

To analyze the importance of features, we used random forest methods to evaluate the importance of each feature by its mean decrease in Gini coefficient. The results are outlined in the table and graph below.

Table 11: Feature Importance by Mean Decrease in Gini

Feature	Mean Decrease in Gini
quantity	7506.126
construction_year	5498.403
extraction_type	4986.375

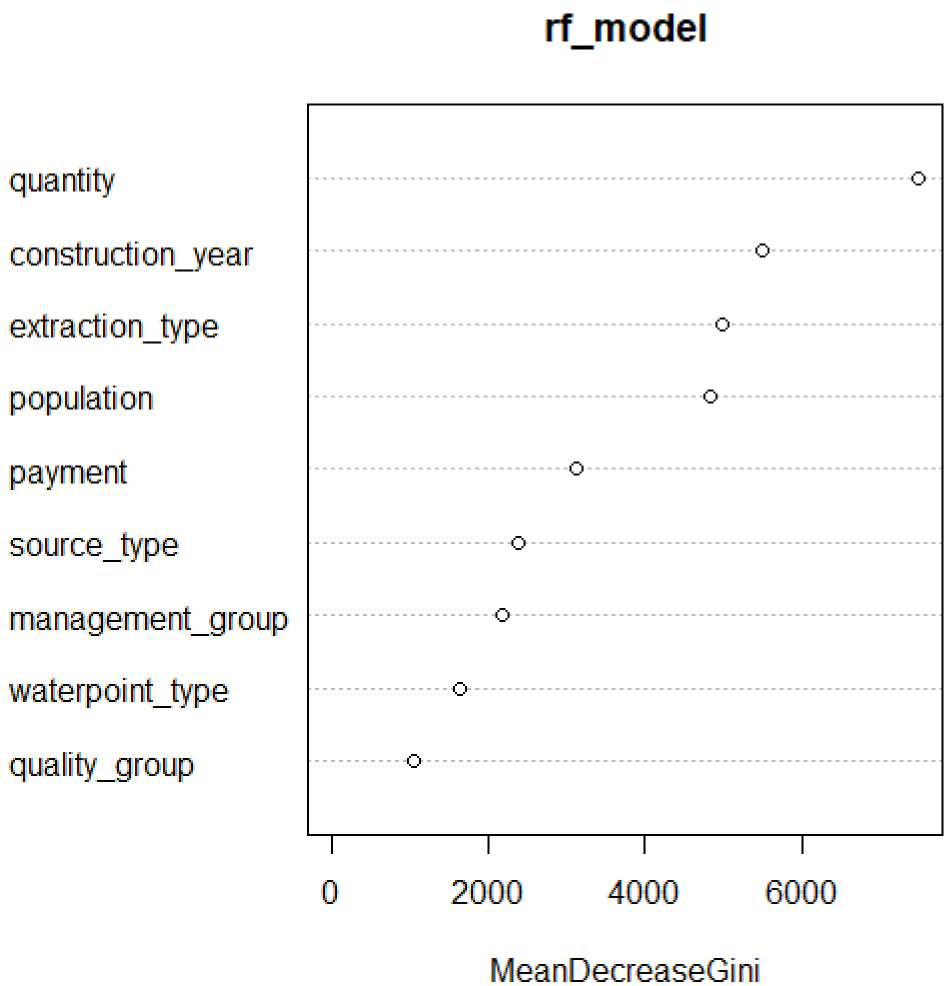


Figure 1: Feature Importance Plot

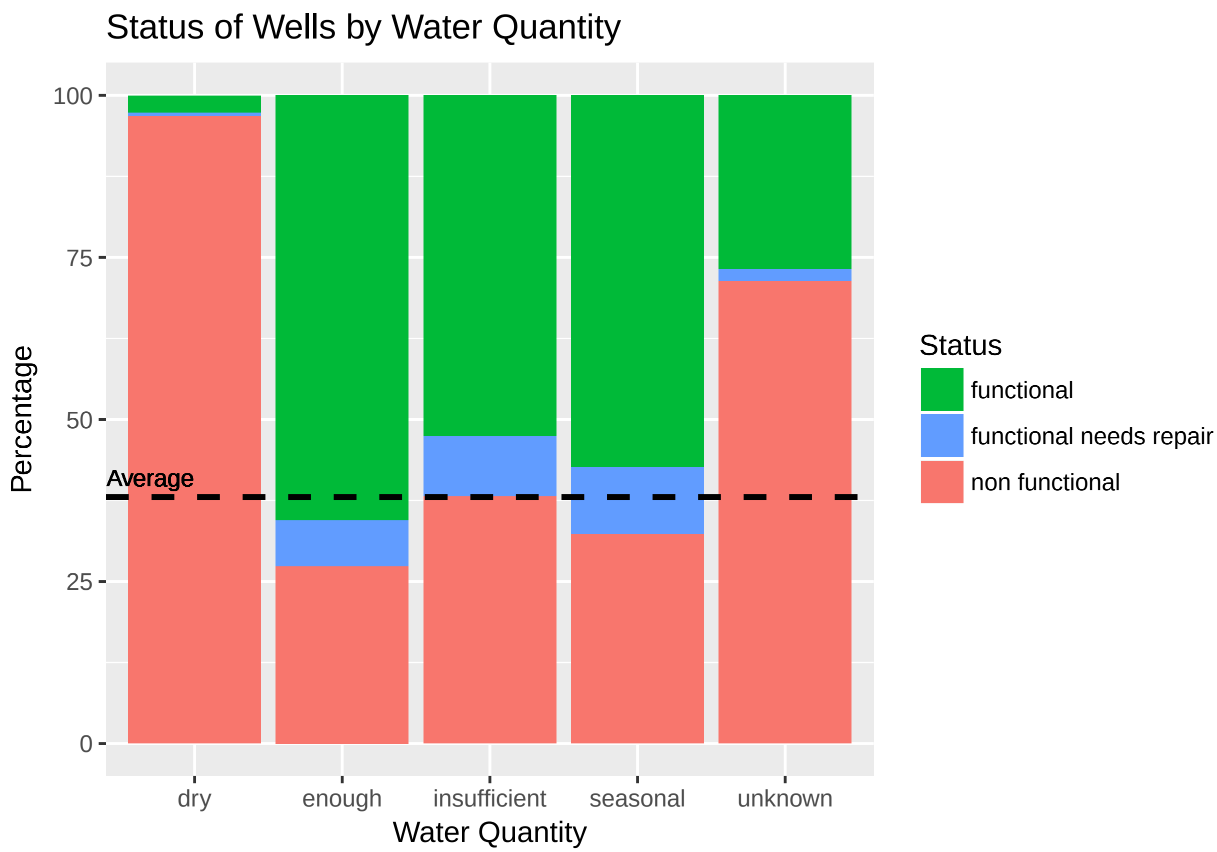
Feature	Mean Decrease in Gini
population	4827.229
payment	3117.150
source_type	2384.528
management_group	2177.702
waterpoint_type	1632.550
quality_group	1042.618

As seen above, the most important feature was quantity, followed by construction year, extraction type, and population. The remaining variables demonstrated less importance and in order of decrease importance were payment type, source type, well management, waterpoint type, and water quality.

We then examined each of these features in further depth below. The black dotted line on the graphs marks the overall average percentage of non-functional wells (38.02%). Red bars that extend above this dotted line demonstrate a higher than average propensity to be non-functional, and red bars which are below the dotted line are less likely to be non-functional.

Predictive Features

1. Water Quantity



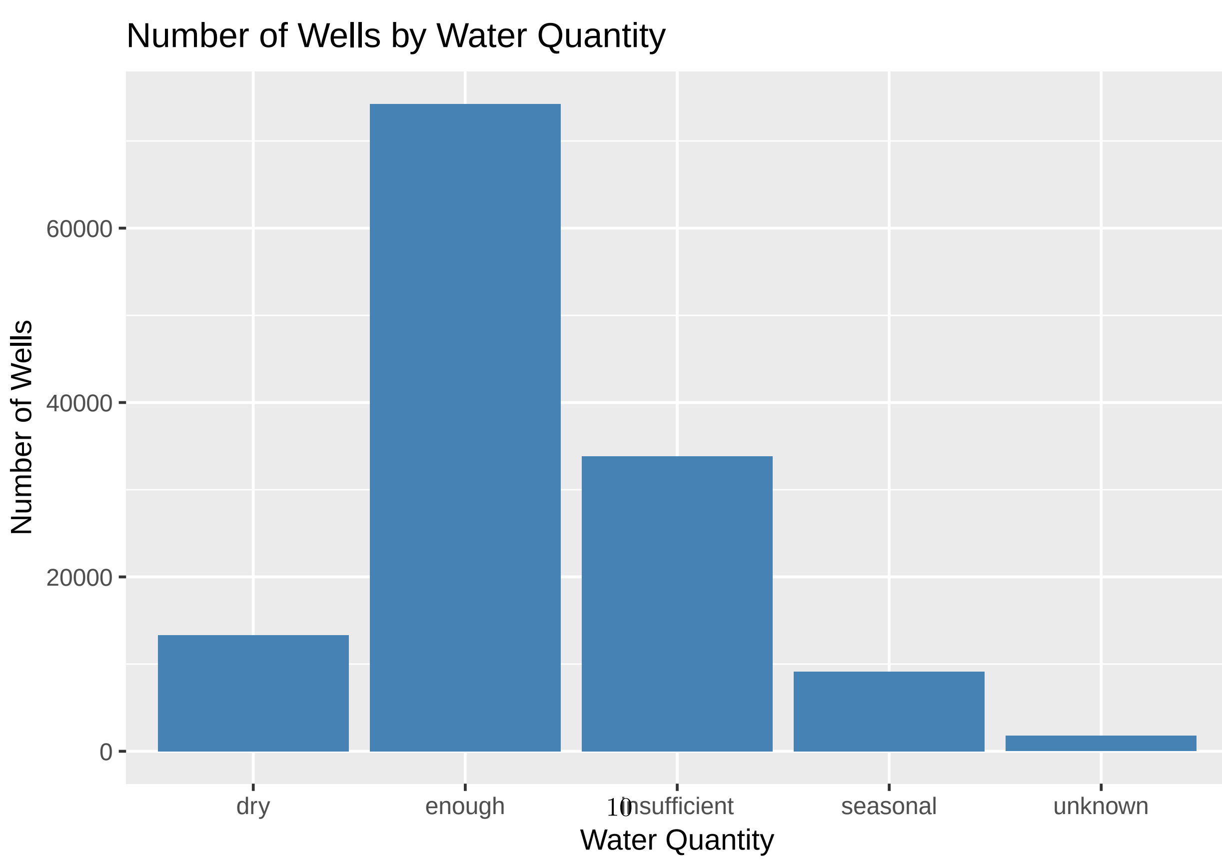
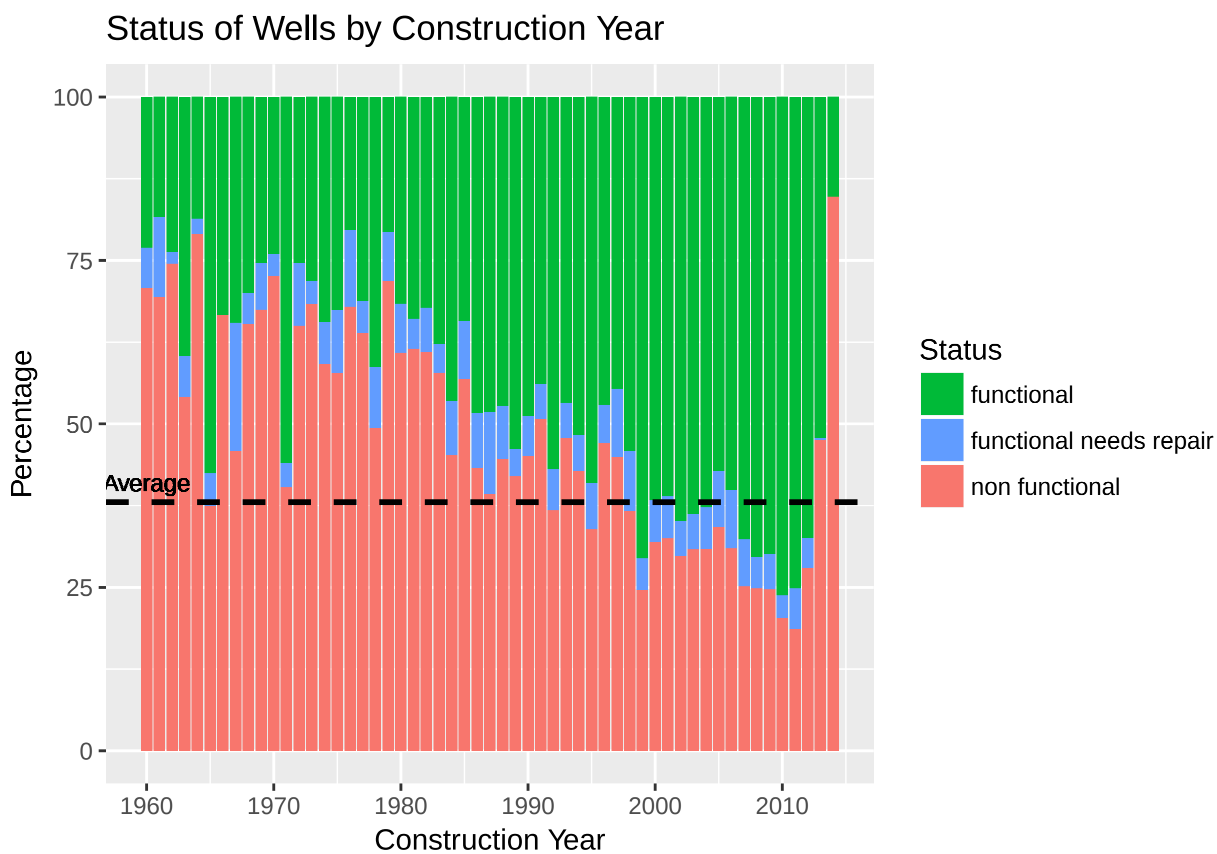


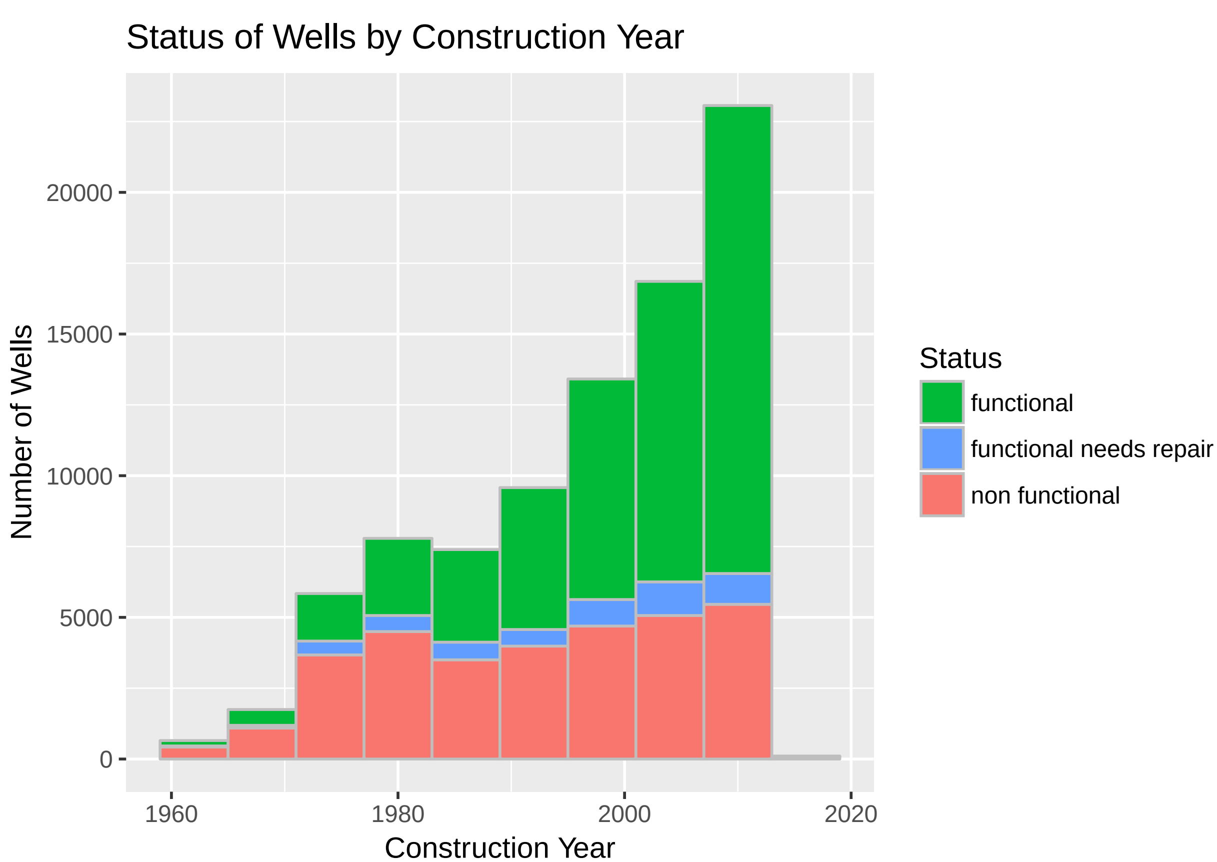
Table 12: Percentage of Non-Functional Wells by Water Quantity

Water Quantity	Number of Non-Functional Wells	Percentage of Non-Functional Wells
dry	12877	96.77
unknown	1265	71.39
insufficient	12905	38.13
seasonal	2959	32.41
enough	20303	27.34

It is noteworthy that 96.77% of dry wells are non-functional, while just 27.3% of wells with enough water quantity being non-functional. Clearly, wells with dry or insufficient water quantity are much more likely to be non-functional than those with seasonal or enough water quantity and thus water quantity is one of the most significant features when trying to predict whether a well is functional or not.

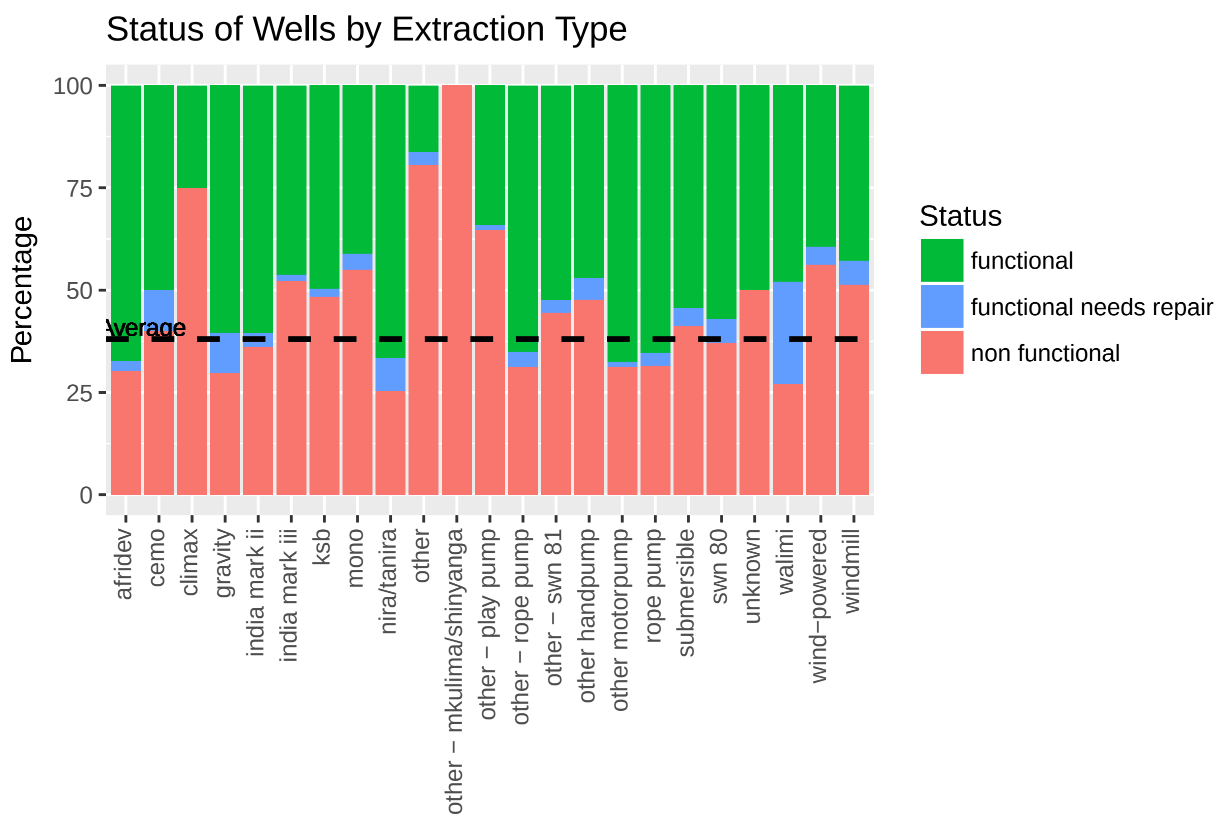
2. **Construction Year**





Wells that are constructed later are generally likelier to be functional as well age is proportional to the likelihood of non-functionality. However, only looking at the construction year does not take into account when the well has been last serviced, which would also be important in determining whether a well is functional.

3. Extraction Type



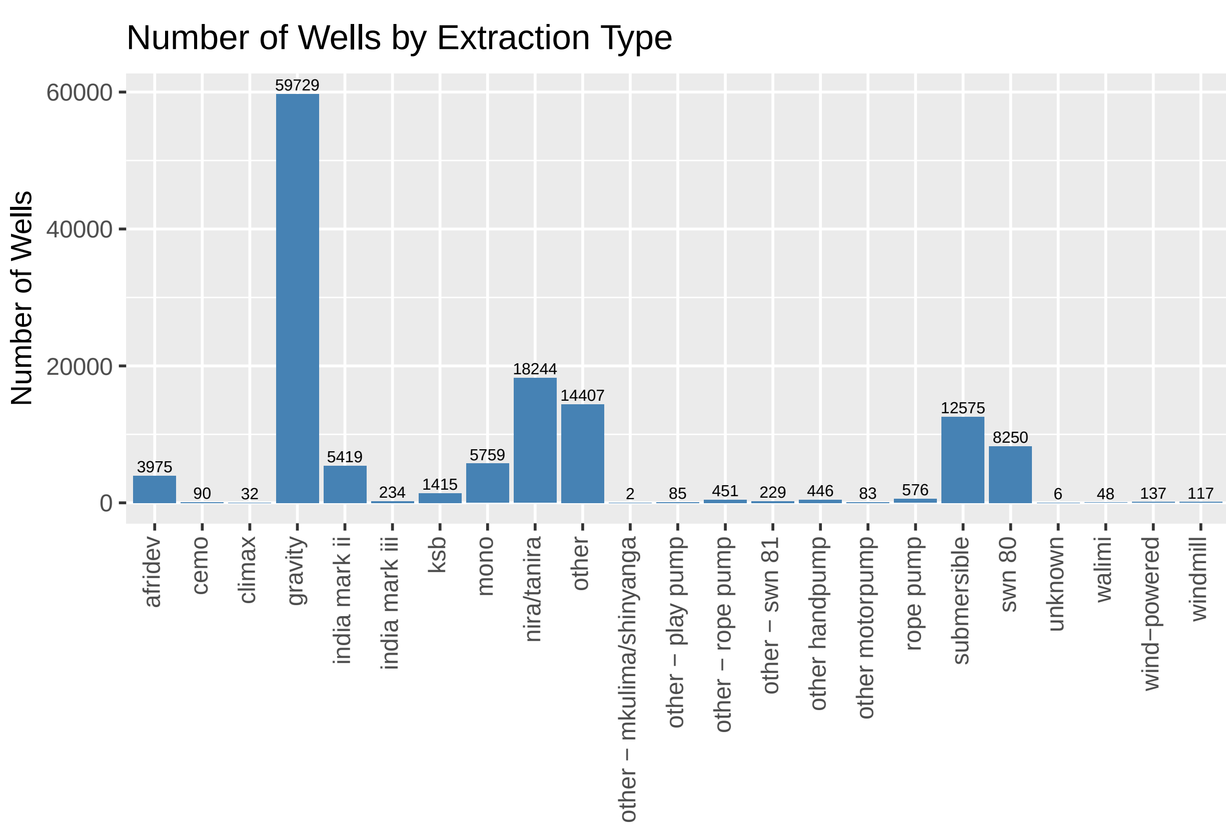
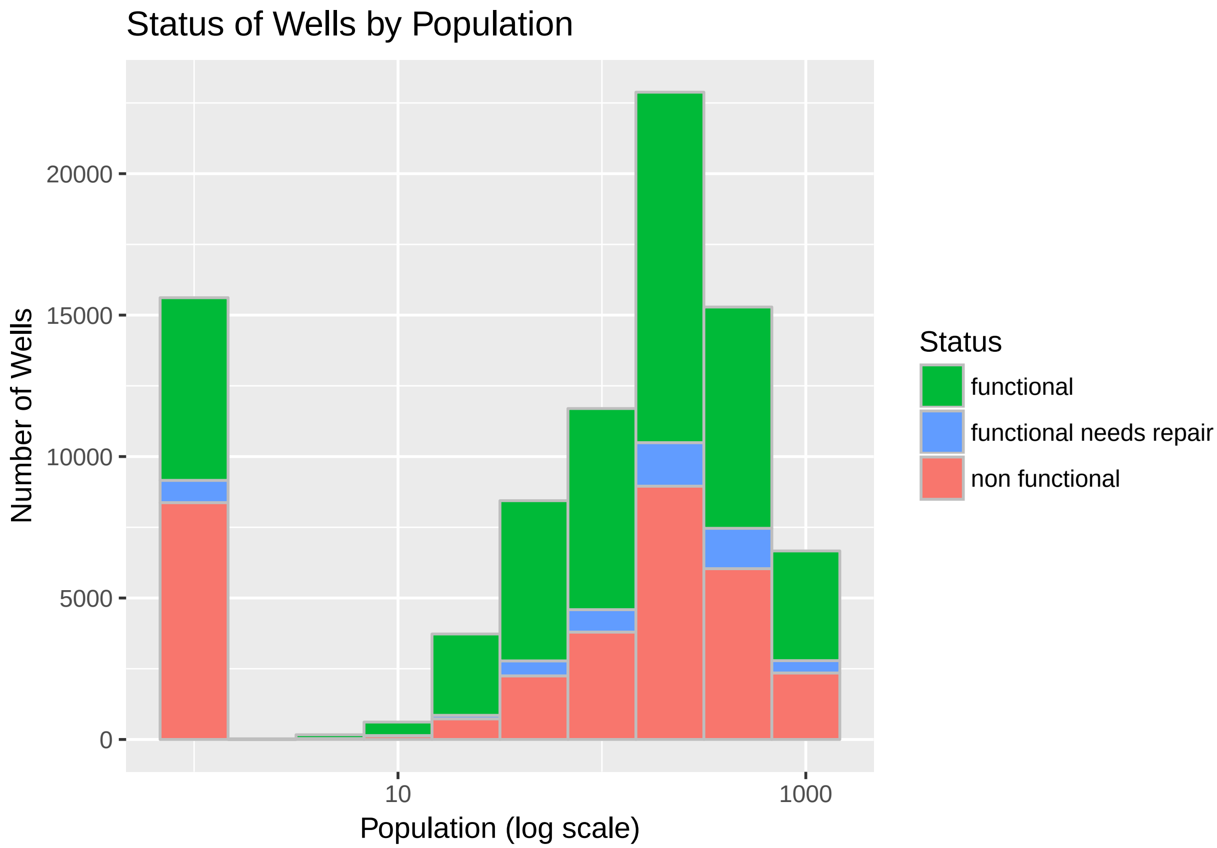


Table 13: Percentage of Non-Functional Wells by Extraction Type

Extraction Type	Number of Non-Functional Wells	Percentage of Non-Functional Wells
other - mkulima/shinyanga	2	100.00
other	11612	80.60
climax	24	75.00
other - play pump	55	64.71
wind-powered	77	56.20
mono	3172	55.08
india mark iii	122	52.14
windmill	60	51.28
unknown	3	50.00
ksb	686	48.48
other handpump	213	47.76
other - swn 81	102	44.54
submersible	5190	41.27
cemo	36	40.00
swn 80	3071	37.22
india mark ii	1959	36.15
rope pump	182	31.60
other motorpump	26	31.33
other - rope pump	141	31.26
afridev	1199	30.16
gravity	17735	29.69
walimi	13	27.08
nira/tanira	4629	25.37

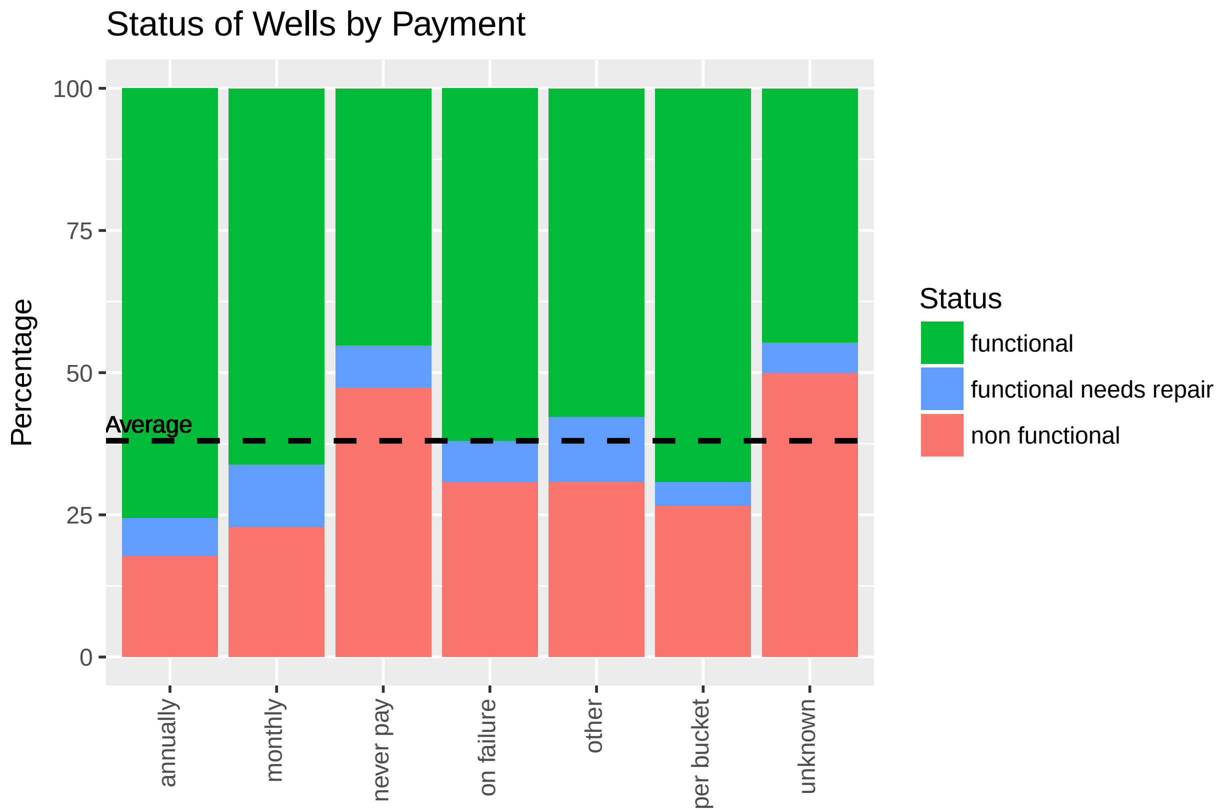
Gravity pumps are the most reliable extraction method for waterpumps, with a non-functional rate of just 29.7%. The afridev handpump also has a below-average non-functional rate at 30.2%, while other handpumps such as the India mark ii and Swn 80 are just under the average non-functional rate at 36.2% and 27.2% respectively. These findings are likely due to the fact that umps with more complicated extraction types such as mono (motor pump), climax (motor pump), ksb (submersible) and wind-powered, all of which have non-functional rates around 50% or higher, are more prone to failure as they may be less resilient to poor weather and maintenance conditions. It is noteworthy that wells with an 'other' extraction type have an extremely high 80.6% non-functional rate. Possible explanations for this are that less well-known extraction types are more likely to fail because they are not used as widely or that it is more difficult to determine the exact extraction type of a non-functional well and therefore it is more likely to be listed as other.

4. Population

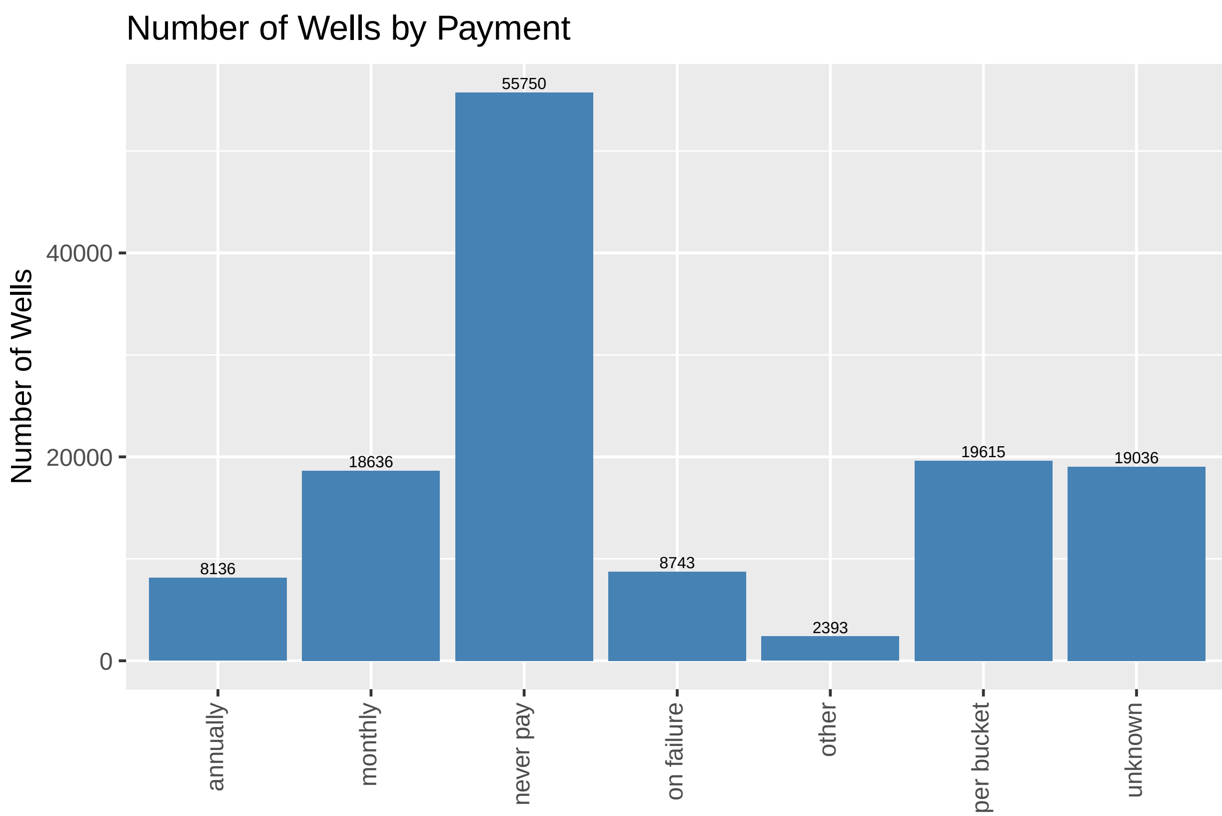


Note this only includes 64.33% of the dataset because the rest are missing this factor. In general, wells with a very low surrounding population of between 0 and 10 (note this does *not* include the missing population values of 0) have an extremely high failure rate over 50% while the rest of the wells demonstrate somewhat similar failure rates between 30 and 40%. Somewhat surprisingly, there is no clear evidence of a link between higher population and increasing well non-functionality. This may be due to the fact that their heavy usage is compensated for by better maintenance and resources in larger population areas. In addition, it may be that people naturally settle in large population areas close to natural bodies of water such as a river or spring, which was shown in the section above to have a lower non-functional rate than wells with other sources.

5. Payment



Status of Wells by Payment
Percentage
100
75
50
25
0
Average
annually
monthly
never pay
on failure
other
per bucket
unknown
Status
functional
functional needs repair
non functional



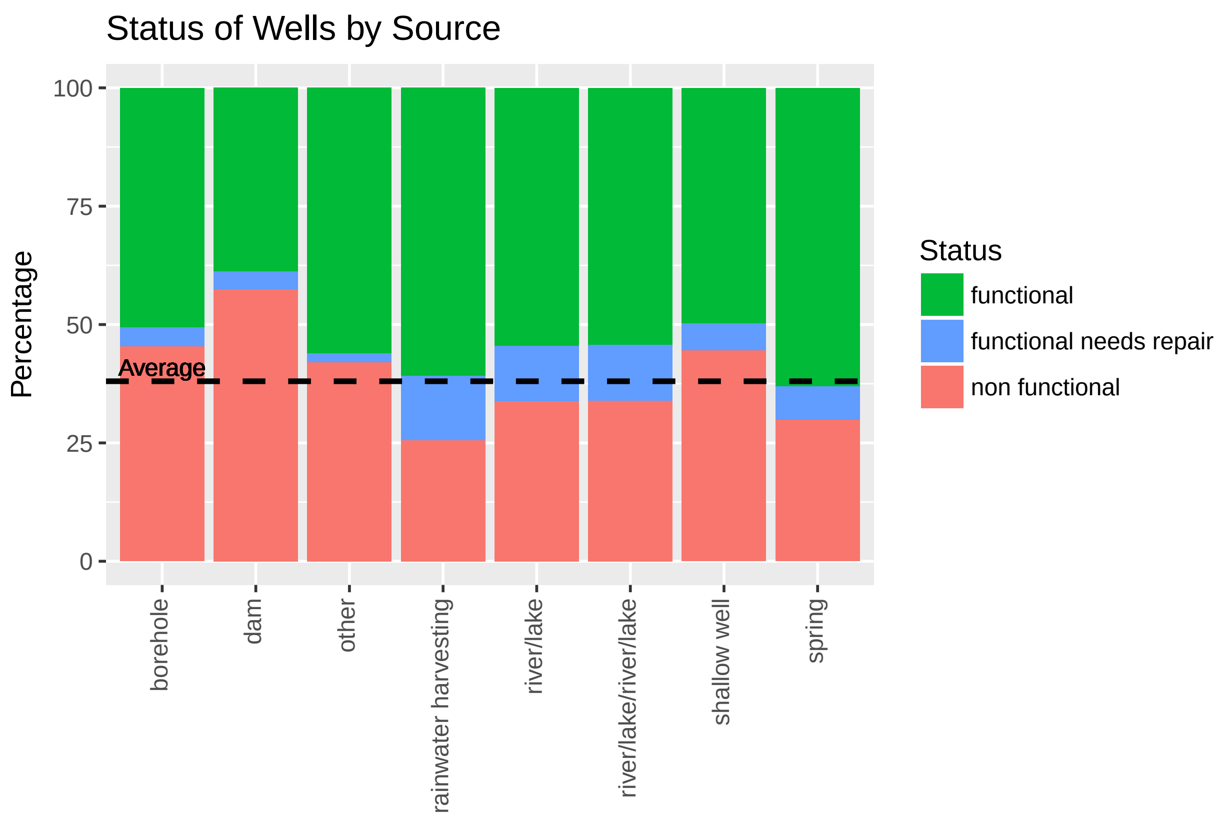
Number of Wells by Payment
Number of Wells
40000
20000
0
8136
18636
55750
8743
2393
19615
19036
annually
monthly
never pay
on failure
other
per bucket
unknown

Table 14: Percentage of Non-Functional Wells by Payment

Payment	Number of Non-Functional Wells	Percentage of Non-Functional Wells
unknown	9503	49.92
never pay	26450	47.44
on failure	2700	30.88
other	737	30.80
per bucket	5215	26.59
monthly	4260	22.86
annually	1444	17.75

Wells with a known payment method are more likely to be functional - wells with a payment type of 'never pay' have a 47.4% non-functional rate, much higher than the overall average of 38%. Those with annual payments have the lowest non-functional rate at 17.8%, followed by those with monthly payments at 22.9% and then per bucket payments at 26.6%.

6. Source


Status of Wells by Source
Percentage
100
75
50
25
0
Average
borehole
dam
other
rainwater harvesting
river/lake
river/lake/river/lake
shallow well
spring
Status
functional
functional needs repair
non functional

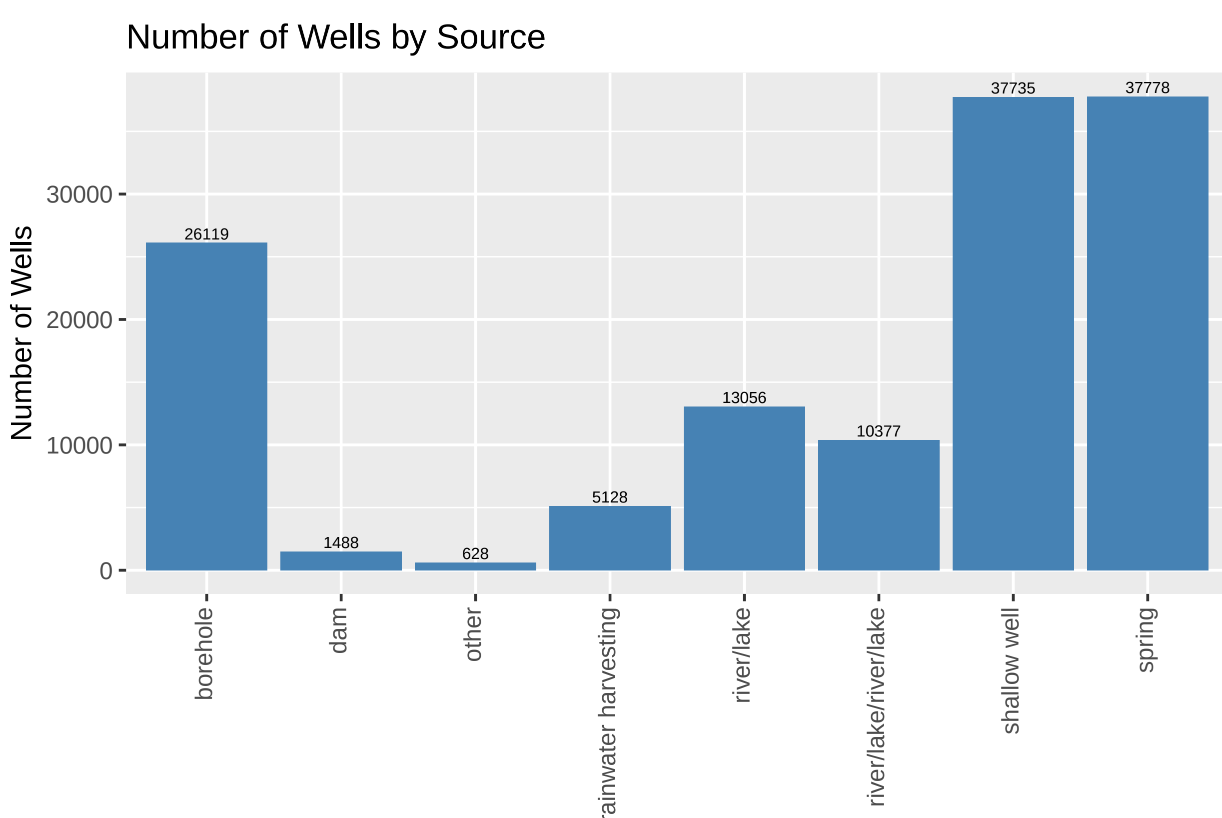
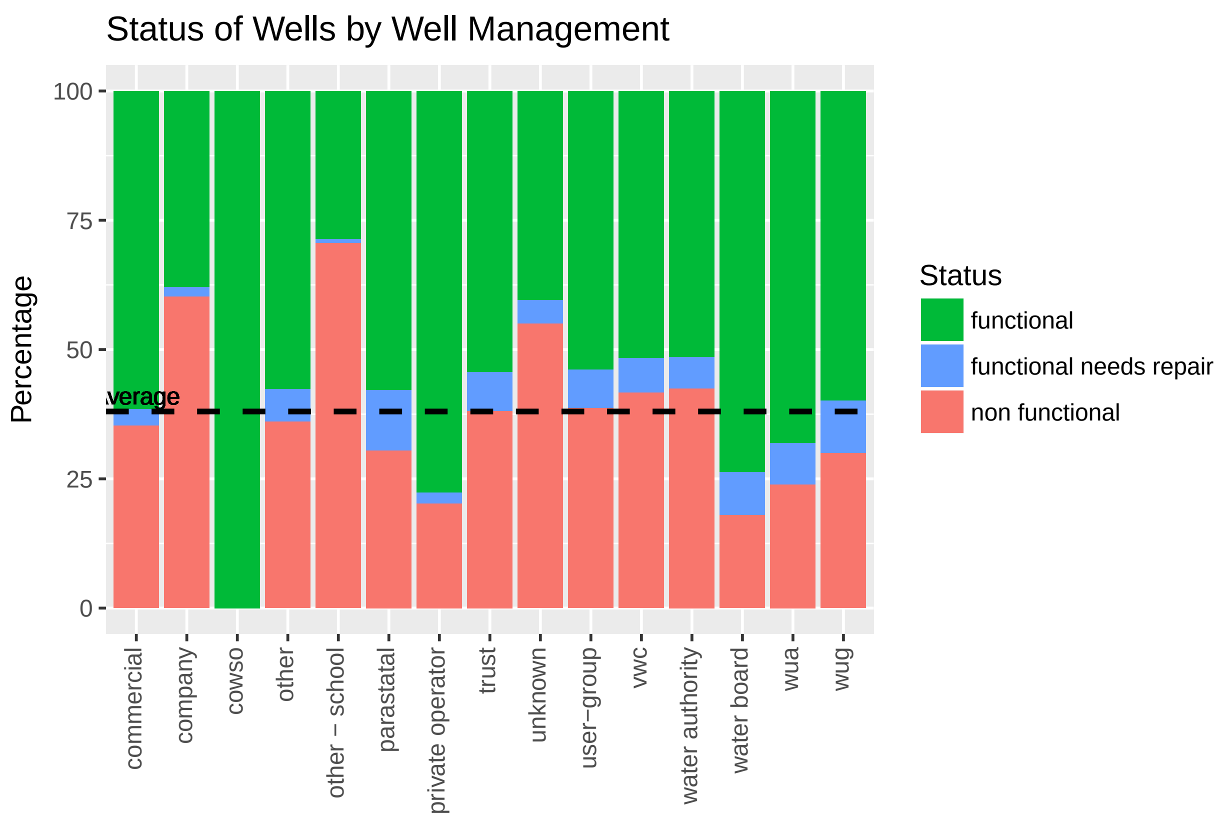

Number of Wells by Source
Number of Wells
30000
20000
10000
0
26119
1488
628
5128
13056
10377
37735
37778
borehole
dam
other
rainwater harvesting
river/lake
river/lake/river/lake
shallow well
spring

Table 15: Percentage of Non-Functional Wells by Source

Source	Number of Non-Functional Wells	Percentage of Non-Functional Wells
dam	855	57.46
borehole	11872	45.45
shallow well	16804	44.53
other	264	42.04
river/lake/river/lake	3517	33.89
river/lake	4412	33.79
spring	11274	29.84
rainwater harvesting	1311	25.57

Wells with a dam source have the highest non-functional rate at 57.5%, followed by machine dbh with 46.6% and borehole wells at 44.8%. Wells that have a rainwater, spring, or river/lake source are much less likely to experience failure with non-functional rates of 25.6%, 29.8% and 33.8% respectively.

7. Well Management



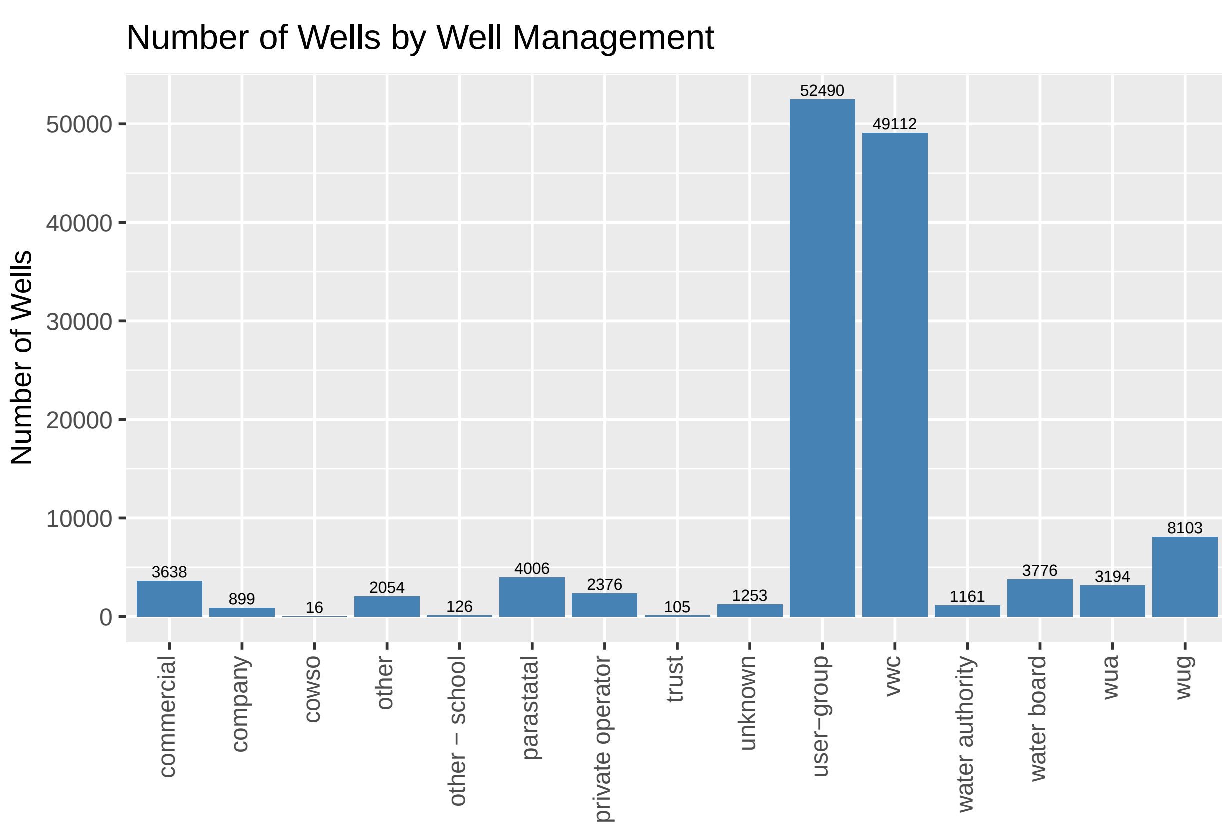
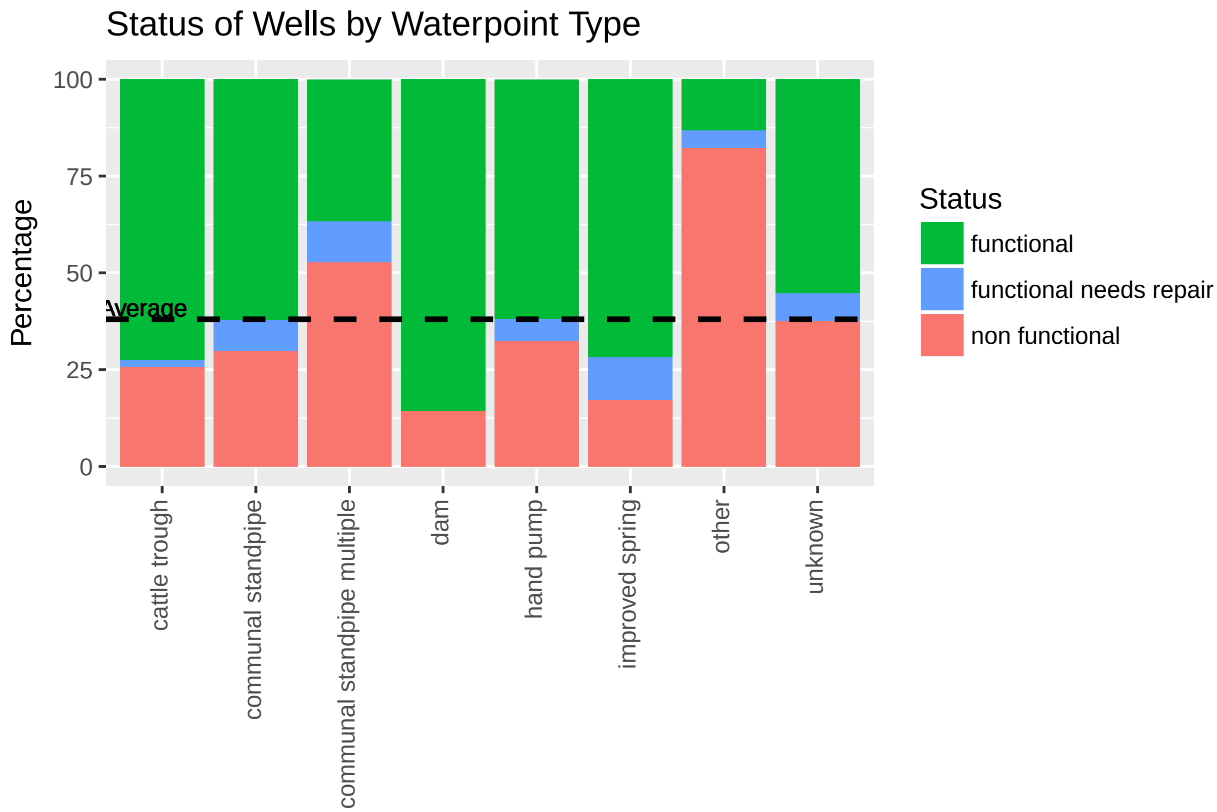


Table 16: Percentage of Non-Functional Wells by Well Management

Well Management	Number of Non-Functional Wells	Percentage of Non-Functional Wells
other - school	89	70.63
company	542	60.29
unknown	690	55.07
water authority	493	42.46
vwc	20516	41.77
user-group	20332	38.73
trust	40	38.10
other	742	36.12
commercial	1286	35.35
parastatal	1221	30.48
wug	2435	30.05
wua	763	23.89
private operator	481	20.24
water board	679	17.98

Wells managed by schools saw the highest non-functional rate of 71%, although such management types were rare. Most of the wells were managed by user-groups or vwc's, which had similar non-functioal rates around the average for the entire dataset. Private operators and water boards had the lowest non-functional rates at 20.2% and 18%, although again the number of wells with such management types is much smaller than those managed by user-groups or vwc's.

8. Waterpoint Type



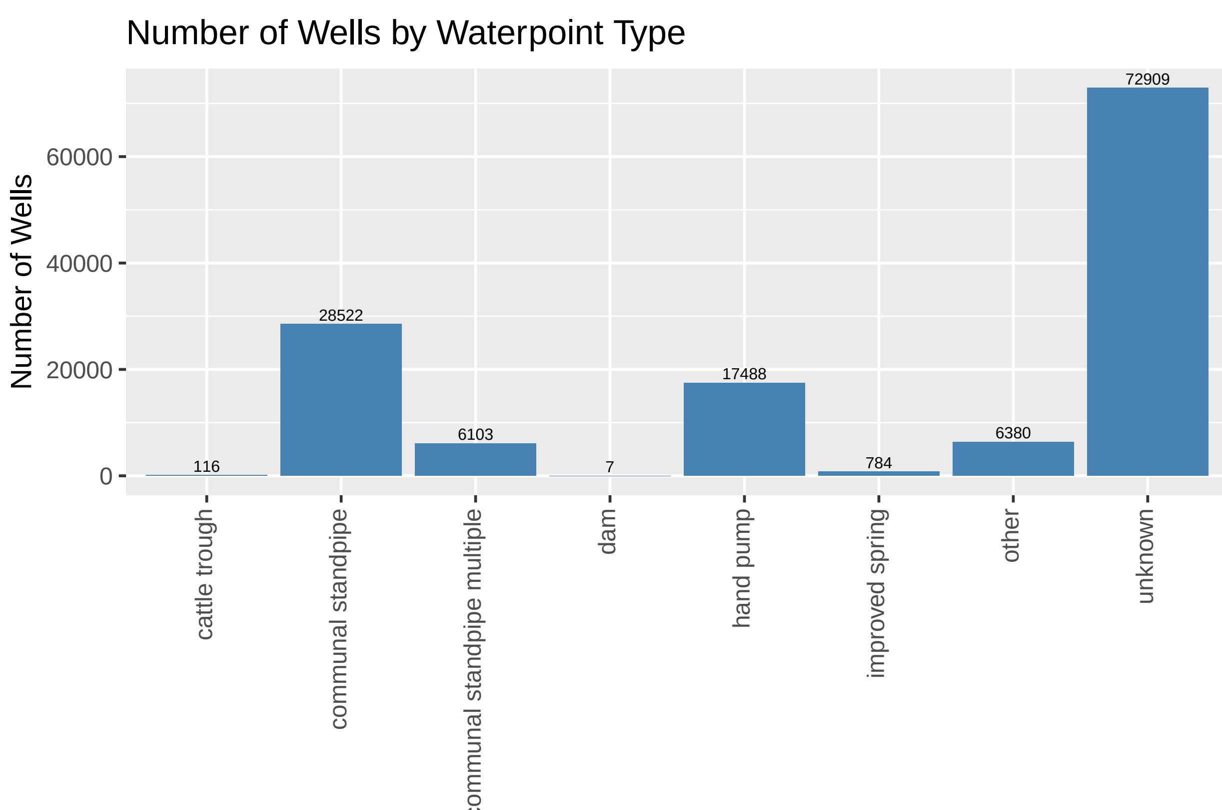
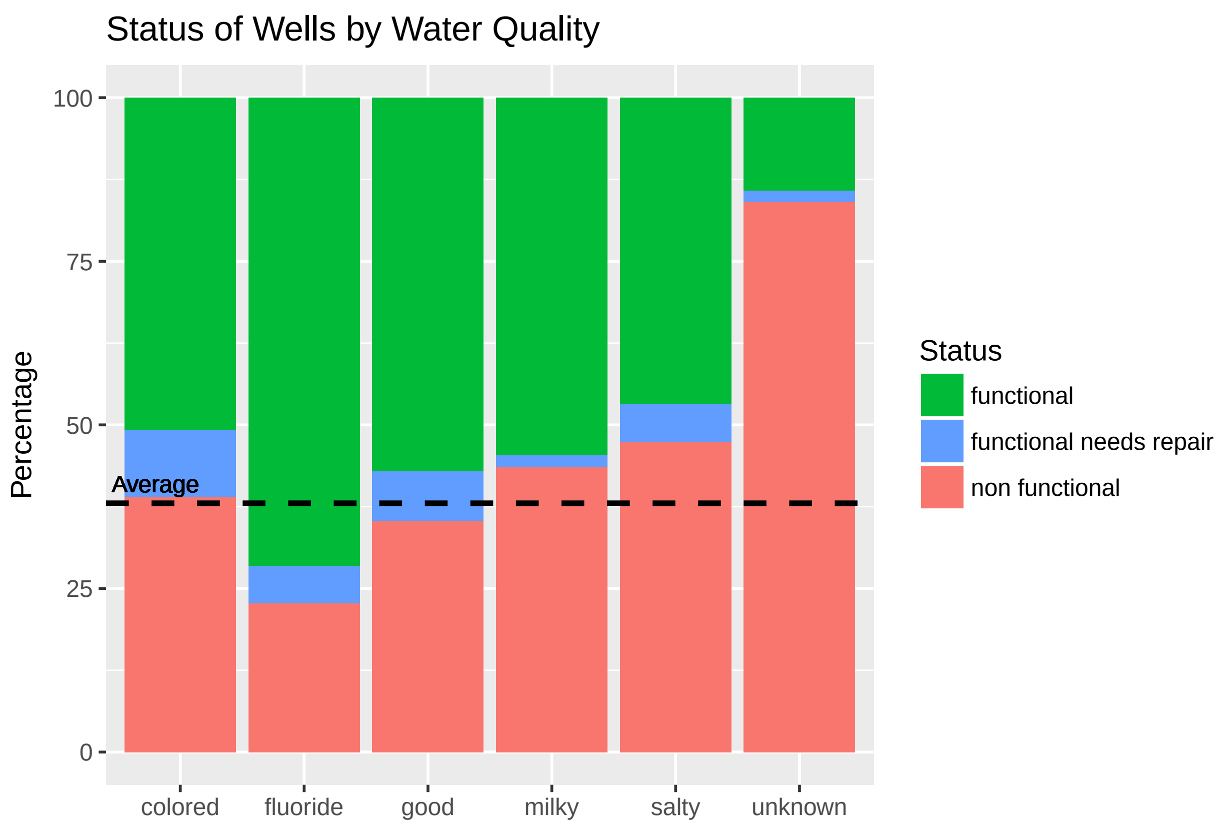


Table 17: Percentage of Non-Functional Wells by Waterpoint Type

Waterpoint Type	Number of Non-Functional Wells	Percentage of Non-Functional Wells
other	5247	82.24
communal standpipe multiple	3220	52.76
unknown	27485	37.70
hand pump	5654	32.33
communal standpipe	8536	29.93
cattle trough	30	25.86
improved spring	136	17.35
dam	1	14.29

The findings in this section come with the caveat that over half of the dataset did not report the waterpoint type, so most of the data falls into the unknown category. Just 29.9% of communal standpipes are non-functional, which is significantly less than the overall average of 38%. Likewise, hand pumps are below average at 32.3%. Multiple communal standpipes have a high failure rate of 52.8% while wells marked 'other' have an extremely high 82.2% non-functional rate. However, this may be due to the fact that it is more difficult to determine the type of a non-functional well and therefore non-functional wells are more likely to be listed as other, which inflates the non-functional rate.

9. Water Quality



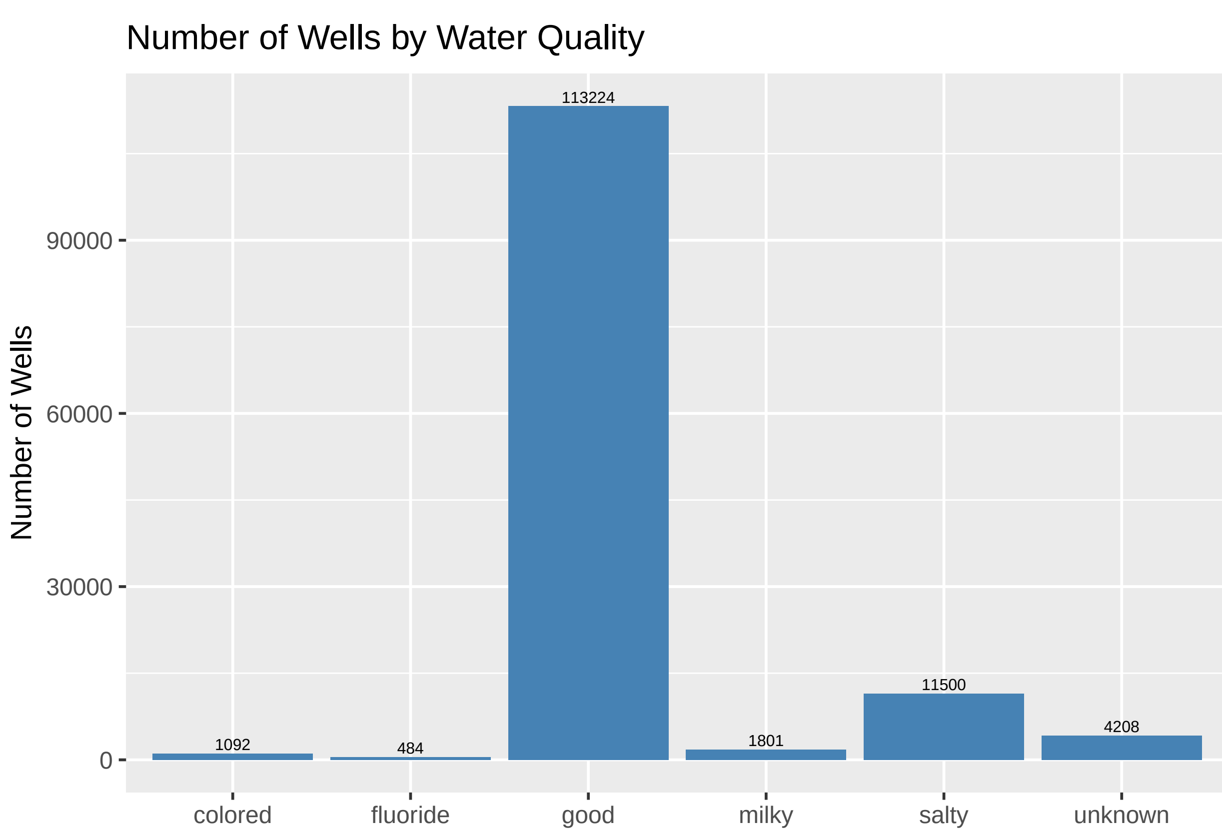
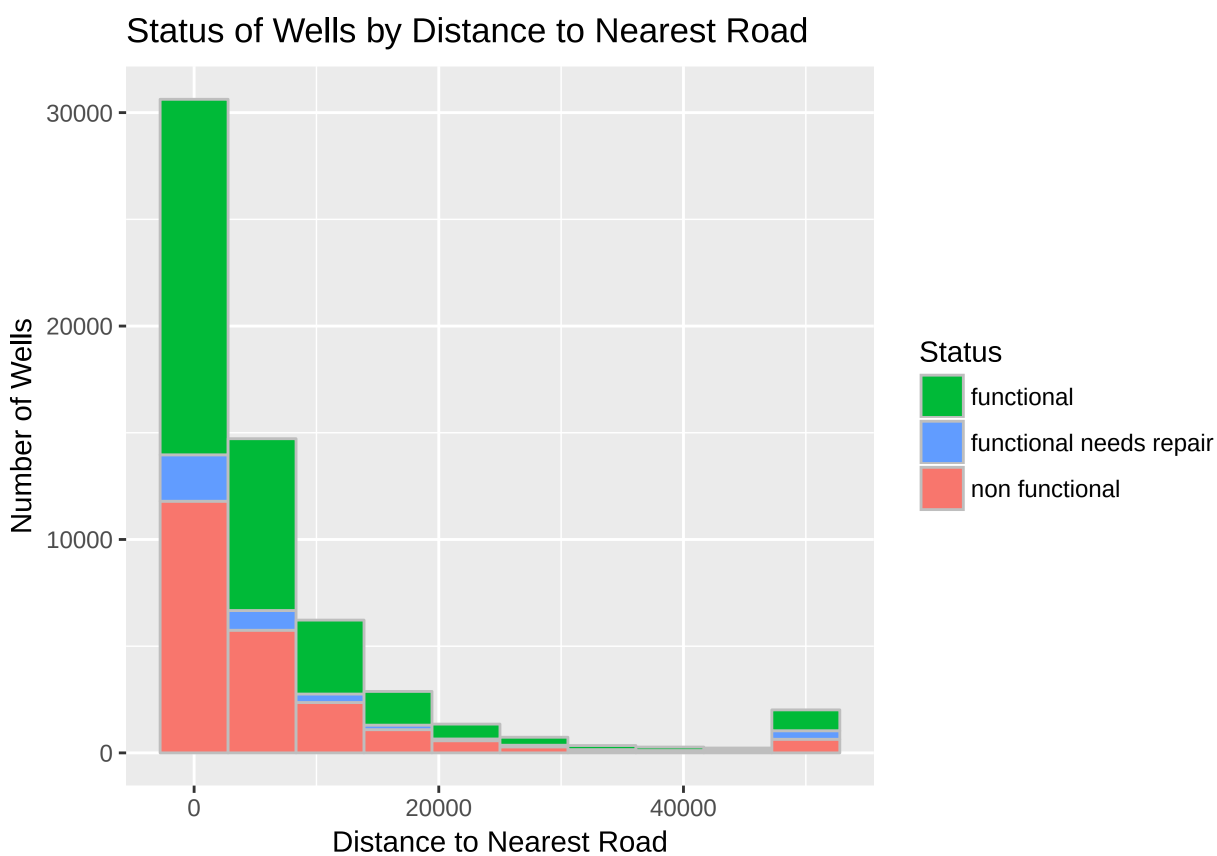


Table 18: Percentage of Non-Functional Wells by Water Quality

Water Quality	Number of Non-Functional Wells	Percentage of Non-Functional Wells
unknown	3536	84.03
salty	5444	47.34
milky	784	43.53
colored	426	39.01
good	40009	35.34
fluoride	110	22.73

The vast majority of wells reported good water quality, and their non-functional rate was slightly lower than the overall average at 35.34%. The wells with the lowest non-functional rates had fluoride water quality and just 22.7% of such wells were non-functional. All other water qualities observed were correlated with higher non-functional rates, with those of unknown water quality topping the list at 84% - this is likely because wells which are non-functional are much more likely to not have any water and thus making it more difficult to determine water quality for water that is not present or only present in limited amounts. Out of wells with a known water quality, salty wells had the highest non-functional rate at 47/3%, followed by milky and coloured water at 43.5% and 39% respectively.

10. Distance to Nearest Road



Wells close to roads saw a slightly lower than average nonfunctional rate but there was no significant difference for wells observed that were somewhat close to a road. However, for wells located farther away, especially noticable for those located about 50,000 or more from the nearest road, the non-functional rate increased a noticable amount.

Model Results

We first split the 132,309 observations randomly into training and testing sets using a 75-25 split, with 75% of the wells in the data going into the training set (99,231 wells) and 25% into the testing set (33,078 wells). We then trained a random forest model on only the training set, before applying our model to the testing set. A confusion matrix comparing the predicted counts and the actual counts is displayed below.

Table 19: Confusion Matrix for Random Forest Model

	Predicted Functional	Predicted Functional/Repair	Predicted Non-Functional
Actually Functional	16769	1707	3611
Actually Functional/Repair	157	293	98
Actually Non-Functional	1268	332	8843

The wells on the diagonal were correctly classified by our model while off-diagonal entries were incorrectly classified. The model was most accurate at predicting the status of a non-functional well with 84.7% of actual non-functional wells predicted as non-functional. However, the model was much worse at predicting the status of functional wells and wells functioning but in need of repair, predicting the correct status 75.9% and 53.5% of the timerespectively. Overall summary statistics of the model are found below.

Table 20: Overall Statistics for Random Forest Model

Statistic	Value
Accuracy	0.7831489
Kappa	0.5762644

The accuracy of our model was 78.3%, lower than the 81.1% accuracy found by Topor et. al in their analysis when using a subset of our data. This is likely because we only focused on features that are applicable for other datasets, thus not including features such as province, latitude, and longitde, which would have made our model more accurate.

References

Topor et. al *Predicting Tanzanian Water Pump Maintenance Needs*