Washington Wetland Soil Carbon

Anthony Stewart

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Introduction

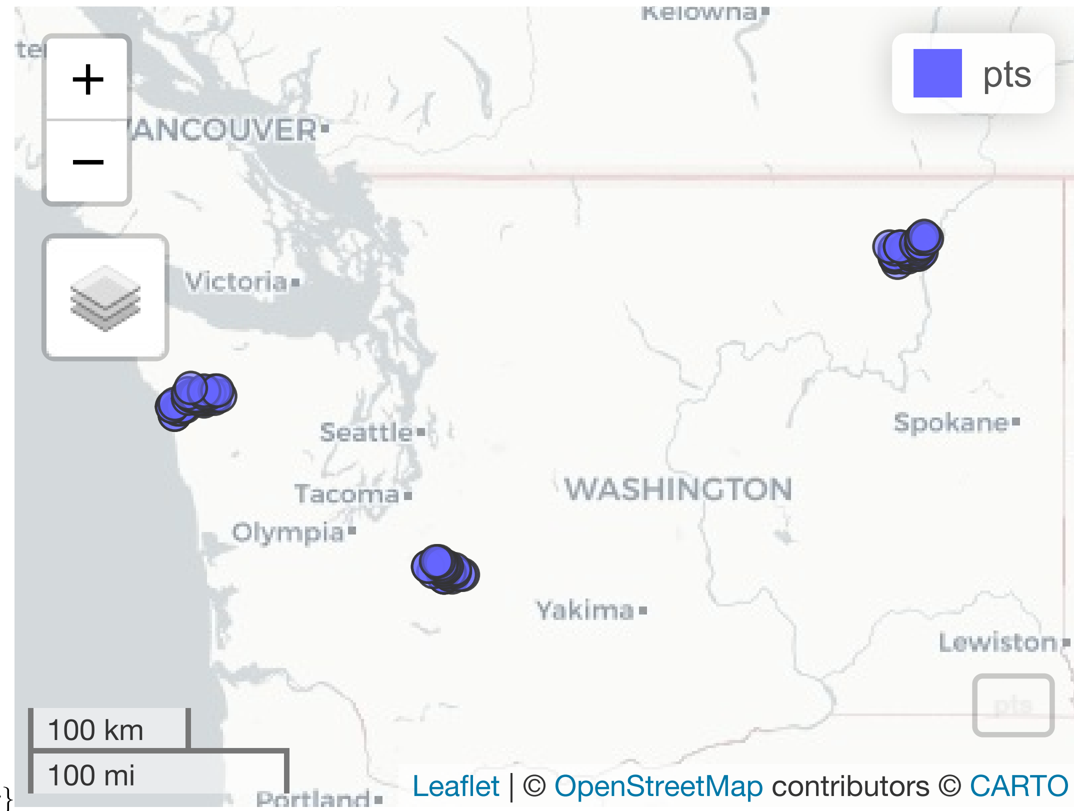
Freshwater wetlands contain greater than 30% of the total soil organic carbon (SOC) stock of 1,500-2,400 PgC but only cover approximately 6% of the land surface (Campbell et al., 2022; Poulter et al., 2021; Reis et al., 2017; Scharlemann et al., 2014; Zhang et al., 2021). However, wetland identification and wetland soil carbon mapping research overlooks more complex and finer spatial variations in water saturation and potential wetland formation due to their coarse resolution or utilization of inventory-based extrapolations (Bridgham et al., 2006; Gorham, 1991; Hugelius et al., 2020; Poggio et al., 2021; Zhang et al., 2021). Smaller aquatic ecosystems have been known to disproportionately contribute towards global carbon cycling and exist at a more manageable scale, but their extent is difficult to assess in a spatially explicit analysis (Holgerson and Raymond, 2016). This leaves a significant gap in understanding the spatial distribution of smaller freshwater WC ecosystems and SOC storage.

This project aims to develop a SOC mapping approach with a statistical model that leverages a continuous wetland identification metric to predict spatially explicit SOC. Our expected results from this mapping approach development would provide fine, spatially explicit estimates of SOC stocks that highlights wetland areas.

Methods

The data for this study were collected across three study areas in Washington State; the Hoh, Mashel, and Colville watersheds. Each study area represents a climate zone with the Hoh being the wettest, the Mashel being intermediate, and the Colville being the driest. Each study area is mapped with a wetland intrinsic probability (WIP) measurement, a heat loading index (HLI) measurement, enhanced vegetation index (EVI), lithology, and surficial geology. Across study areas, a total of 96 sample locations were used to collect measurements of SOC stocks. Statistical models were built for predicting SOC from the combination of WIP, HLI, EVI, and site fixed effects with interaction random effects of lithology and surficial geology. Lithology was chosen to be a nested random effect within surficial geology. Both effects are categorical variables and the distribution of SOC across the categories is assumed to follow a normal distribution that was not accounted for in the original sampling scheme.

```
pts <- st_as_sf(wa, coords = c("x.x", "y"), crs = "EPSG:26910")


mapView(pts)
```

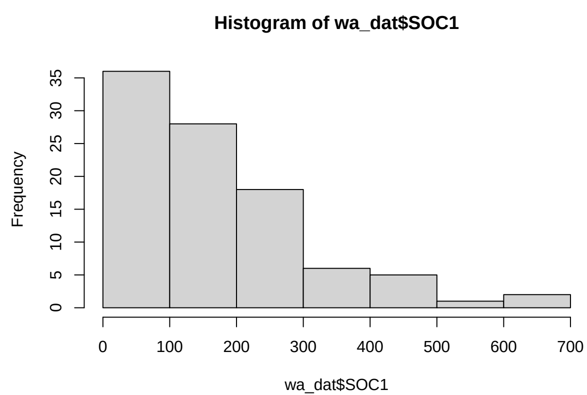


\begin{center}

../../../../../../../../../../private/var/folders/zl/0vy_zjm14sj4lycq01nznh0m0000gn/T/RtmpI6F9xb/file35021bbae2e1.png

```
## 'data.frame':    96 obs. of  25 variables:
##  $ site     : Factor w/ 3 levels "COL","HOH","MAS": 2 2 2 3 3 3 3 3 3 3 ...
##  $ name     : Factor w/ 96 levels "CC_S26_R3","CC_S27_R3",..: 51 52 53 64 72 76 77 78 79 81 ...
##  $ SOC30    : num  36 89.6 30.1 154.7 75.7 ...
##  $ SOC90    : num  36.5 125 34.4 235.9 124.7 ...
##  $ SOC1     : num  36.5 125 34.4 265.7 150.5 ...
##  $ SOC120   : num  36.5 125 34.4 271.9 162.9 ...
##  $ WIP      : num  0.03564 0.00429 0.08626 0.495 0.195 ...
```

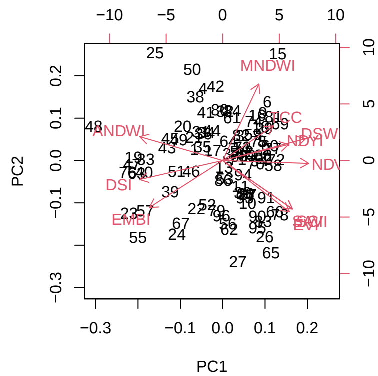
```
##  $ GEO_Label: Factor w/ 4 levels "Eocene","Pleistocene",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ geomorph : int  6 6 2 7 9 8 7 4 8 6 ...
##  $ x        : num  422318 423727 422264 567191 567209 ...
##  $ y        : num  5294791 5298102 5293455 5184714 5188124 ...
##  $ hli      : num  0.905 0.746 0.536 0.799 0.842 ...
##  $ LITHOL   : Factor w/ 18 levels "alluvium","alpine glacial drift, Fraser-age",..: 15 15 14 8 8 8 8
##  $ EVI      : num  0.382 0.574 0.491 0.408 0.456 ...
##  $ DSI      : num  0.52 0.301 0.34 0.408 0.373 ...
##  $ EMBI     : num  0.0988 -0.1251 -0.0587 -0.0606 -0.0183 ...
##  $ NDVI     : num  0.78 0.886 0.84 0.775 0.869 ...
##  $ SAVI     : num  0.394 0.549 0.484 0.407 0.447 ...
##  $ NDYI     : num  0.373 0.487 0.49 0.342 0.371 ...
##  $ SCI      : num  0.621 0.668 0.612 0.531 0.68 ...
##  $ DSWI1    : num  1.92 3.32 2.94 2.45 2.68 ...
##  $ ANDWI    : num  -0.657 -0.739 -0.709 -0.625 -0.717 ...
##  $ MNDWI    : num  -0.522 -0.456 -0.477 -0.431 -0.489 ...
##  $ TCC      : num  72 67 66 72 71 73 67 70 72 69 ...
##  $ TCC_fact : Factor w/ 4 levels "HFOR","LFOR",..: 1 3 3 1 1 1 3 1 1 3 ...
```

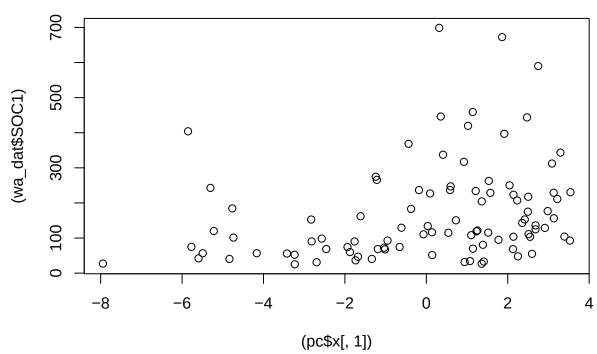



```
## Importance of components:
##                           PC1   PC2     PC3     PC4     PC5     PC6     PC7
## Standard deviation     2.6638 1.523 0.79233 0.69405 0.53615 0.33177 0.23611
## Proportion of Variance 0.6451 0.211 0.05707 0.04379 0.02613 0.01001 0.00507
## Cumulative Proportion  0.6451 0.856 0.91312 0.95691 0.98305 0.99305 0.99812
```

```
##                             PC8     PC9    PC10    PC11
## Standard deviation     0.10057 0.07415 0.05752 0.04172
## Proportion of Variance 0.00092 0.00050 0.00030 0.00016
## Cumulative Proportion  0.99904 0.99954 0.99984 1.00000
```

```
## [1] 0.005864229
```



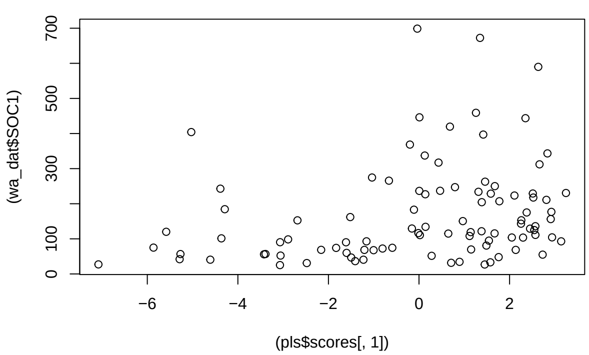


Partial Least Squares Regression

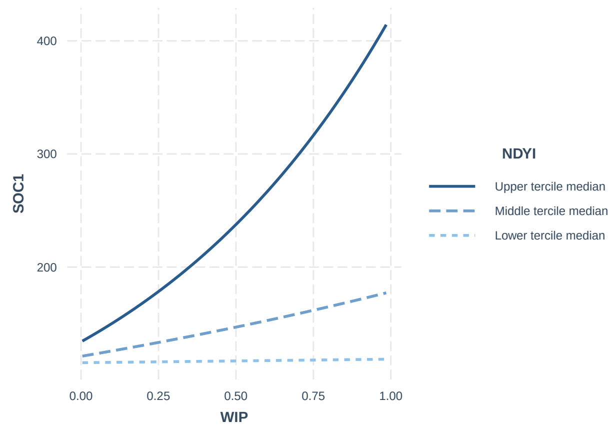
```
## Data:    X dimension: 96 10
##  Y dimension: 96 1
## Fit method: kernelpls
## Number of components considered: 10
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
```

```
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           140.2    138.7    141.6    133.4    132.5    128.7    125.6
## adjCV        140.2    138.5    140.4    133.2    132.2    128.1    124.9
##        7 comps  8 comps  9 comps  10 comps
## CV       126.9    130.2    128.5     128.3
## adjCV    126.3    129.1    127.6     127.4
##
## TRAINING: % variance explained
##          1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X         65.492    76.05    92.48    96.56    98.42     98.8    99.88    99.91
## (SOC1)     6.757    13.69    17.53    24.73    30.87     33.4    33.59    35.64
##          9 comps  10 comps
## X          99.94    100.00
## (SOC1)     35.66     35.66
```

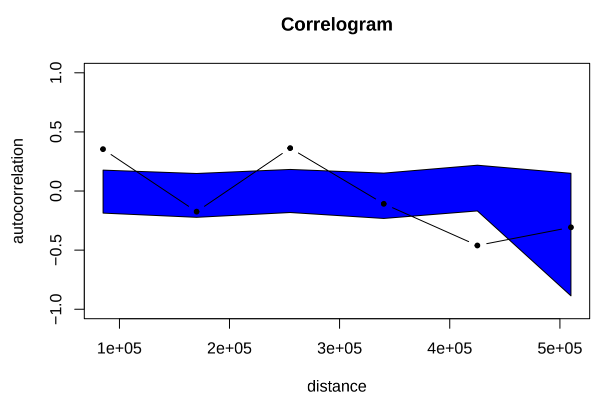
```
## [1] 0.2599492
```



Interactions



A check for spatial autocorrelation was conducted using correlograms. These did not reveal much spatial structure to the data across and within study areas except for somewhat in the Mashel. But this was considered negligiable.




```
## $autocorrelation
##    autocorrelation dist        lci       uci
## 1       0.32447750 1000 -0.3702638 0.3656408
## 2       0.36928335 2000 -0.3648403 0.2668340
## 3      -0.13969181 3000 -0.3457113 0.3660227
## 4       0.22134410 4000 -0.3869469 0.4099802
## 5      -0.05708800 5000 -0.4181067 0.3678535
## 6      -0.04344192 6000 -0.3988188 0.3049645
## 7      -0.20692642 7000 -0.4004986 0.2721512
## 8      -0.03506136 8000 -0.3925708 0.2889516
## 9      -0.29577486 9000 -0.4075357 0.3026277
```

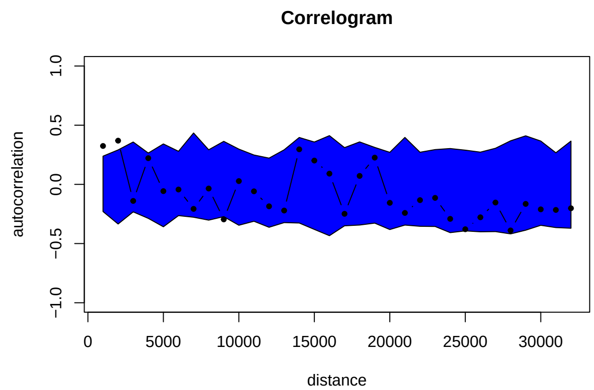
```
## 10      0.02775145 10000 -0.3555122 0.2937552
## 11     -0.05860456 11000 -0.3539044 0.2714021
## 12     -0.18535280 12000 -0.3436176 0.3964200
## 13     -0.22098324 13000 -0.3813043 0.2707042
## 14      0.29612241 14000 -0.3272363 0.3123336
## 15      0.20115122 15000 -0.3433506 0.3586963
## 16      0.09066884 16000 -0.3500087 0.3103800
## 17     -0.24867663 17000 -0.4332538 0.4114990
## 18      0.07154579 18000 -0.3801797 0.3577088
## 19      0.22605447 19000 -0.3263229 0.3959482
## 20     -0.15589476 20000 -0.3229289 0.2918901
## 21     -0.24123601 21000 -0.3622144 0.2217713
## 22     -0.13303190 22000 -0.3115172 0.2480565
## 23     -0.11406462 23000 -0.3451537 0.2977842
## 24     -0.29129042 24000 -0.2724818 0.3633329
## 25     -0.37897741 25000 -0.3020793 0.2920965
## 26     -0.27815734 26000 -0.2774164 0.4340368
## 27     -0.15334133 27000 -0.2638252 0.2793193
## 28     -0.38907134 28000 -0.3581254 0.3414675
## 29     -0.16490755 29000 -0.2870622 0.2645743
## 30     -0.21099523 30000 -0.2320622 0.3578013
## 31     -0.21572215 31000 -0.3346260 0.2910014
## 32     -0.20172812 32000 -0.2292894 0.2382352
##
## $CorrPlot
```

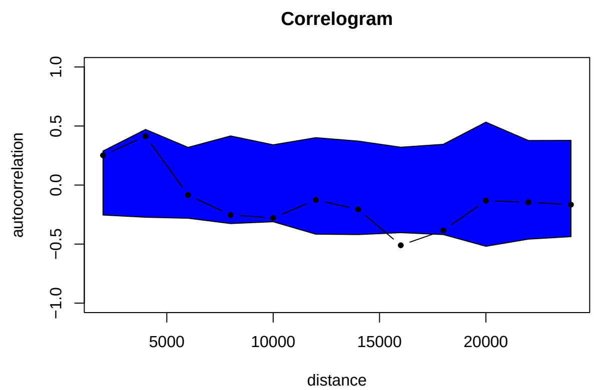
```
## $autocorrelation
##    autocorrelation  dist        lci       uci
## 1        0.2514957  2000 -0.4369071 0.3783490
## 2        0.4137116  4000 -0.4579040 0.3772237
## 3       -0.0846446  6000 -0.5185568 0.5326174
## 4       -0.2529130  8000 -0.4192665 0.3450790
## 5       -0.2784204 10000 -0.4031350 0.3202449
```

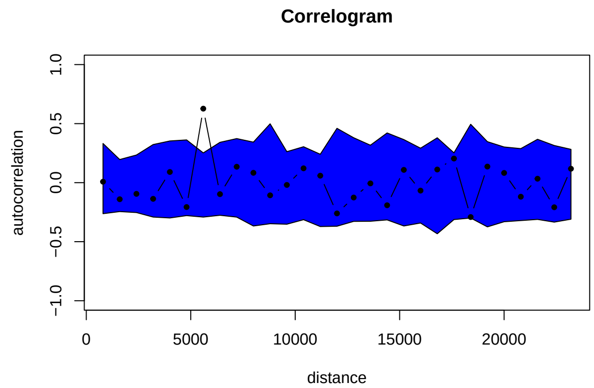
```
## 6       -0.1259811 12000 -0.4191827 0.3723027
## 7       -0.2061018 14000 -0.4157094 0.4012139
## 8       -0.5101568 16000 -0.3106349 0.3408753
## 9       -0.3848336 18000 -0.3260376 0.4158152
## 10      -0.1320485 20000 -0.2809889 0.3189734
## 11      -0.1461977 22000 -0.2724788 0.4707378
## 12      -0.1661551 24000 -0.2537367 0.2879581
##
## $CorrPlot
```

```
## $autocorrelation
##    autocorrelation  dist        lci       uci
## 1      0.007970326   800 -0.3092369 0.2820913
## 2     -0.140317973  1600 -0.3339292 0.3145645
## 3     -0.094726476  2400 -0.3109988 0.3671654
## 4     -0.136902288  3200 -0.3208491 0.2883156
## 5      0.090599657  4000 -0.3306711 0.3020756
## 6     -0.206668362  4800 -0.3741889 0.3469951
## 7      0.626802150  5600 -0.2990999 0.4942243
## 8     -0.097255099  6400 -0.3123637 0.2523778
## 9      0.134727510  7200 -0.4325286 0.3796894
## 10     0.083424085  8000 -0.3414559 0.2917955
## 11    -0.107097253  8800 -0.3666773 0.3646725
## 12    -0.019326411  9600 -0.3150958 0.4208970
## 13     0.121535221 10400 -0.3266067 0.3170297
## 14     0.059132293 11200 -0.3277475 0.3801648
## 15    -0.260435593 12000 -0.3686875 0.4599613
## 16    -0.125818484 12800 -0.3714740 0.2404872
## 17    -0.006268772 13600 -0.3133995 0.3041138
## 18    -0.191431072 14400 -0.3516131 0.2623864
## 19     0.108414044 15200 -0.3475740 0.4982833
## 20    -0.067295354 16000 -0.3667317 0.3431119
## 21     0.111417738 16800 -0.2914929 0.3730800
```

```
## 22      0.204203184 17600 -0.2760851 0.3415354
## 23     -0.291287015 18400 -0.2912793 0.2519646
## 24      0.136266821 19200 -0.2789057 0.3619131
## 25      0.082431540 20000 -0.2987094 0.3529745
## 26     -0.118997209 20800 -0.2912523 0.3227159
## 27      0.033330809 21600 -0.2528185 0.2339560
## 28     -0.208304777 22400 -0.2447670 0.1957634
## 29      0.117926052 23200 -0.2624638 0.3316318
##
## $CorrPlot
```







Model selection: Generalized linear mixed effects models with the Gamma distirbution

Since the goal of the analysis is to improve SOC mapping with wetland inclusion, the model selection needs to determine which of the hypothesized predictors creates the best model. Generalized linear mixed effects models were initially built from a global model with all potential fixed effects then filtered down progressively in order to identify the best model with Akaike's Information Criterion (AIC).

The potential fixed effects also includes an interaction term between WIP and a spectral metric, the normalized difference yellow index (NDYI) which was hypothesized to indicate water stressed vegetation and therefore higher accumulation of SOC. The interaction with the WIP metric would hypothetically relate the combination of high WIP values and high NYDI to high SOC.

The gamma distribution with a log-link function was used after investigating the shape of the histogram for the SOC response variable

Results

Model selection favored the model with WIP and HLI but not site or EVI. However, the delta AIC was <2 between the lowest and 2nd lowest AICs, which is a threshold for deciding on keeping model effects. The best two models according to AIC were evaluated using the Chi Square test in an ANOVA. The ANOVA showed that there is a negligiable difference between the two models, or that resulting deviance is not more extreme indicating support for the simpler model without site effects.

```
## Data: wa_dat
## Models:
```

AIC	formula	name	delta
1107.79	WIP + NDYI + (1 + WIP | LITHOL)	wa_gmod1	1.56
1109.58	WIP + pca + (1 + WIP | LITHOL)	wa_gmod2	3.35
1111.3	WIP + (1 + WIP:NDYI | LITHOL)	wa_gmod3	5.07
1110.4	TCC + (1 + WIP | LITHOL)	wa_gmod4	4.17
1109.29	WIP + (1 + WIP | LITHOL)	wa_gmod5	3.06
1106.23	WIP:NDYI + (1 + WIP | LITHOL)	wa_gmod6	0.00
1109.94	WIP:NDYI + site + (1 + WIP | LITHOL)	wa_gmod7	3.71
1116.77	site + NDYI + pca + (1 + WIP | LITHOL)	wa_gmod8	10.54
1114.46	1 + (1 + WIP | LITHOL)	wa_gmod9	8.23
1114.46	1 + (1 + WIP | LITHOL)	wa_gmod10	8.23
1114.46	1 + (1 + WIP | LITHOL)	wa_gmod11	8.23
1108.05	WIP:NDYI + pca + (1 + WIP | LITHOL)	wa_gmod12	1.82
1109.14	WIP:NDYI + GEO_Label + (1 + WIP | LITHOL)	wa_gmod13	2.91
1106.23	WIP:NDYI + (1 + WIP | LITHOL)	wa_gmod14	0.00
1114.46	1 + (1 + WIP | LITHOL)	wa_gmod15	8.23

```
## wa_gmod14: (SOC1) ~ WIP:NDYI + (1 + WIP | LITHOL)
## wa_gmod1: (SOC1) ~ WIP + NDYI + (1 + WIP | LITHOL)
##           npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## wa_gmod14    6 1106.2 1121.6 -547.12   1094.2
## wa_gmod1     7 1107.8 1125.7 -546.90   1093.8 0.4383  1     0.5079
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: Gamma  ( log )
## Formula: (SOC1) ~ WIP:NDYI + (1 + WIP | LITHOL)
##    Data: wa_dat
##
##      AIC      BIC   logLik deviance df.resid
##   1106.2   1121.6   -547.1   1094.2       90
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.3595 -0.6760 -0.1037  0.4622  4.5267
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  LITHOL   (Intercept) 0.2705   0.5201
```

```
##           WIP         0.4144   0.6437   -0.67
##  Residual             0.2990   0.5468
## Number of obs: 96, groups:  LITHOL, 18
##
## Fixed effects:
##             Estimate Std. Error t value Pr(>|z|)
## (Intercept)   4.3852     0.1990  22.031  < 2e-16 ***
## WIP:NDYI      2.6256     0.6982   3.761 0.000169 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr)
## WIP:NDYI -0.621
```

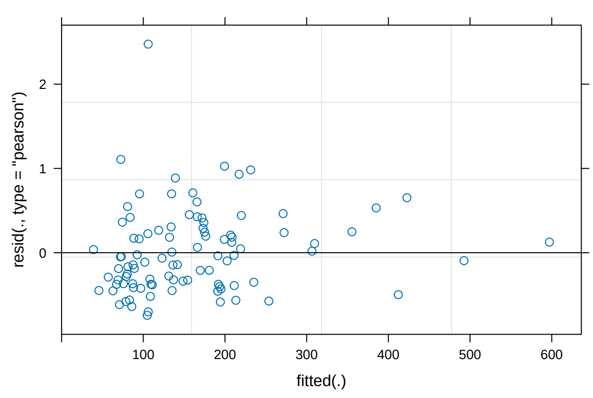
The `pchisq` function showed the gamma distribution was a close match to our fitted model and was a good choice for the family within the GLMER.

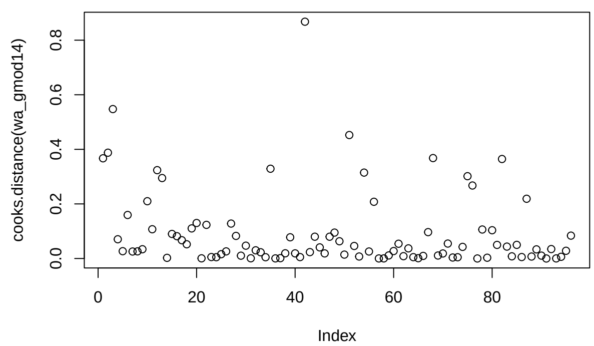
```
## [1] 21.58206
```

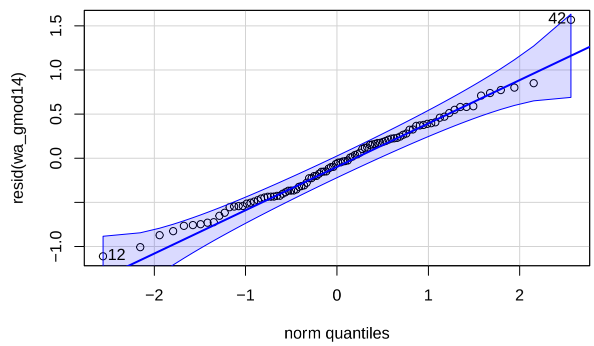
```
## Warning in hatvalues.merMod(model): the hat matrix may not make sense for GLMMs
```

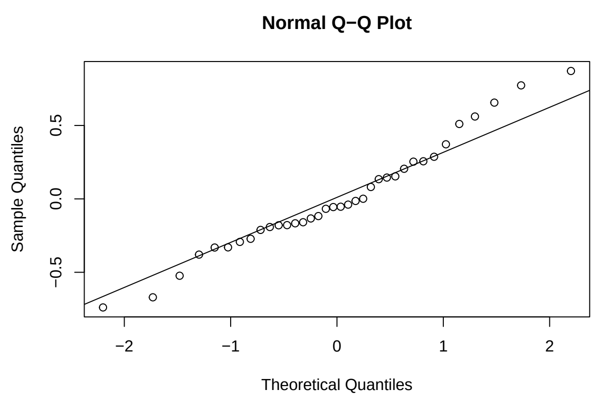
```
## [1] 42 12
```

```
## [1] 1
```

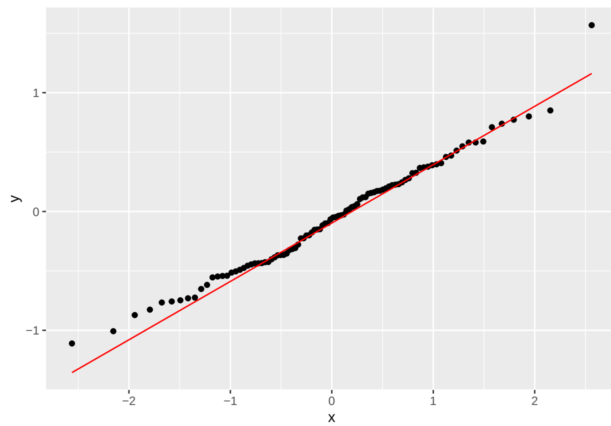


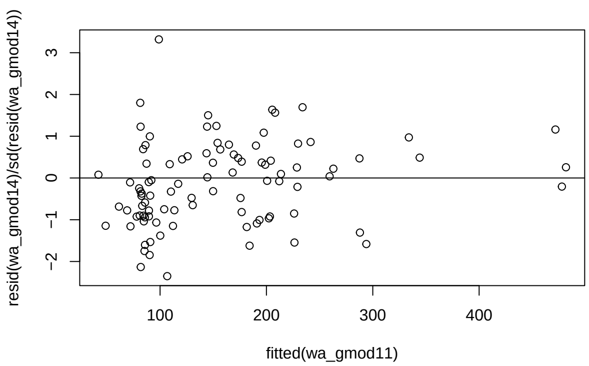






Diagnostics of the top two models showed that there was minimal amount of residual structure but maybe a slight bit of right skew. However, the DHARMa package was used to simulate residuals and showed a quite a bit of skew in the residuals. But this package contains some uncertainty as to the underlying methods for calculating the goodness of fit for GLMER Gamma models.





Overall model fit estimations showed that the there was a root mean square error of 93.53055 and an R^2 of 0.55.

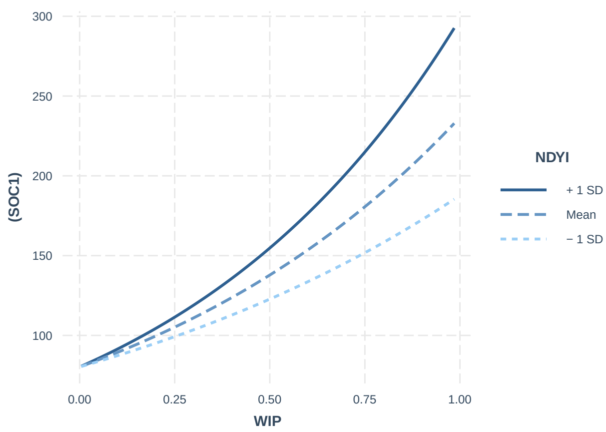
```
## [1] "model RMSE"

## [1] 82.15152

## [1] "model R^2"

## [1] 0.6493373

## [1] 597.1515
```

Confidence intervals based on bootstrapping showed that our fixed effect parameters of site and HLI straddled 0 in the 90% range, indicating they may not be significant predictors. The WIP was a significant predictor according to these confidence intervals. However, bootstrapping was very limited with GLMER and there

	5 %	95 %
.sig01	0.0000000	1.398258
.sig02	-1.0000000	1.000000
.sig03	0.0000014	2.057265
.sigma	1.0653527	1.572256
(Intercept)	3.6489909	4.987887
WIP:NDYI	0.0957579	5.125224

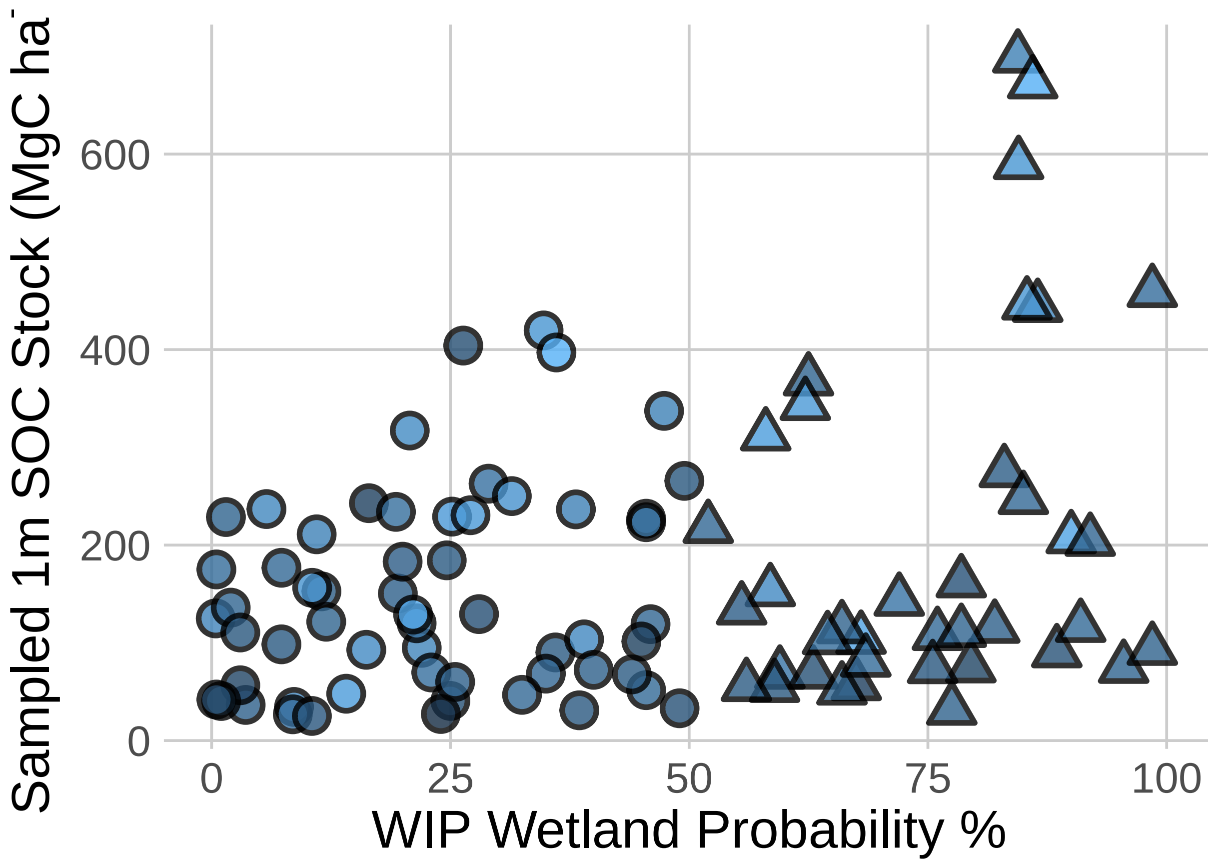
were >50% warnings that there was a singluar fit for the model and ~10% of the model runs failed to converge completely.

```
## Warning in predictInterval(wa_gmod14, which = c("full"), level = 0.9, n.sims =
## 1000, : Prediction for NLMMs or GLMMs that are not mixed binomial regressions
## is not tested. Sigma set at 1.
```

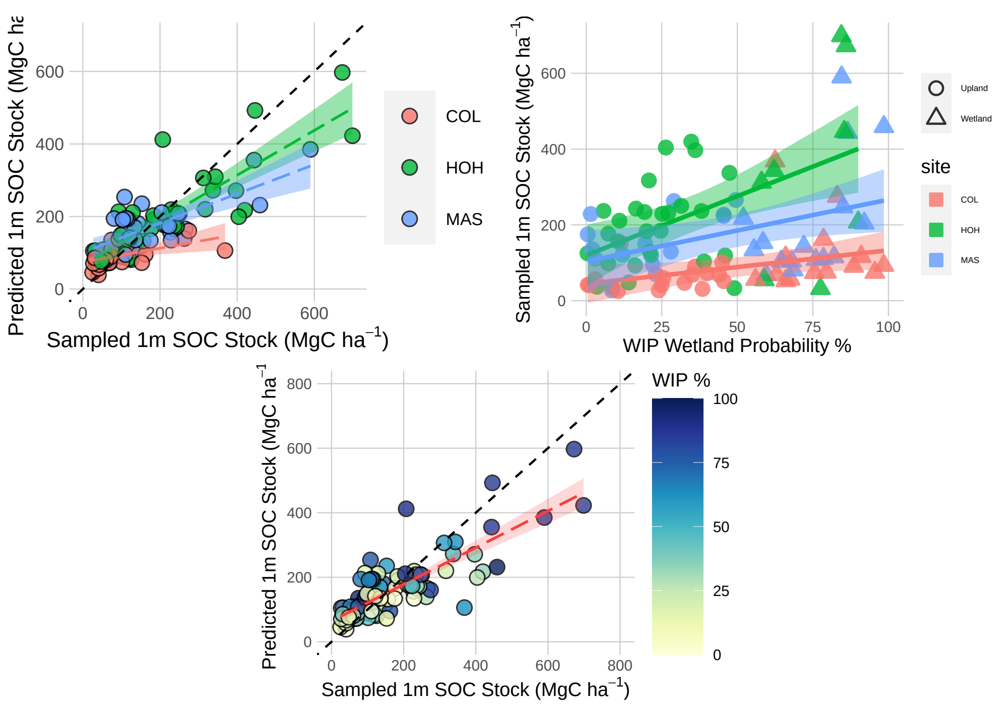


Plotting the WIP probability with the SOC stocks colored by site shows there are some patterns in the data with Colville being a lower SOC range than the Hoh or Mashel. However there is still overlap between sites.

fit	upr	lwr
81.46867	465.1454	13.789552
80.13743	512.2913	13.981758
60.53709	362.3348	10.036386
133.43168	787.0321	25.419069
115.72077	669.7850	19.482820
298.74989	1640.5629	54.083364
114.51209	716.0495	18.101934
194.38920	1087.9152	32.752465
279.38107	1487.2582	52.900514
119.28605	663.8942	21.898605
200.06584	1174.4247	32.529410
103.16735	569.1759	17.668456
162.81225	986.1888	25.016689
76.49636	439.6869	12.992460
178.04754	1031.4875	28.872158
116.32165	679.0890	19.798416
110.51294	682.7222	17.758965
187.38577	1061.3410	34.330553
73.00723	387.4832	12.357940
113.20018	641.5076	18.104401
102.26430	605.1776	16.063577
109.42497	651.5268	20.066024
101.42136	553.2882	19.204626
123.32745	667.4977	22.626985
104.44907	566.5303	14.892334
89.33887	629.1398	16.032457
124.00679	702.9986	20.958754
94.63158	520.2252	15.524551
102.59100	544.2858	18.031145
93.55655	552.4370	17.543955
40.90977	225.2085	7.604235
66.92468	369.6749	11.066554
53.16477	297.1340	10.475955
55.02536	298.3844	9.147846
80.84922	465.3440	15.813884
53.86208	294.8580	9.695555
70.35121	438.0446	12.253792
55.14007	296.0093	8.941639
40.53702	253.0866	7.274611
48.09839	253.8835	8.253294
95.83654	515.8388	16.613123
118.09116	691.8318	21.877961
114.48281	647.9620	20.551469
177.14741	1065.8226	29.198860
136.36781	703.3384	23.924119
140.34947	762.7763	27.798717
72.53188	390.3176	12.097527
76.69042	397.2447	13.092253
90.35759	530.4750	17.459767
88.16580	570.0089	15.232766
73.50531	437.6994	13.952960
182.53770	1047.2302	34.720823
181.28942	999.1836	29.651869
69.58248	442.1943	12.768744
196.03231	971.5302	35.227852
440.60528	2369.4158	77.420801
200.41075	1086.0933	38.515922
215.35547	1074.4413	40.974373



The predicted vs. actual plot of SOC values shows that there is an underestimation of high wetland SOC stocks.



Discussion

The choice of a GLMER vs. a LMER preserved interpretation of the response variable and relaxed the restrictions needed to meet the normally distributed errors and independence. The data also fit the Gamma distribution well and allows for easy prediction to the response units using the log-link function. The goal of this study was to evaluate a prediction model that included WIP probability and this can be evaluated by making spatial predictions across the three study areas using the GLMER with response units.

The top two models from the GLMER model selection according to AIC represent a stark difference in potential inference but with very little effect on the overall prediction. Including the site fixed effect in the model was not strongly supported with AIC but was within the 2 delta AIC threshold for model differences. By including site, some inference can be made towards the size of the effect of region and climate on SOC stocks and compared to the WIP probability. However, the range of the confidence intervals seems to span 0 which indicates lack of significance for the site parameter. Again, using both models in spatial prediction could better evaluate potential model performance.

For all models, there was still a high amount of under-prediction on the high end of SOC stocks especially in wetlands. Further investigation of additional geologic and lithologic factors did not reveal large improvements in the upper range of SOC stock values. Further landforms derived from lidar digital elevation models could improve predictions but there is uncertainty in how they would be included in the model structure. Likely, improvement may need to come from the search for another fixed effect that can explain the higher range of SOC stocks related to biomass productivity and/or SOC accumulation more directly.

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