

# Potatoes

```
library(tidyverse)
```

```
-- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
v dplyr      1.1.4      v readr      2.1.5
v forcats    1.0.0      v stringr    1.5.1
v ggplot2    3.5.1      v tibble     3.2.1
v lubridate  1.9.3      v tidyr      1.3.1
v purrr      1.0.2
-- Conflicts ----- tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()     masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become
```

```
library(spmodel)
library(vroom)
```

Attaching package: 'vroom'

The following objects are masked from 'package:readr':

```
as.col_spec, col_character, col_date, col_datetime, col_double,
col_factor, col_guess, col_integer, col_logical, col_number,
col_skip, col_time, cols, cols_condense, cols_only, date_names,
date_names_lang, date_names_langs, default_locale, fwf_cols,
fwf_empty, fwf_positions, fwf_widths, locale, output_column,
problems, spec
```

```
library(viridis)
```

Loading required package: viridisLite

```
library(FRK)
```

Warning: package 'FRK' was built under R version 4.4.3

Attaching package: 'FRK'

The following object is masked from 'package:stats':

simulate

```
library(fields)
```

Loading required package: spam

Spam version 2.11-0 (2024-10-03) is loaded.

Type 'help( Spam)' or 'demo( spam)' for a short introduction and overview of this package.

Help for individual functions is also obtained by adding the suffix '.spam' to the function name, e.g. 'help( chol.spam)'.

Attaching package: 'spam'

The following objects are masked from 'package:base':

backsolve, forwardsolve

Try help(fields) to get started.

```
df <- vroom('PotatoCWSI.csv')
```

Rows: 3889 Columns: 8

-- Column specification -----

Delimiter: ","

dbl (8): POINT\_X, POINT\_Y, SLOPE, TWI, ASPECT, ECA\_SHALLOW, NDVI, CWSI

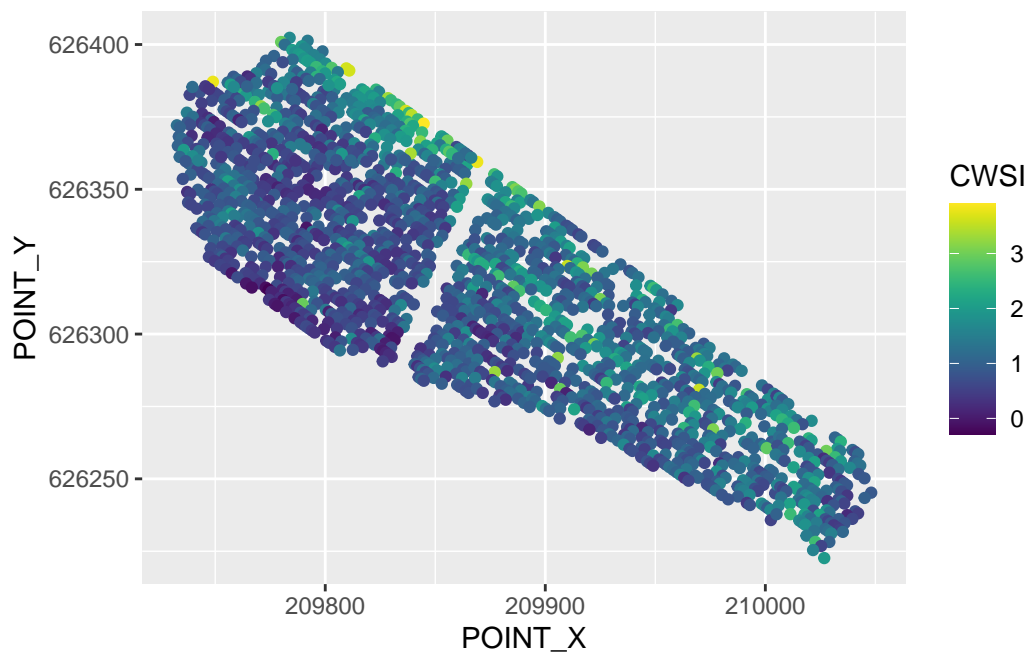
i Use `spec()` to retrieve the full column specification for this data.

i Specify the column types or set `show\_col\_types = FALSE` to quiet this message.

```
obs <- df %>%
  filter(!is.na(CWSI))
new <- df %>%
  filter(is.na(CWSI))
```

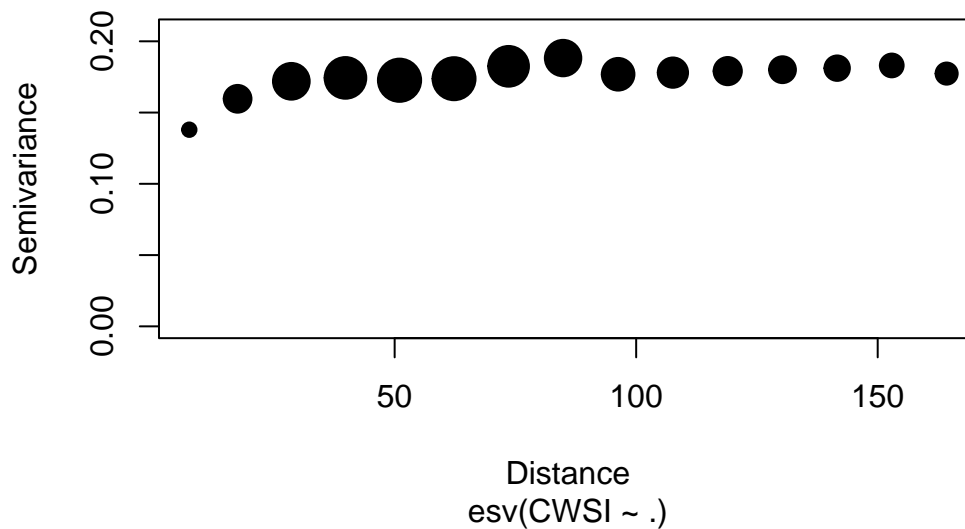
## EDA

```
obs %>%
  ggplot(aes(x=POINT_X,y=POINT_Y, color=CWSI)) +
  geom_point() +
  scale_color_viridis()
```



```
# variogram
variogram <- esv(CWSI~., data=obs, xcoord=POINT_X, ycoord=POINT_Y)
plot(variogram)
```

## Empirical Semivariogram



## Feature Engineering

```
# Make obs loc matrix
observed_loc_matrix <- matrix(data=cbind(obs$POINT_X,obs$POINT_Y), ncol=2)

## Number of Spatial Features
K <- 20

## "Centers" of Features
## cover.design() choose K centers spread out over spatial region
centers <- cover.design(observed_loc_matrix, nd=K)$design

## Use 1.5 rule of thumb for scale
dist_between_centers <- rdist(centers)
the_scale <- 1.5*max(apply(dist_between_centers,1,function(x){sort(x)[2]}))

## Define spatial features
spatial_features <- local_basis(
  manifold=plane(),
  loc=centers,
  scale=rep(the_scale, K),
```

```

type="bisquare" #or "Gaussian" or "exp"
)

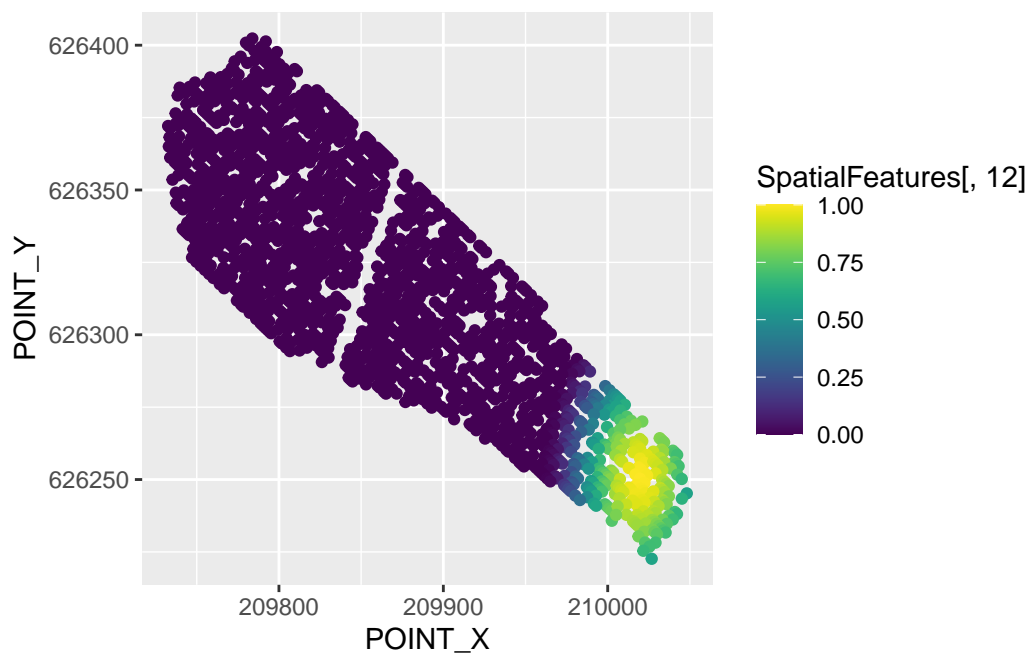
## Mutate new spatial features in data frame
obs <- obs %>%
  mutate(SpatialFeatures=as.matrix(eval_basis(spatial_features, observed_loc_matrix)))

```

```

# Plot
obs %>%
  ggplot(aes(x=POINT_X,y=POINT_Y, color=SpatialFeatures[,12])) +
  geom_point() +
  scale_color_viridis()

```



## Model

```

obs.sp <- splm(CWSI~SLOPE+TWI+ASPECT+ECA_SHALLOW+NDVI+SpatialFeatures[,1]+SpatialFeatures[,2],
xcoord=POINT_X, ycoord=POINT_Y)
summary(obs.sp)

```

Call:

```
splm(formula = CWSI ~ SLOPE + TWI + ASPECT + ECA_SHALLOW + NDVI +
      SpatialFeatures[, 1] + SpatialFeatures[, 2] + SpatialFeatures[,
      3] + SpatialFeatures[, 4] + SpatialFeatures[, 5] + SpatialFeatures[,
      6] + SpatialFeatures[, 7] + SpatialFeatures[, 8] + SpatialFeatures[,
      9] + SpatialFeatures[, 10] + SpatialFeatures[, 11] + SpatialFeatures[,
      12] + SpatialFeatures[, 13] + SpatialFeatures[, 14] + SpatialFeatures[,
      15] + SpatialFeatures[, 16] + SpatialFeatures[, 17] + SpatialFeatures[,
      18] + SpatialFeatures[, 19] + SpatialFeatures[, 20], data = obs,
      spcov_type = "exponential", xcoord = POINT_X, ycoord = POINT_Y)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.2543	-0.4032	-0.1314	0.1753	2.0094

Coefficients (fixed):

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	3.0025855	0.7524782	3.990	6.6e-05 ***
SLOPE	0.0059379	0.0177375	0.335	0.738
TWI	0.0023441	0.0133474	0.176	0.861
ASPECT	0.0002179	0.0003477	0.627	0.531
ECA_SHALLOW	0.0005355	0.0052826	0.101	0.919
NDVI	-4.8873120	0.1350701	-36.184	< 2e-16 ***
SpatialFeatures[, 1]	0.7298364	0.7616013	0.958	0.338
SpatialFeatures[, 2]	0.0544470	0.6432089	0.085	0.933
SpatialFeatures[, 3]	-0.0581519	0.6840561	-0.085	0.932
SpatialFeatures[, 4]	-0.0274428	0.8541085	-0.032	0.974
SpatialFeatures[, 5]	0.4862680	0.5870894	0.828	0.408
SpatialFeatures[, 6]	-0.5598174	0.9798524	-0.571	0.568
SpatialFeatures[, 7]	-0.6117252	0.6037053	-1.013	0.311
SpatialFeatures[, 8]	-0.5796139	0.7498070	-0.773	0.440
SpatialFeatures[, 9]	-0.1678815	0.6721241	-0.250	0.803
SpatialFeatures[, 10]	0.1274221	0.8309479	0.153	0.878
SpatialFeatures[, 11]	-0.0415590	0.5812196	-0.072	0.943
SpatialFeatures[, 12]	0.2837621	0.6381664	0.445	0.657
SpatialFeatures[, 13]	-0.0502747	0.5399202	-0.093	0.926
SpatialFeatures[, 14]	0.9546484	0.6939404	1.376	0.169
SpatialFeatures[, 15]	0.4152727	0.6339386	0.655	0.512
SpatialFeatures[, 16]	0.8469551	0.5781594	1.465	0.143
SpatialFeatures[, 17]	0.0283579	0.7525846	0.038	0.970
SpatialFeatures[, 18]	0.0494055	0.8215509	0.060	0.952
SpatialFeatures[, 19]	0.5591974	0.9579389	0.584	0.559
SpatialFeatures[, 20]	-0.1740933	0.8850562	-0.197	0.844

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Pseudo R-squared: 0.4083

Coefficients (exponential spatial covariance):

de	ie	range
1.06403	0.09373	138.86010

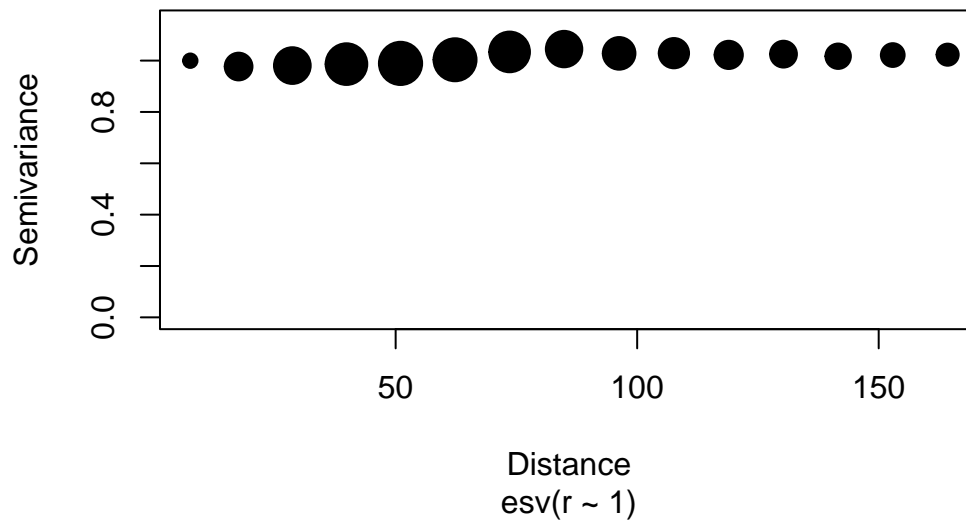
```
# obs.sp2 <- splm(CWSI ~ SLOPE+TWI+ASPECT+ECA_SHALLOW+NDVI+SpatialFeatures, data = obs,  
#               spcov_type = 'exponential', xcoord = POINT_X, ycoord = POINT_Y)  
# summary(obs.sp2)
```

## Validation

### Line Assumptions

```
std_and_decorr_resid <- rstandard(obs.sp)  
# Independence  
resids.sp <- data.frame(r=std_and_decorr_resid,  
                        x = obs$POINT_X,  
                        y = obs$POINT_Y)  
variogram_sp <- esv(r~1, data=resids.sp, xcoord=x, ycoord=y)  
plot(variogram_sp)
```

## Empirical Semivariogram

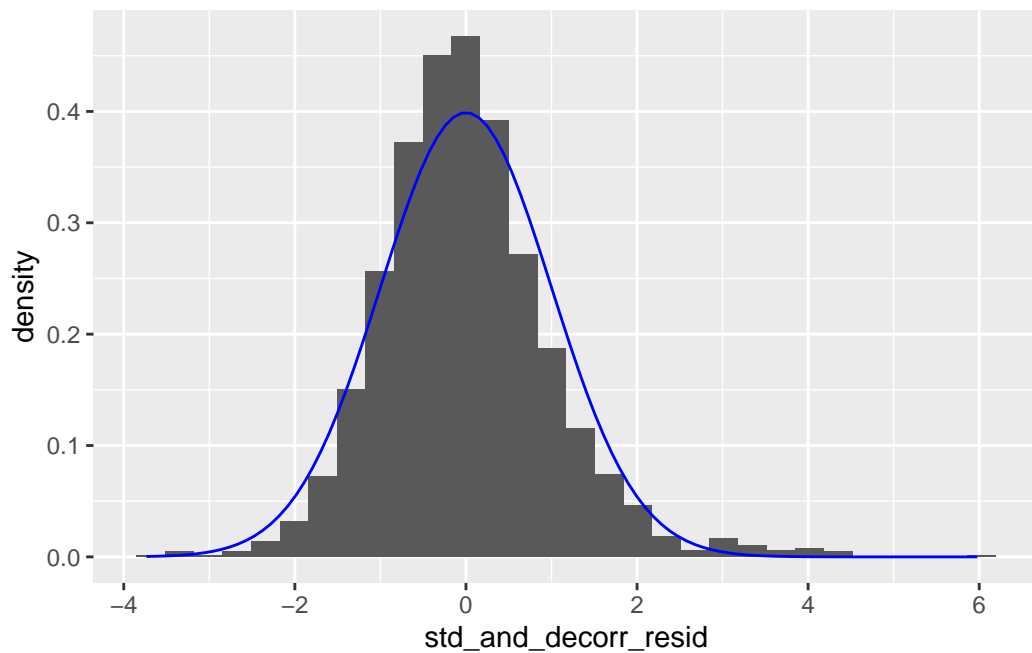


```
# Normality
ggplot() +
  geom_histogram(mapping = aes(x=std_and_decorr_resid, y=..density..)) +
  stat_function(fun = dnorm, color='blue')
```

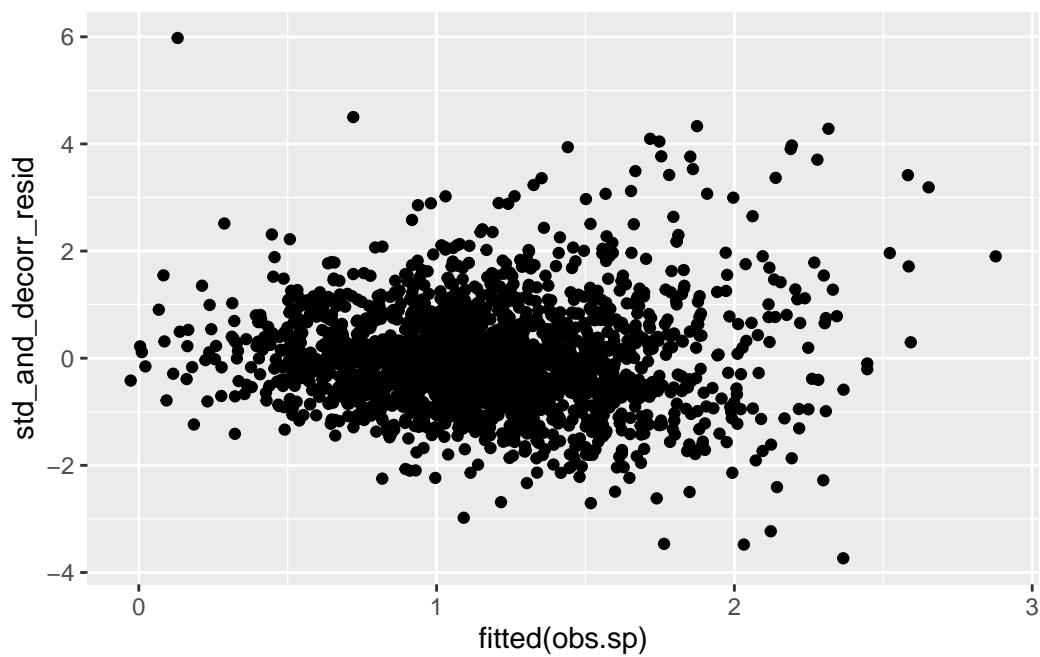
Warning: The dot-dot notation (`..density..`) was deprecated in ggplot2 3.4.0.  
i Please use `after_stat(density)` instead.

``stat_bin()`` using ``bins = 30``. Pick better value with ``binwidth``.





```
# Equal Variance  
ggplot() +  
  geom_point(mapping = aes(y=std_and_decorr_resid, x=fitted(obs.sp)))
```



## Cross Validation

```
cv_sp <- function(fold_num){
  ## Split into train-validation sets
  validationSet <- obs %>%
    filter(folds==fold_num)
  trainSet <- obs %>%
    filter(folds!=fold_num)

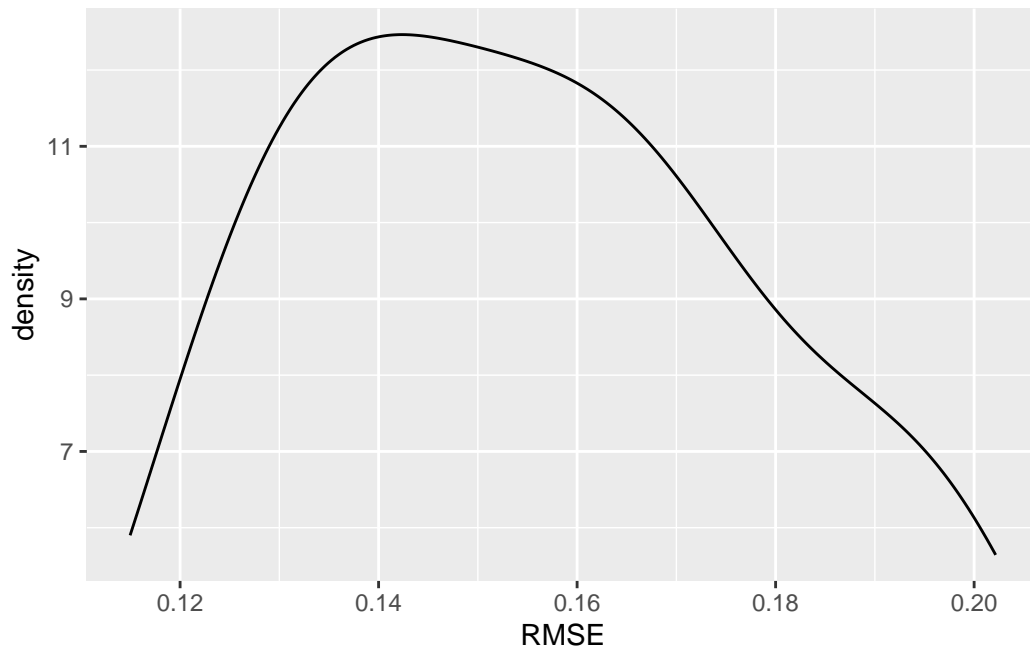
  # Ensure factors have at least two levels (drop unused levels)
  trainSet <- droplevels(trainSet)
  validationSet <- droplevels(validationSet)

  ## Fit a model and predict
  trainModel <- splm(CWSI~SLOPE+TWI+ASPECT+ECA_SHALLOW+NDVI+SpatialFeatures[,1]+SpatialFeatures[,2],
    xcoord=POINT_X, ycoord=POINT_Y, local=TRUE)
  preds <- predict(trainModel, newdata=validationSet)

  ## Validate the predictions
  rmse <- yardstick::rmse_vec(truth=validationSet$CWSI, estimate=preds)

  return(rmse)
}

K <- 20
folds <- rep(1:K, length = nrow(obs)) %>% #Rep K folds n times
  sample()
## CV for spatial linear model w/ spatial features
rmse_results_splm <- sapply(1:K, FUN=cv_sp) %>%
  unlist()
rmse_results <- data.frame(RMSE = rmse_results_splm)
ggplot(rmse_results, aes(x=RMSE)) +
  stat_density(geom="line",position="identity")
```



```
# average rmse across folds  
mean(rmse_results_splm)
```

```
[1] 0.1569842
```

```
# standard deviation (approximate error if we just predicted the mean for everything)  
sd(obs$CWSI) # about 4 times worse than our model
```

```
[1] 0.6007423
```

## R-Squared

```
pseudoR2(obs.sp)
```

```
[1] 0.4082934
```

## Save Model

```
saveRDS(obs.sp, 'PotatoModel.rds')
```

## Predict to New Locations

```
# Make obs loc matrix
new_loc_matrix <- matrix(data=cbind(new$POINT_X,new$POINT_Y), ncol=2)

## Number of Spatial Features
K <- 20

## "Centers" of Features
## cover.design() choose K centers spread out over spatial region
centers <- cover.design(new_loc_matrix, nd=K)$design

## Use 1.5 rule of thumb for scale
dist_between_centers <- rdist(centers)
the_scale <- 1.5*max(apply(dist_between_centers,1,function(x){sort(x)[2]}))

## Define spatial features
spatial_features <- local_basis(
  manifold=plane(),
  loc=centers,
  scale=rep(the_scale, K),
  type="bisquare" #or "Gaussian" or "exp"
)

## Mutate new spatial features in data frame
new <- new %>%
  mutate(SpatialFeatures=as.matrix(eval_basis(spatial_features, new_loc_matrix)))

# Read in model
sp_model <- readRDS('PotatoModel.rds')

# Save predictions
new$preds <- predict(sp_model, newdata = new)

# Plot predictions
```

```
new %>%  
  ggplot(aes(x=POINT_X,y=POINT_Y, color = preds)) +  
  geom_point() +  
  scale_color_viridis()
```

