# WI chloride randomforest

Hilary Dugan 3/4/2019

#### Tidy data

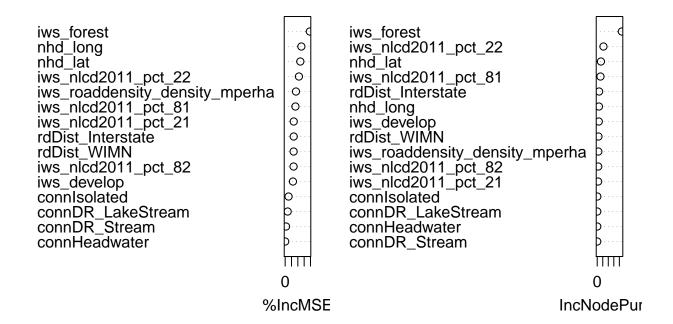
```
dat <- datin %>% dplyr::filter(Chloride < 10000 & Chloride >=0) %>%
  dplyr::mutate(Chloride = ifelse(Chloride == 0, 0.0001, Chloride)) %>%
  dplyr::filter(!(coastdist < 4 | Chloride > 1000)) %>%
  dplyr::filter(state_zoneid == 'State_9' | state_zoneid == 'State_14') %>% # Wisconsin and Minnesota
  dplyr::filter(Date > as.Date('1990-01-01')) %>%
  dplyr::mutate(rdDist_WIMN = pmin(rdDist_WI,rdDist_MN)) %>%
  dplyr::mutate(iws_forest = iws_nlcd2011_pct_41 + iws_nlcd2011_pct_42 +iws_nlcd2011_pct_43) %>%
  dplyr::mutate(iws develop = iws nlcd2011 pct 24 + iws nlcd2011 pct 23) %%
  dplyr::group_by(lagoslakeid) %>%
  dplyr::summarise_if(is.numeric,funs(mean)) %>%
  dplyr::left_join(distinct(dplyr::select(datin,lagoslakeid,lakeconnection,gnis_name,state_zoneid)))
## Warning: funs() is soft deprecated as of dplyr 0.8.0
## please use list() instead
## # Before:
## funs(name = f(.)
##
## # After:
## list(name = \sim f(.))
## This warning is displayed once per session.
## Joining, by = "lagoslakeid"
#adding connectivity dummies
oneHot=function(x) {
  conn = factor(x)
  apply(data.frame(model.matrix(~conn+0)),2,FUN=factor)
dat_conn_dummy<-oneHot(dat$lakeconnection)</pre>
dat<-cbind(dat,dat_conn_dummy)</pre>
log01 \leftarrow function(x)\{log(x + 0.001)\} \# log of columns
dat rf <- dat %>%
  mutate_at(vars(Chloride,iws_ha:rdDist_WIMN,iws_forest,iws_develop),log01) %>%
 filter(!is.na(iws_nlcd2011_pct_22))
```

#### Random Forest model

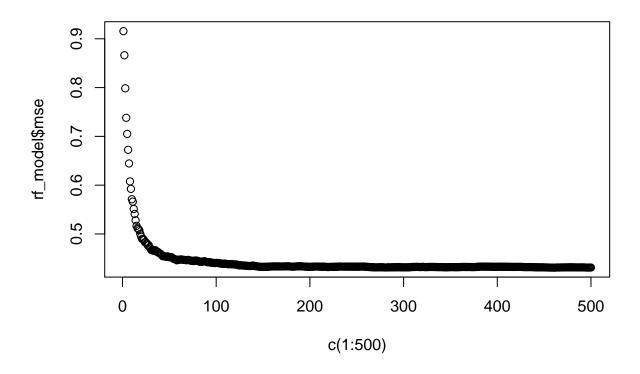
```
iws_nlcd2011_pct_82,
                                    iws_nlcd2011_pct_21,
                                    iws_nlcd2011_pct_22,
                                    iws_develop,
                                    iws_roaddensity_density_mperha,
                                    rdDist_Interstate,rdDist_WIMN,connDR_LakeStream:connIsolated)
##grid search to select random forest hyperparameters
control <- trainControl(method="oob", number=10, search="random")</pre>
rf_random <- train(y=dat_rf$Chloride, x = rf_cov, method="rf",tuneLength=15, trControl=control)
#best r2 model has mtry=4, but I like maximizing mtry to better interpret interactions in forestFloor p
#small grid search for the right sampsize. Lower sampsize decorrelates trees a bit, which is important
sampsize<-c(100,200,500,1000,length(dat_rf$Chloride))</pre>
samp_df<-data.frame()</pre>
for(i in 1:length(sampsize) ){
rf_sampsize<-randomForest(y=dat_rf$Chloride,
                       x = rf_cov,
                       keep.inbag = T,
                       importance = T,
                       ntree=500,
                       sampsize = sampsize[i],
                       # mtry=4,
                       mtry=length(rf_cov) )
samp_df<-rbind(samp_df,</pre>
               data.frame(sampsize=sampsize[i],
                          r2=rf_sampsize$rsq[length(rf_sampsize$rsq)],
                          mse=rf_sampsize$mse[length(rf_sampsize$mse)])
               )
}
samp_df
##
     sampsize
                     r2
## 1
         100 0.7983260 0.5042481
## 2
          200 0.8132195 0.4670097
## 3
          500 0.8229908 0.4425783
## 4
         1000 0.8273348 0.4317169
         1936 0.8280910 0.4298263
#sampsize around the max is pretty good, though it's not the worst idea to reduce this value to decorre
rf model<-randomForest(y=dat rf$Chloride,
                       x = rf_{cov}
                       keep.inbag = T,
                       importance = T,
                       ntree=500,
                       sampsize = 1739,
                       # mtry=4,
                       mtry=length(rf_cov) )
rf_model
##
## Call:
## randomForest(x = rf_cov, y = dat_rf$Chloride, ntree = 500, mtry = length(rf_cov),
                                                                                              sampsize = 1
```

```
## Type of random forest: regression
## No. of trees: 500
## No. of variables tried at each split: 15
##
## Mean of squared residuals: 0.4312293
## % Var explained: 82.75
varImpPlot(rf_model)
```

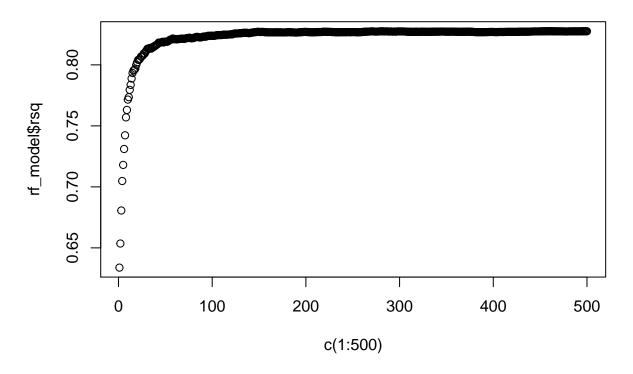
### rf\_model



#you'll notice that your interpretation of the forestfloor plot will change as you adjust mtry and samp
#determining # of trees to stabilize error
plot(rf\_model\$mse~c(1:500))



plot(rf\_model\$rsq~c(1:500))



```
#pretty good by 100 trees

ff_model<-forestFloor(rf_model,X = rf_cov,y= rf_model$y )
Col = fcol(ff_model, 1, orderByImportance=T)
plot(ff_model, col=Col, orderByImportance=T)</pre>
```

## [1] "compute goodness-of-fit with leave-one-out k-nearest neighbor(guassian weighting), kknn package

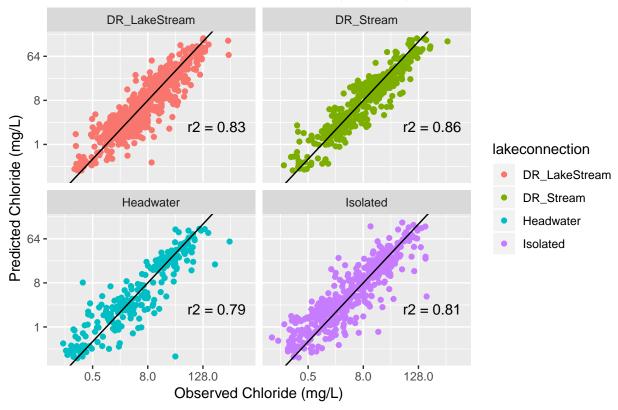
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  iws nlcd2011 pct 22,R^2= 0.7roaddensity density mperha,R^2 iws nlcd2011 pct 81,R^2= 0.61
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                        2
                                         -4 -2
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         -4
                   0
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  iws nlcd2011 pct 21,R^2= 0.3
                                    rdDist Interstate, R^2= 0.39
                                                                      rdDist WIMN,R^2= 0.49
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 iws_nlcd2011_pct_82,R^2= 0.27
                                      iws_develop,R^2= 0.63
                                                                      connIsolated,R^2= 0.47
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 connDR LakeStream,R^2= 0.17
                                    connDR Stream,R^2= 0.23
                                                                     connHeadwater,R^2= 0.05
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dat rf = dat rf %>% mutate(predicted = rf model$predicted)
library(lme4)
## Warning: package 'lme4' was built under R version 3.5.2
## Loading required package: Matrix
## Attaching package: 'Matrix'
## The following object is masked from 'package:tidyr':
##
##
       expand
fits <- lmList(predicted ~ Chloride | lakeconnection, data=dat_rf)</pre>
fits1 = data.frame(r2 = paste0('r2 = ',round(summary(fits)$r.squared,2)), lakeconnection = unique(fits@
                    Chloride = rep(7,4),
                    predicted = rep(0.1,4))
p = ggplot(dat_rf, aes(x = exp(Chloride), y = exp(predicted), color = lakeconnection)) + geom_point() +
  #scale_colour_viridis_d() +
  facet_wrap(~lakeconnection) +
  ylab('Predicted Chloride (mg/L)') + xlab('Observed Chloride (mg/L)') +
  labs(title = paste0('Modeled chloride in Wisconsin Lakes (n = ',nrow(dat rf),')')) +
  scale_y_continuous(trans = log2_trans()) + scale_x_continuous(trans = log2_trans()) +
  geom_text(data = fits1, aes(label = r2),hjust = 1,vjust = -1, color = 'black')
p
```

 $nhd_long_R^2 = 0.4$ 

iws\_forest,R^2= 0.99

nhd\_lat,R^2= 0.42

## Modeled chloride in Wisconsin Lakes (n =1936)



```
#plotting residuals over space
library(tigris)
```

```
## To enable
## caching of data, set `options(tigris_use_cache = TRUE)` in your R script or .Rprofile.
##
## Attaching package: 'tigris'
## The following object is masked from 'package:graphics':
##
##
       plot
states <- states(cb = TRUE)</pre>
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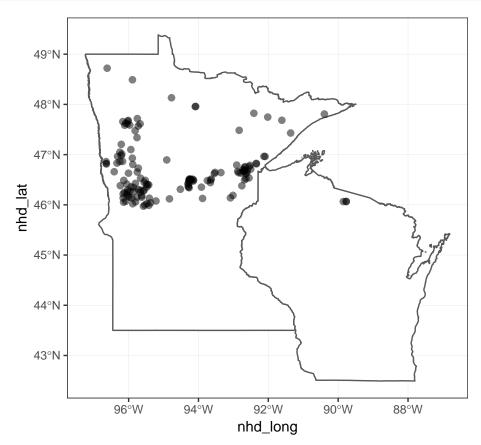
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states_sf<- st_as_sf(states)</pre>
dat_rf$residuals<-dat_rf$predicted-dat_rf$Chloride</pre>
```

```
r_map<-ggplot(data=dat_rf) +
  geom_sf(data=states_sf[states_sf$NAME %in% c("Wisconsin", "Minnesota"),], fill="white")+
  geom_point(aes(x=nhd_long, y=nhd_lat, col=abs(residuals), size = abs(residuals)), alpha=.5 )+
  scale_color_viridis_c(option="magma")+
  theme_bw()

#plotting the location of the weird points in the nhd_lat forest floor plot
ggplot()+
  geom_sf(data=states_sf[states_sf$NAME %in% c("Wisconsin", "Minnesota"),], fill="white")+
  geom_point(data=dat_rf[ff_model$FCmatrix[,"nhd_lat"]< (-.5),],aes(x=nhd_long, y=nhd_lat), size=2, alpitheme_bw()</pre>
```

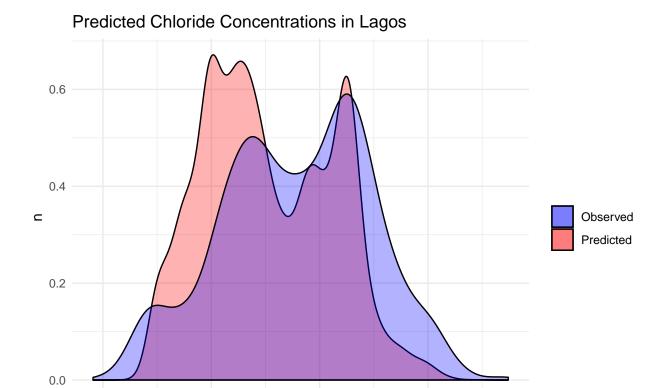


### ## Prediction for LAGOS

```
datPred2 = read_csv('data/LAGOS_allLakes.csv') %>%
    dplyr::filter(state_zoneid == 'State_9' | state_zoneid == 'State_14') %>% # Wisconsin and Minnesota
    dplyr::mutate(rdDist_WIMN = pmin(rdDist_WI,rdDist_MN)) %>%
        dplyr::mutate(iws_forest = iws_nlcd2011_pct_41 + iws_nlcd2011_pct_42 + iws_nlcd2011_pct_43) %>%
        dplyr::mutate(iws_develop = iws_nlcd2011_pct_24 + iws_nlcd2011_pct_23)

## Parsed with column specification:
## cols(
## .default = col_double(),
## nhdid = col_character(),
## gnis_name = col_character(),
## state_zoneid = col_character(),
```

```
##
     lakeconnection = col_character(),
##
     latewisconsinglaciation_glacial = col_character()
## )
## See spec(...) for full column specifications.
datPred2 <- datPred2 %>%
 mutate_at(vars(iws_nlcd2011_ha_0:iws_develop),log01) %>%
 filter(!is.na(iws_nlcd2011_pct_22))
dat conn dummy<-oneHot(datPred2$lakeconnection)</pre>
datPred2<-cbind(datPred2,dat_conn_dummy)</pre>
datPred2<- datPred2 %>% select(nhd_lat,nhd_long,
                               iws_forest,
                               iws_nlcd2011_pct_81,
                               iws_nlcd2011_pct_82,
                               iws_nlcd2011_pct_21,
                               iws_nlcd2011_pct_22,
                               iws_develop,
                          iws_roaddensity_density_mperha,
                          rdDist_Interstate,rdDist_WIMN,connDR_LakeStream:connIsolated)
preds <- predict(rf_model, newdata = datPred2)</pre>
datPred2$clPred = preds
# Plot prediction histogram
ggplot() +
  geom_density(data = datPred2, aes(x = exp(clPred), fill = "r"), alpha = 0.3) +
  geom_density(data = dat_rf, aes(x = exp(Chloride), fill = "b"), alpha = 0.3) +
 scale_colour_manual(name ="", values = c("r" = "red", "b" = "blue"), labels=c("b" = "Observed", "r" =
  scale_fill_manual(name ="", values = c("r" = "red", "b" = "blue"), labels=c("b" = "Observed", "r" = "]
  scale_x_continuous(trans='log10') +
  labs(x = "Chloride (mg/L)", y = "n") +
  ggtitle("Predicted Chloride Concentrations in Lagos") +
  theme_minimal()
```



10.0 Chloride (mg/L)

100.0

1.0

0.1