Georeference_Village_School

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Bring all schools together

In this part, I'm binding all the georeferenced data. After removing the duplicates by ceni_site_vote_ID, ceni_nom_sv, latitude there are 4121 distinct georeferenced observations in total. There are 3718 distinct ceni_site_vote_IDs.

```
#rm(list=b)

merge <- read_excel(paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "raw")),'ceni
ceni <- read_excel(paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "raw")),'ceni

## Bring together all the matched data from village name=school name
for (i in 1:5){
 temp <- read_excel(paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "raw")),paste

 assign(paste('df', i, sep=""), temp)

}

## Bring together all the matched data from Kinshasa, big cities, and small localities matching
df_list <- c('_bigcities_15km.xlsx', '_kinshasa.xlsx', '_small.xlsx')

for (c in df_list){
  temp <- read_excel(paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),

  assign(paste('df', which(df_list == c)+5, sep=''), temp)
  rm(temp)
}


## Import Google API coordinates
df9 <- read_csv(paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "raw")),'Votings

df_village_school <- bind_rows(df1, df2, df3, df4, df5)
df_temp1 <- rbind_dfs(df_village_school, df6)
df_temp2 <- rbind_dfs(df_temp1, df7)
df_final <- rbind_dfs(df_temp2, df8)

`%notin%` <- Negate(`%in%`)
# Add Google API coordinates if the ceni_site_vote_ID doesn't already exist in the data
df10 <- dplyr::filter(df9, ceni_site_vote_ID %notin% df_final$ceni_site_vote_ID )

# Bring all the data points together and remove duplicates by ceni_site_vote_ID, ceni_nom_sv, and latit
```

```
df_all <- rbind_dfs(df_final, df10, clearRowNames = TRUE) %>% dplyr::filter(!is.na(longitude)) %>% dply


df_all$longitude <- as.numeric(df_all$longitude)
df_all$latitude <- as.numeric(df_all$latitude)

df_all <- df_all  %>% dplyr::filter(!is.na(latitude)) %>% dplyr::distinct(identifier, .keep_all=TRUE)

# Export the data
write_xlsx(df_all,paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'df_
```

Create buffer and add schools

For each admin unit, I'm performing incremental buffering. I take all the schools matched and take the average of coordinates and then create buffers of different km. For the km information, see the excel file names in write_xlsx parts.

1. First buffer

The first buffer is created for province, circonscription, ceni_sect_chef_comm, ceni_group_quart, ceni_address_vill_avenue. For all of the buffers in the first admin variable, there is no increase in the georeferenced school numbers.

2. Second buffer

The second buffer is created for province, circonscription, ceni_sect_chef_comm, ceni_group_quart. To begin with there are 4121 observations, and the number of observations for each buffer is as follows:

- Initial: 3756
- 5 km buffer: 4137
- 8 km buffer: 4398
- 10 km buffer: 4562

3. Third buffer

The third buffer is created for province, circonscription, ceni_sect_chef_comm.The final number of observations for each buffer is as follows:

- Initial: 4562
- 8 km buffer: 4949
- 20 km buffer: 6160
- 30 km buffer: 7125

4. Fourth buffer

The fourth buffer is created for province, circonscription. The final number of observations for each buffer is as follows:

- Initial: 7125
- 20 km buffer: 7420
- 25 km buffer: 7609
- 30 km buffer: 7786
- 35 km buffer: 7965
- 40 km buffer: 8154
- 45 km buffer: 8404
- 50 km buffer: 8630

```
#rm(list=b)
`%notin%` <- Negate(`%in%`)
df <- read_excel(paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'mate
df[,8:11] <- lapply(df[,8:11], as.numeric)
df$ceni_site_vote_ID <- as.numeric(df$ceni_site_vote_ID)
matching_adm1 <- df %>% dplyr::mutate(ceni_nom_sv = gsub("[[:blank:]]", "",ceni_nom_sv)) %>% dplyr::muta

matching_adm1$longitude <- as.numeric(matching_adm1$longitude)
matching_adm1$latitude <- as.numeric(matching_adm1$latitude)


temp1 <- matching_adm1  %>% group_by(admvar) %>% dplyr::summarise(across(c("latitude", "longitude"), ~ m

ceni <- read_excel(paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "raw")),'ceni

sige <- sigeschools.all %>% dplyr::mutate(NomEcole = gsub("[[:blank:]]", "", NomEcole)) %>% dplyr::muta

sige$longitude <- as.numeric(sige$longitude)
sige$latitude <- as.numeric(sige$latitude)

coordinates_sf = st_as_sf(sige, coords = c("GPS_longitude", "GPS_latitude"),
                                    crs = 4326)



small_villes <-  unique(temp1$admvar)

for(s in small_villes) {

  temp <- temp1 %>% dplyr::filter(admvar == s)

  temp_admin <- matching_adm1 %>% dplyr::filter(admvar == s)

  temp_ceni <- ceni %>% dplyr::filter(admvar == s) %>% dplyr::filter(ceni_nom_sv %notin% df$ceni_nom_sv)



  temp_sf = st_as_sf(temp, coords = c("longitude", "latitude"),
                                    crs = 4326)

  temp_buffer <- st_buffer(temp_sf, 50000)


  admin <- st_join(coordinates_sf,  temp_buffer, left=FALSE)


  matching <- left_join(temp_ceni,admin, by = "school")
  matching_f <- rbind_dfs(temp_admin, matching, clearRowNames = TRUE)
  assign(s, matching)

}

a = ls()
```

```r
#index = which(str_detect(a, "[[:upper:]]|Â"))
index = which(a %in% small_villes)
b = a[index]


matching_binded1 <- do.call(bind_rows, lapply(b, get, env=environment()))
matching_binded1 <- matching_binded1 %>% dplyr::mutate(source = "adm4_50km")
matching_adm1$ceni_site_vote_ID <- as.numeric(matching_adm1$ceni_site_vote_ID)
matching_final1 <- dplyr::bind_rows(matching_adm1, matching_binded1)

test <- matching_final1  %>% dplyr::filter(!is.na(latitude)) %>% dplyr::mutate(identifier = paste(ceni_s

test<- test[, 1:15]

#write_xlsx(test,paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'mat
#write_xlsx(test,paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'mat
#write_xlsx(test,paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'mat
#write_xlsx(test,paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'mat
#write_xlsx(test,paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'mat
#write_xlsx(test,paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'mat
write_xlsx(test,paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'match

uniques <- unique(test$ceni_site_vote_ID)

rm(list=b)
```

I'm keeping the code chunk above to show the process, the same code was run for other admin units with varying buffers.

In the code below, I'm merging the final georeference data with the ceni dataset by ceni_site_vote_ID:

```r
df <- read_excel(paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'mat
ceni_raw <- read_csv(paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "raw")),'cen

final <- merge(df, ceni_raw, by="ceni_site_vote_ID", all=TRUE) %>% dplyr::mutate(georeferenced = ifelse

write_xlsx(final,paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'geo
```

Statistics

1. Comparison Table Below are the basic distribution of matched/unmatched observations by the output of interest.

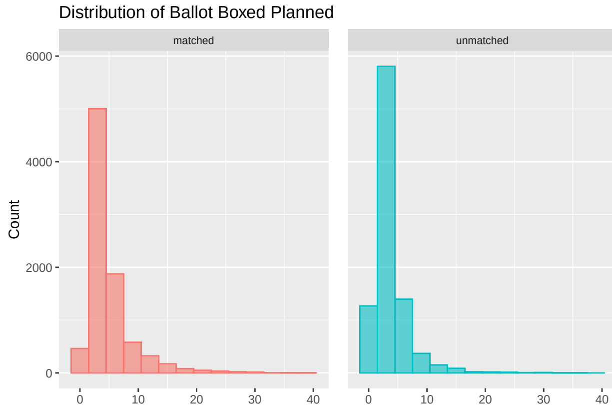
```r
df <- read_excel(paste((file.path(here::here(current_path) %>% dirname() %>% dirname(), "output")),'geo



df2 <- df %>% mutate_if(is.numeric, ~replace_na(., 0)) %>% group_by(georeferenced) %>%
  dplyr::summarise(across(c(bv_prevus, bv_traites, electeurs_attendus, votants, Tshisekedi, Fayulu, Sha
                  .groups='drop') %>%
  as.data.frame() %>%
  mutate(votants_to_inscrits = votants/electeurs_attendus) %>%
  mutate(share_Tshisekedi = Tshisekedi / votants*100) %>%
  mutate(share_Fayulu = Fayulu / votants*100) %>%
  mutate(share_Shadary = Shadary / votants*100)
```

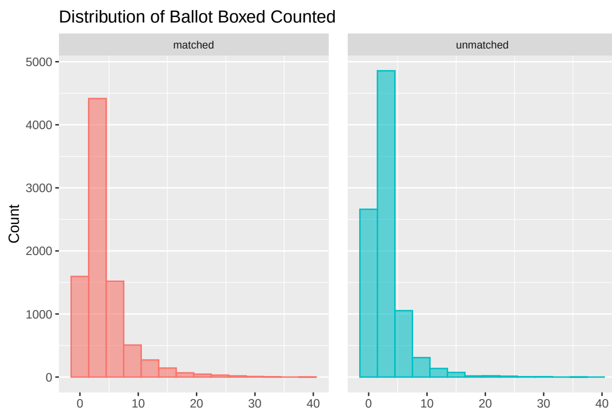
```
tbl <- knitr::kable(df2[, 1:12], "latex", booktabs = T, caption = "Comparison of Matched and Unmatched (
tbl
```

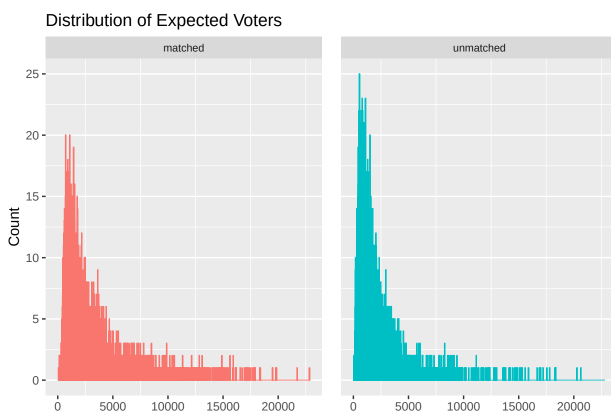
Table 1: Comparison of Matched and Unmatched Obs by Output of Interest

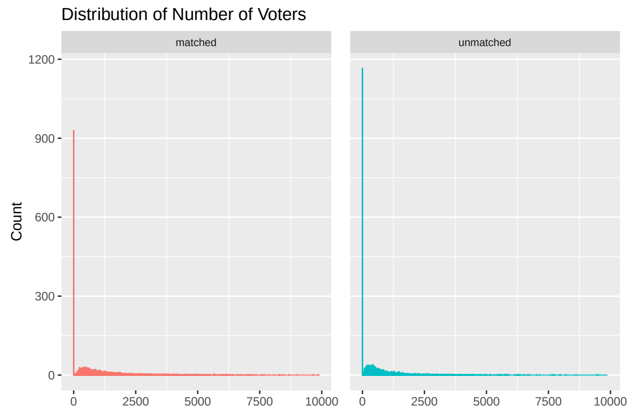
georeferenced	bv_prevus	bv_traites	electeurs_attendus	votants	Tshisekedi	Fayulu	Shadary	votants_to_inscrits	share_Tshisekedi	share_Fayulu	share_Shadary
matched	41605	35338	22648781	9050685	3589471	7614454	3555497	0.3996102	39.65966	84.13125	39.28429
unmatched	33059	27355	17126090	6689764	3384416	5708919	3353865	0.3906183	50.59096	85.33812	50.13428

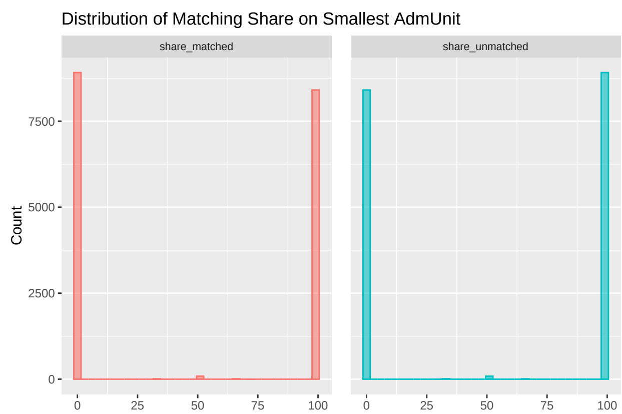
2. Distribution Graphs

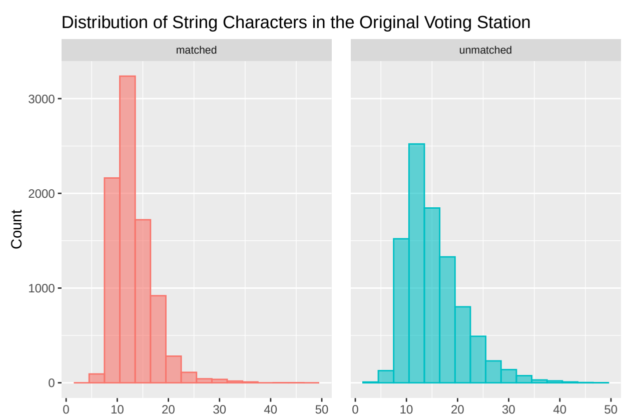


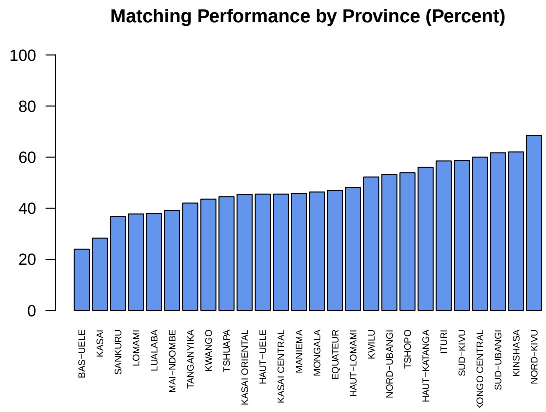





Distribution of Number of Voters
matched
unmatched
Count
0
300
600
900
1200
0
2500
5000
7500
10000


Distribution of Matching Share on Smallest AdmUnit
share_matched
share_unmatched
Count
0
2500
5000
7500
0
25
50
75
100


Distribution of String Characters in the Original Voting Station
matched
unmatched
Count
0
1000
2000
3000
0
10
20
30
40
50



3. Distances Next, I'm taking the smallest admin unit (i.e. province, circonscription, ceni_sect_chef_comm, ceni_group_quart, ceni_address_vill_avenue) and for the regions where there is more than one school matched, I'm creating the statistics for the distances (min, max, mean, sd). Additionally, the count column gives the number of georeferenced schools in the respective admin unit.

Table 2: Summary Statistics of Distances

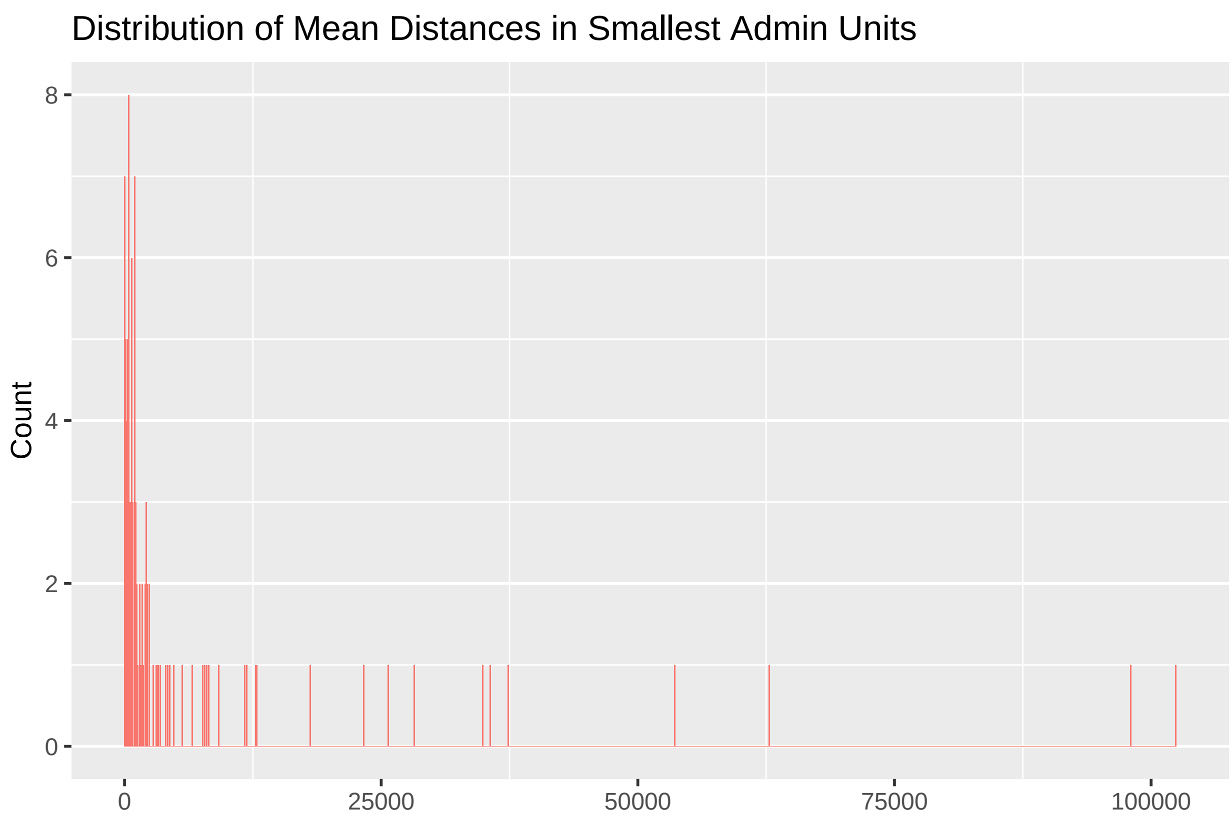
admvar	matched	mean	sd	min_dist	max_dist
KASAILUEBOLUEBO-KABAMBAIENAWETUMANDE	2	0.000000	NA	0.000000	0.000000
KWANGOKASONGO-LUNDAKIBUNDANAKASANZA	2	0.000000	NA	0.000000	0.000000
NORD-KIVUWALIKALEWANIANGANABUHIMBA	2	0.000000	NA	0.000000	0.000000
NORD-KIVUMASISIOSSOBANYUNGUNAMASHAKI	2	4.541762	NA	4.541762	4.541762
EQUATEURBIKOROEKONDANABOSOLO	2	5.114436	NA	5.114436	5.114436
BAS-UELEBONDOKASSANAKOYADOLI	2	13.939094	NA	13.939094	13.939094
EQUATEURBIKOROEKONDANALOPANZO	2	23.948801	NA	23.948801	23.948801
EQUATEURBIKOROEKONDANABOKONGO	2	59.681308	NA	59.681308	59.681308
KINSHASAKIMBANSEKEKIMBANSEKENAAV.KIMPIOKANO01	2	69.023921	NA	69.023921	69.023921
SUD-KIVUIDJWINTAMBUKANABUNYAMA	2	91.715474	NA	91.715474	91.715474
KASAICENTRALKANANGAVILLENDESHANALULUA	2	106.231932	NA	106.231932	106.231932
EQUATEURBASANKUSUWAKABOKEKANANDEKESOCIETE	2	134.971747	NA	134.971747	134.971747
SUD-KIVUUVIRAUVIRANAKALIMABENGE	2	152.634643	NA	152.634643	152.634643
EQUATEURBOLOMBADIANGANAITOTELA	2	157.857950	NA	157.857950	157.857950
NORD-KIVULUBEROBASWAGHANAMUTAMBI	2	161.098185	NA	161.098185	161.098185
KINSHASAMATETEMATETENALOC.BAHUMBUI	2	188.045870	NA	188.045870	188.045870
TANGANYIKAKABALOLUKUSWANAKITULEGARE	2	251.677930	NA	251.677930	251.677930
NORD-KIVUBENIBULONGONABULONGO	2	259.202160	NA	259.202160	259.202160
NORD-KIVULUBEROBASWAGHANAMAMBIRA	2	309.537104	NA	309.537104	309.537104
ITURIBUNIAVILLENYAKASANZANAQ.SALONGO	2	325.521025	NA	325.521025	325.521025
EQUATEURLUKOLELAMPAMANABONGONDA	2	345.773092	NA	345.773092	345.773092
KWILUBULUNGUMIKWINABILILICITE	2	353.702940	NA	353.702940	353.702940
MANIEMAPUNIAULINDINAMATENGENYA	2	358.505816	NA	358.505816	358.505816
NORD-KIVULUBEROBASWAGHANAVUGHANGAMABAMBI	2	370.663988	NA	370.663988	370.663988
NORD-UBANGIYAKOMAABUMOMBAZINASANGA	2	379.673943	NA	379.673943	379.673943
ITURIIRUMUWALENDUBINDINANZIGO	2	389.217649	NA	389.217649	389.217649
SUD-KIVUUVIRAUVIRANAAV.FAZA	2	397.451859	NA	397.451859	397.451859
NORD-KIVULUBEROBAMATENAMANGA	2	403.853603	NA	403.853603	403.853603
MAI-NDOMBEKUTUBOKORONABOKORO	2	413.789884	NA	413.789884	413.789884
SUD-KIVUBUKAVUVILLEIBANDANAPANZI	2	454.324235	NA	454.324235	454.324235
EQUATEURMANKANZAMWEKONALUSENGO	2	467.292966	NA	467.292966	467.292966
KASAICENTRALKANANGAVILLENGANZANAQSALONGOMUIMBA	2	518.634676	NA	518.634676	518.634676
HAUT-KATANGALUBUMBASHIVILLEKENYANA10AVBUKAMA	2	573.435613	NA	573.435613	573.435613
NORD-KIVURUTSHURUBWITONABAMBO	2	586.563532	NA	586.563532	586.563532
MAI-NDOMBEKUTUMFIMINAMONGOBELECITE	2	627.506706	NA	627.506706	627.506706
KASAIORIENTALMIABIMIABINACITEDEMIABI	2	691.604308	NA	691.604308	691.604308
NORD-KIVULUBEROBATANGINABINGI	2	715.510754	NA	715.510754	715.510754
KWANGOKAHEMBAKAHEMBANAAVKOLA	2	733.323261	NA	733.323261	733.323261
NORD-KIVULUBEROBATANGINAKAGHERI	2	742.117426	NA	742.117426	742.117426
KWILUBAGATABAGATANACOMMUNERURALEDEBAGATA	2	805.436593	NA	805.436593	805.436593
TSHOPOOPALATOOLINAYAKOKOI	2	817.448062	NA	817.448062	817.448062
NORD-KIVUWALIKALEWANIANGANAMUBI	2	979.321771	NA	979.321771	979.321771
SUD-KIVUKABAREKABARENACIRHOGOLE	2	980.808009	NA	980.808009	980.808009

Table 2: Summary Statistics of Distances *(continued)*

admvar	matched	mean	sd	min_dist	max_dist
NORD-KIVULUBEROBATANGINAKAMANDI/GITE	2	981.303329	NA	981.303329	981.303329
SUD-KIVUUVIRALUVUNGINALUVUNGI	2	1026.361011	NA	1026.361011	1026.361011
NORD-KIVULUBEROBATANGINAKASUGHO	2	1029.296523	NA	1029.296523	1029.296523
SUD-KIVUBUKAVUVILLEIBANDANANYALUKEMBA	2	1030.846805	NA	1030.846805	1030.846805
SANKURULODJALODJANAEDINGO	3	694.039166	436.6510	203.749297	1041.046820
LUALABAKOLWEZIVILLEDILALANA852,AV.LUSANGA	2	1045.182593	NA	1045.182593	1045.182593
MAI-NDOMBEKUTUTOLONATOLO	2	1055.070626	NA	1055.070626	1055.070626
NORD-UBANGIYAKOMAYAKOMANACENTREVILLE	2	1058.561463	NA	1058.561463	1058.561463
HAUT-LOMAMIKABONGOKAYAMBANAMWALA	2	1096.663413	NA	1096.663413	1096.663413
SUD-KIVUBUKAVUVILLEIBANDANANDENDERE	3	814.626353	444.8872	315.530261	1169.540226
NORD-UBANGIYAKOMAABUMOMBAZINABAKONGO	2	1175.975268	NA	1175.975268	1175.975268
NORD-KIVULUBEROBATANGINAKIKUVO	2	1184.642711	NA	1184.642711	1184.642711
NORD-KIVUBENIKYONDONAKYONDO	5	730.027463	466.1377	69.424547	1284.761308
HAUT-KATANGAMITWABABALOMOTWANAMUFUNGA	2	1301.351593	NA	1301.351593	1301.351593
HAUT-KATANGALIKASIVILLEKIKULANAAVENUELUMUMBA	2	1496.836184	NA	1496.836184	1496.836184
NORD-KIVUMASISIBAHUNDENAKINGI	2	1521.848824	NA	1521.848824	1521.848824
HAUT-UELEWATSAWATSANATOMO	2	1635.799059	NA	1635.799059	1635.799059
LUALABADILOLODILOLONADILOLO	2	1680.565243	NA	1680.565243	1680.565243
KASAICENTRALKANANGAVILLEKANANGANAQPLATEAU	2	1733.184111	NA	1733.184111	1733.184111
SUD-KIVUBUKAVUVILLEBAGIRANALUMUMBA	2	1764.296940	NA	1764.296940	1764.296940
KASAITSHIKAPAVILLEKANZALANAAV.LUMUMBA	2	1987.800104	NA	1987.800104	1987.800104
SUD-KIVUKABAREKABARENACITUZO	2	2003.957185	NA	2003.957185	2003.957185
SUD-KIVUIDJWINTAMBUKANABULEGEYI	2	2053.041908	NA	2053.041908	2053.041908
SUD-KIVUBUKAVUVILLEBAGIRANACIKONYI	2	2124.920178	NA	2124.920178	2124.920178
LOMAMILUBAOLUBAONALUBAOCITE	2	2215.940296	NA	2215.940296	2215.940296
SUD-KIVUKALEHEBUHAVUNAMAFUO	2	2402.377475	NA	2402.377475	2402.377475
KASAICENTRALKANANGAVILLENDESHANAREVOLUTION	3	2164.143974	582.3226	1494.183579	2548.766604
SUD-KIVUUVIRASANGENASANGE	2	2838.533290	NA	2838.533290	2838.533290
KASAIORIENTALTSHILENGEBAKWA-KALONJINABENAKAPIAMBA	2	3120.067295	NA	3120.067295	3120.067295
SUD-KIVUBUKAVUVILLEKADUTUNAMOSALA	3	2107.396076	1455.7242	442.743436	3141.790898
KASAICENTRALKANANGAVILLENGANZANAQLUBIAMPATAGPMTBAKWAMETA	2	3179.896331	NA	3179.896331	3179.896331
NORD-UBANGIYAKOMAYAKOMANAKUSA	3	2418.448767	863.2256	1540.808586	3266.498985
SUD-KIVUKALEHEBUHAVUNAFENDULA	2	3334.486352	NA	3334.486352	3334.486352
KWILUGUNGULOZONAMUKEDI	2	3526.434453	NA	3526.434453	3526.434453
NORD-KIVUMASISIBASHALINAKIRUMBU	2	4001.336981	NA	4001.336981	4001.336981
NORD-UBANGIYAKOMAYAKOMANAGBENGO	2	4213.729697	NA	4213.729697	4213.729697
KASAICENTRALKANANGAVILLEKATOKANAAVLULUA	2	4375.929465	NA	4375.929465	4375.929465
SUD-KIVUKALEHEBUHAVUNABUBALEII	2	4796.744696	NA	4796.744696	4796.744696
ITURIDJUGUWALENDU-PITSINAGOKPA	2	5561.623500	NA	5561.623500	5561.623500
SUD-KIVUKALEHEBUHAVUNAMINGAZI	2	6609.229084	NA	6609.229084	6609.229084
KASAIORIENTALKABEYA-KAMWANGALACMUKAMBANABENAKANYINDA	2	7830.546146	NA	7830.546146	7830.546146
SUD-KIVUWALUNGUKAZIBANAKALEMBA	2	7962.048740	NA	7962.048740	7962.048740
SUD-KIVUMWENGAWAMUZIMUNALULIBA	2	8182.164504	NA	8182.164504	8182.164504

Table 2: Summary Statistics of Distances *(continued)*

admvar	matched	mean	sd	min_dist	max_dist
SUD-UBANGIZONGOVILLENZULUNANZULU	2	9245.072941	NA	9245.072941	9245.072941
LUALABAKOLWEZIVILLEDILALANACAMPMETHODISTE	3	7631.232560	3947.5009	3148.366914	10587.298323
MANIEMAKASONGOMAMBA/KASENGANABWANAALI	2	11698.431616	NA	11698.431616	11698.431616
SUD-KIVUMWENGABURHINYINAKAHANDA	2	11879.280289	NA	11879.280289	11879.280289
SUD-KIVUKABAREKABARENACIBINGU	2	12759.009428	NA	12759.009428	12759.009428
NORD-KIVULUBEROBATANGINANYAMIINDO	2	12858.775837	NA	12858.775837	12858.775837
KONGOCENTRALMBANZA-NGUNGUKWILU-NGONGONAPAROISSEKIMBANGUISTE	2	18147.769655	NA	18147.769655	18147.769655
SUD-KIVUKABAREKABARENALUDAHA	2	23312.132274	NA	23312.132274	23312.132274
KASAILUEBOLUEBO-WEDINATSHIBUNDU	2	25686.182004	NA	25686.182004	25686.182004
ITURIDJUGUWALENDU-PITSINANDALO	2	28230.455346	NA	28230.455346	28230.455346
SUD-KIVUIDJWINTAMBUKANANTALANGWA	2	34889.086319	NA	34889.086319	34889.086319
SUD-KIVUKABAREKABARENALUHIHICENTRE	2	35622.546343	NA	35622.546343	35622.546343
NORD-KIVURUTSHURUBWITONABUGINA	2	37399.502894	NA	37399.502894	37399.502894
NORD-KIVUBENIKYONDONAKAVANDA	2	53634.335162	NA	53634.335162	53634.335162
NORD-KIVUWALIKALEWANIANGANAKAILENGE	2	62796.380657	NA	62796.380657	62796.380657
MANIEMAPANGIWAKABANGOIINAKATUMPI	2	97983.213131	NA	97983.213131	97983.213131
TSHOPOISANGIBOLOMBOKINAYAHISULI	2	102366.805625	NA	102366.805625	102366.805625



I'm putting some admin units where the results seem off:

```
names <- c("TSHOPOISANGIBOLOMBOKINAYAHISULI", "KASAILUEBOLUEBO-KABAMBAIENAWETUMANDE", "KWANGOKASONGO-LU
testdf <- df %>% dplyr::filter(georeferenced == "matched") %>% dplyr::mutate(town_province1 = paste(pro

tbl3 <- knitr::kable(testdf, "latex", booktabs = T, caption = "Example") %>%  kableExtra::kable_styling
tbl3
```

Table 3: Example

ceni_site_vote_ID	ceni_nom_sv	georeferenced	latitude	longitude	admvar
310652	ECOLEPRIMAIREKASANZA2	matched	-7.0346099	17.78387	KWANGOKASONGO-LUNDAKIBUNDANAKASANZA
310680	ECOLEPRIMAIREKASANZA2	matched	-7.0346099	17.78387	KWANGOKASONGO-LUNDAKIBUNDANAKASANZA
540362	INSTITUTSAINTCAMILLE	matched	0.7777479	24.27159	TSHOPOISANGIBOLOMBOKINAYAHISULI
540364	ECOLEPRIMAIREYAHISULI	matched	-0.1086005	24.02278	TSHOPOISANGIBOLOMBOKINAYAHISULI
910039	ECOLEPRIMAIREKABONGOMUTOMBO	matched	-5.8820925	21.18441	KASAILUEBOLUEBO-KABAMBAIENAWETUMANDE
910041	ECOLEPRIMAIREKABONGOMUTOMBO	matched	-5.8820925	21.18441	KASAILUEBOLUEBO-KABAMBAIENAWETUMANDE

There seem to be some schools with same school name but different voting station ID, so when creating buffers since I do matching only on the school name, the same coordinates are matched with those schools.