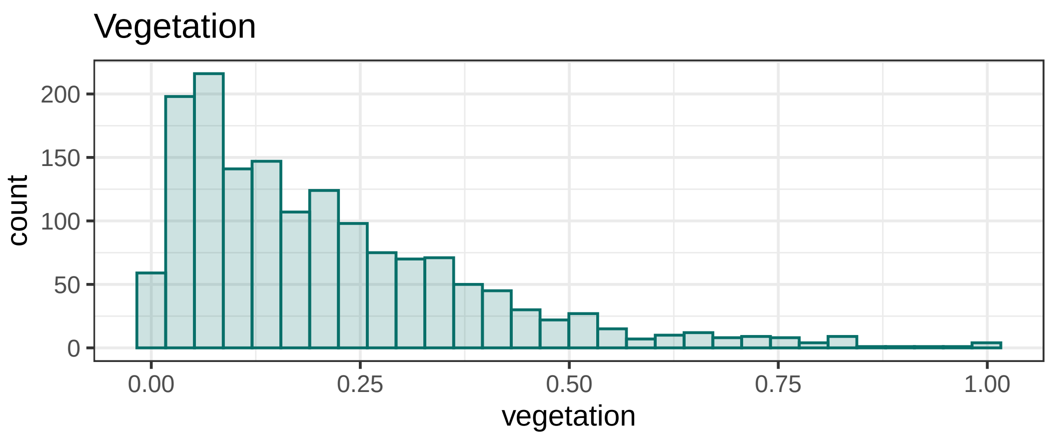
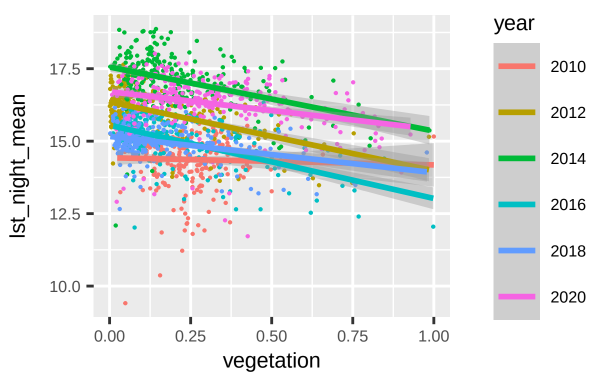
LawnProject Panel Data Analysis / Tensor Flow Data

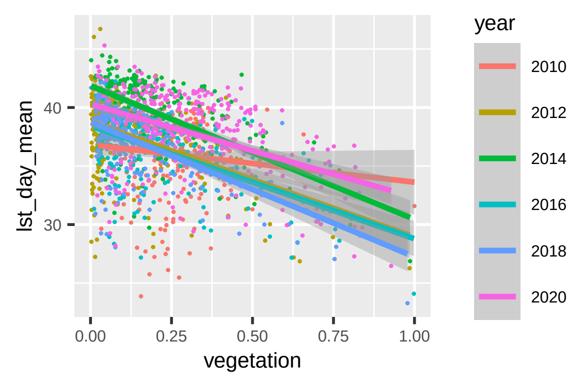
LawnProject Team

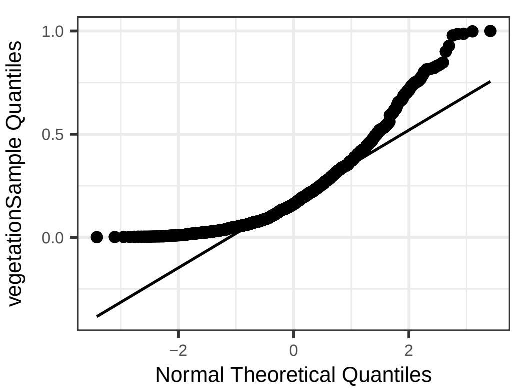
Intro

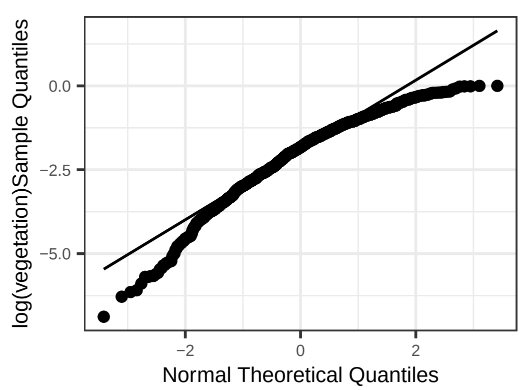
Aggregate Vegetation Area (Trees + Lawn)

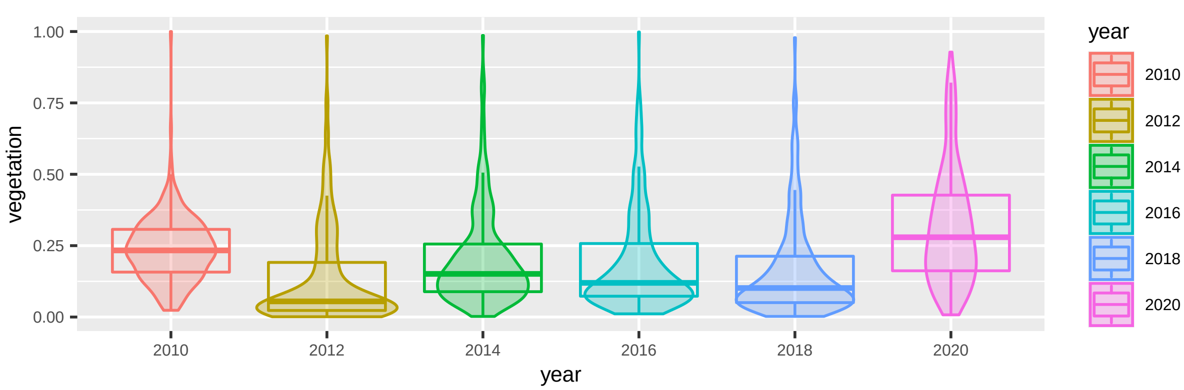




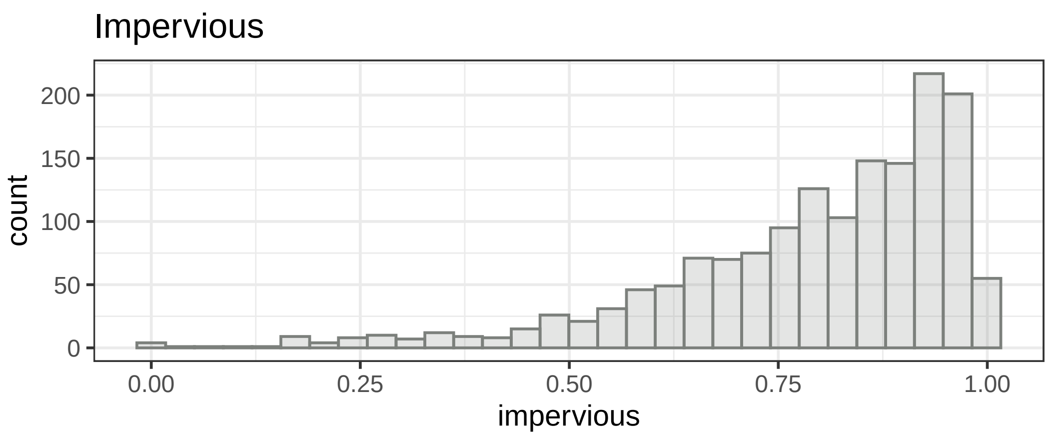


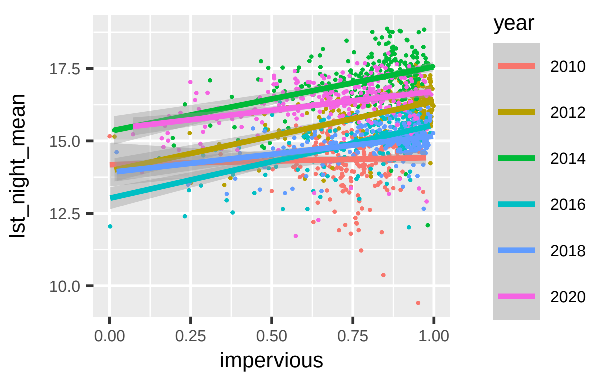


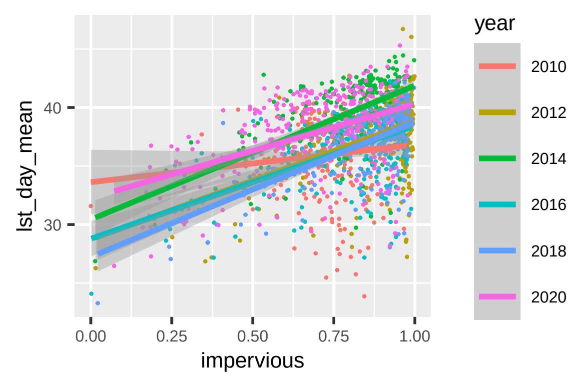


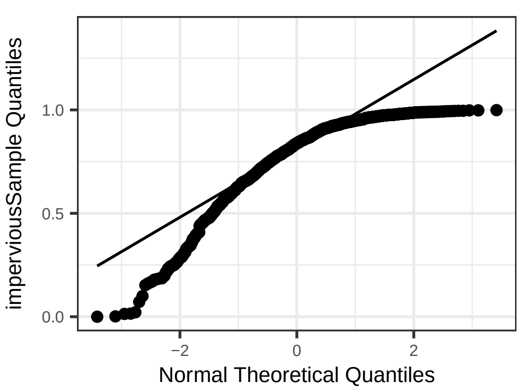


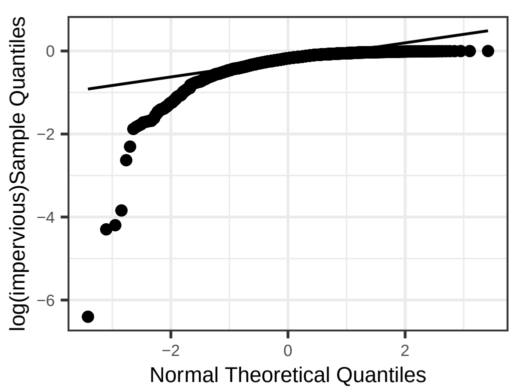
Aggregate Impervious Area (Soil + Turf + Impervious)

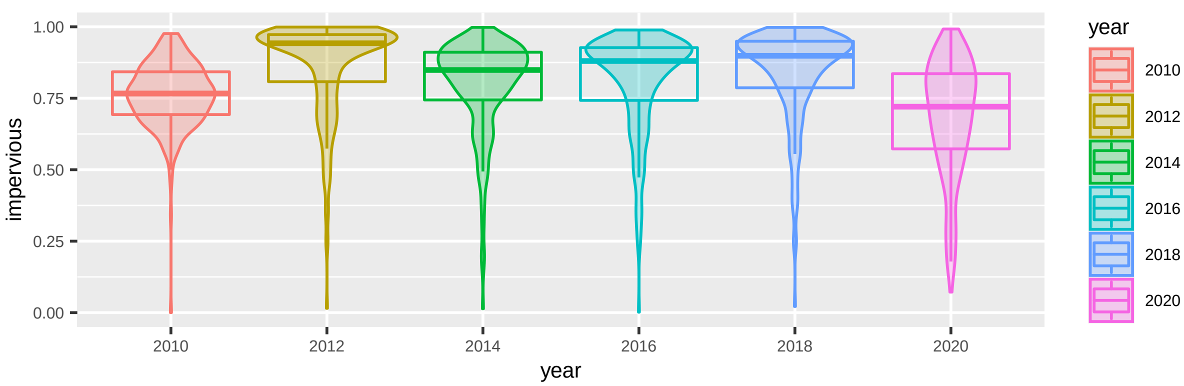




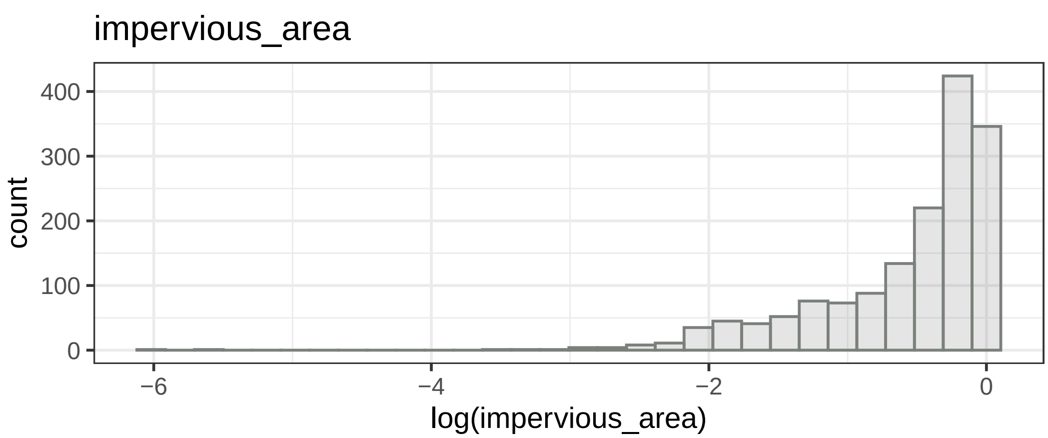


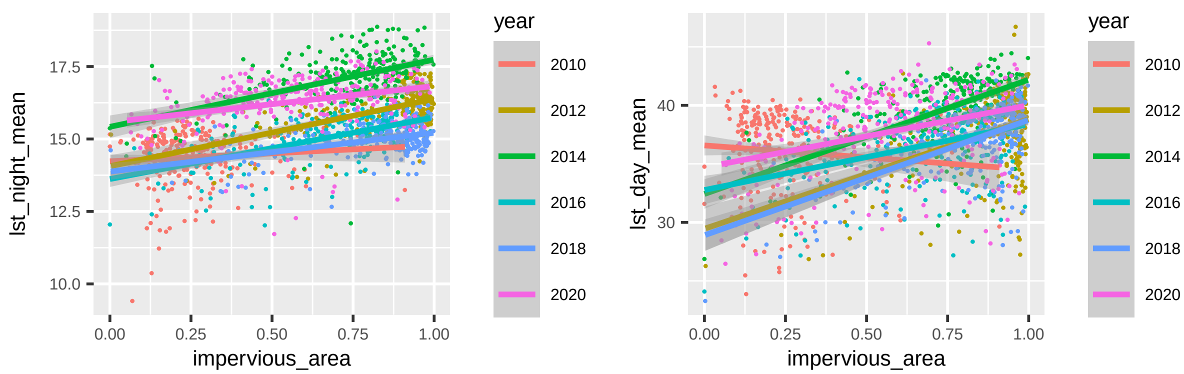


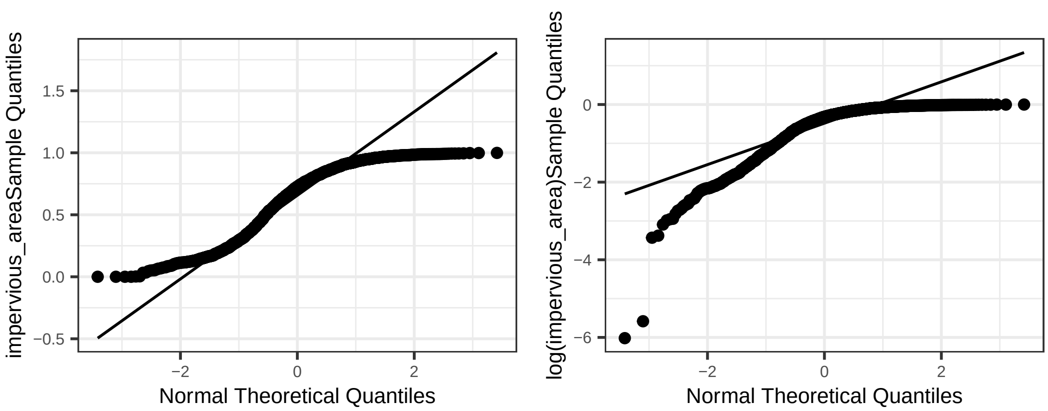


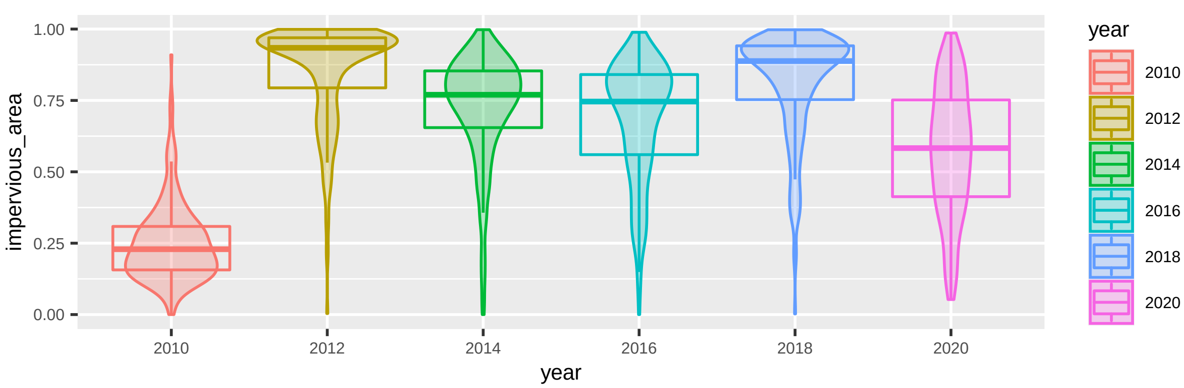


Impervious Area

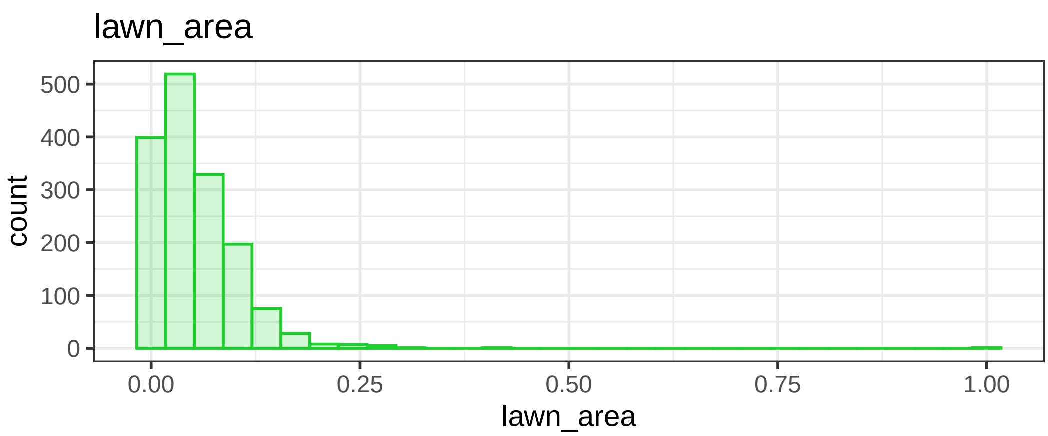


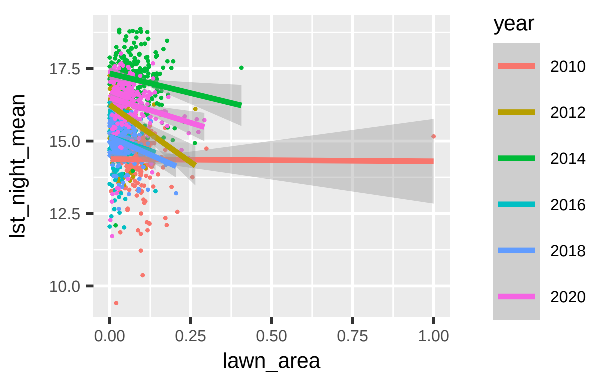


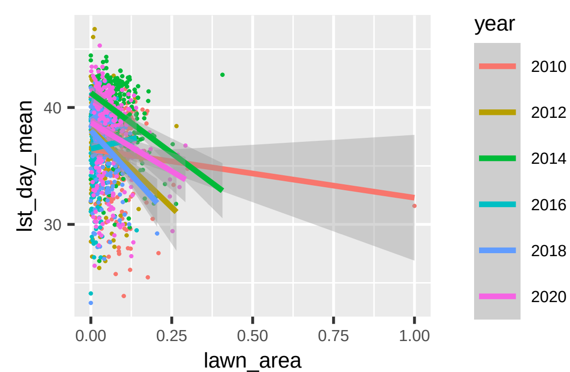


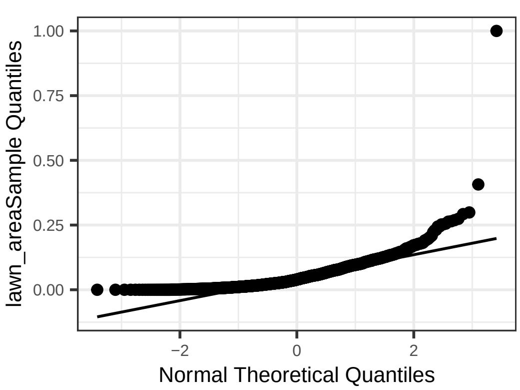


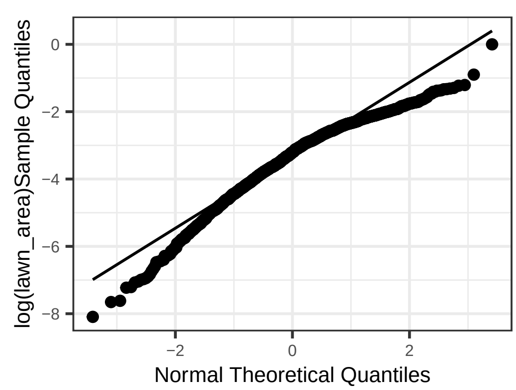
Lawn Area

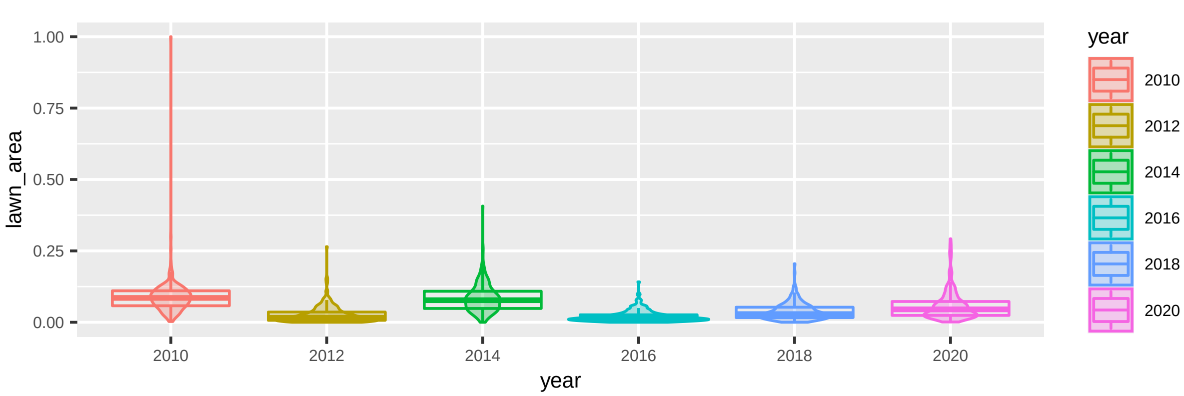

lawn_area
count
500
400
300
200
100
0
0.00
0.25
0.50
0.75
1.00
lawn_area


lst_night_mean
17.5
15.0
12.5
10.0
0.00
0.25
0.50
0.75
1.00
lawn_area
year
2010
2012
2014
2016
2018
2020

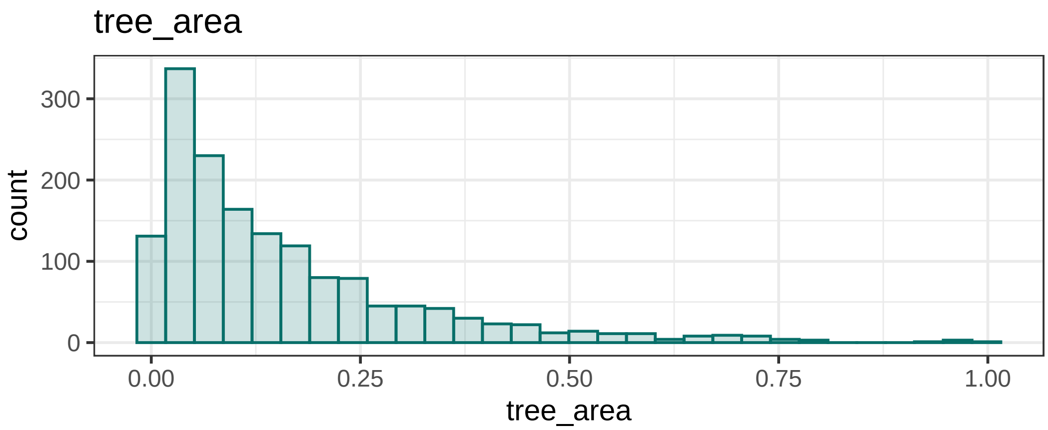

lst_day_mean
40
30
0.00
0.25
0.50
0.75
1.00
lawn_area
year
2010
2012
2014
2016
2018
2020

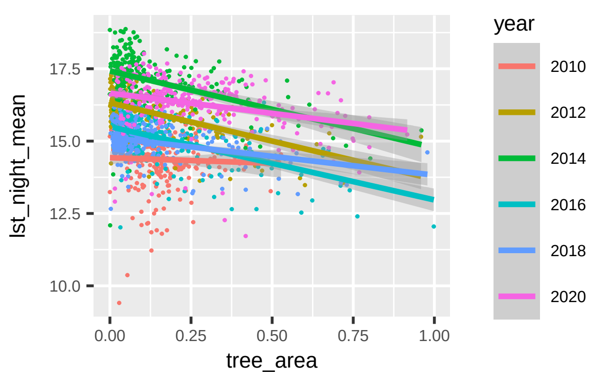

lawn_areaSample Quantiles
1.00
0.75
0.50
0.25
0.00
−2
0
2
Normal Theoretical Quantiles

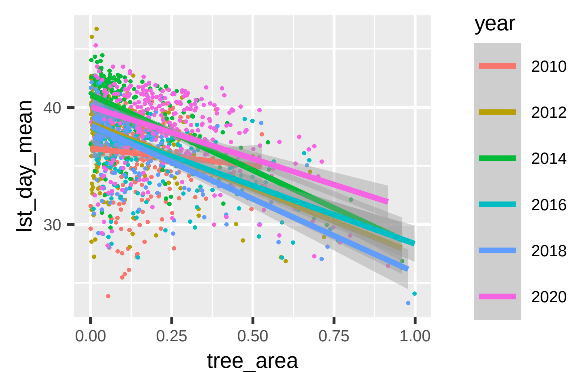

log(lawn_area)Sample Quantiles
0
−2
−4
−6
−8
−2
0
2
Normal Theoretical Quantiles

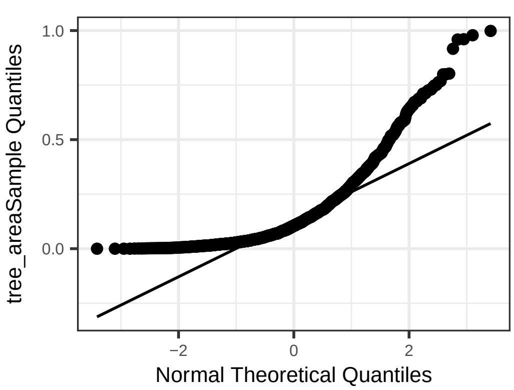

lawn_area
1.00
0.75
0.50
0.25
0.00
2010
2012
2014
2016
2018
2020
year
year
2010
2012
2014
2016
2018
2020

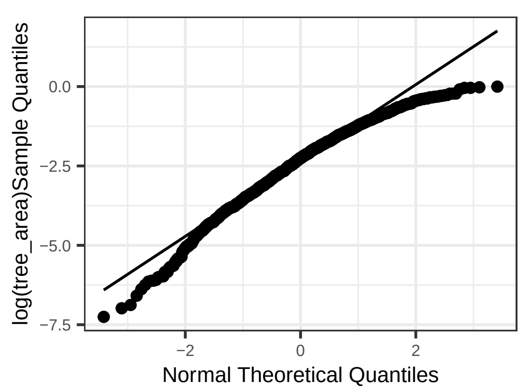
Tree Area

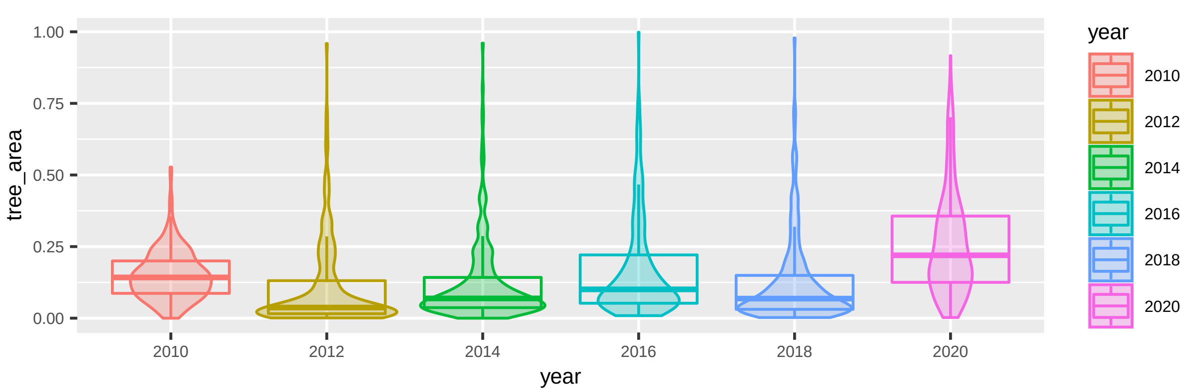

tree_area
count
300
200
100
0
0.00
0.25
0.50
0.75
1.00
tree_area


lst_night_mean
17.5
15.0
12.5
10.0
0.00
0.25
0.50
0.75
1.00
tree_area
year
2010
2012
2014
2016
2018
2020

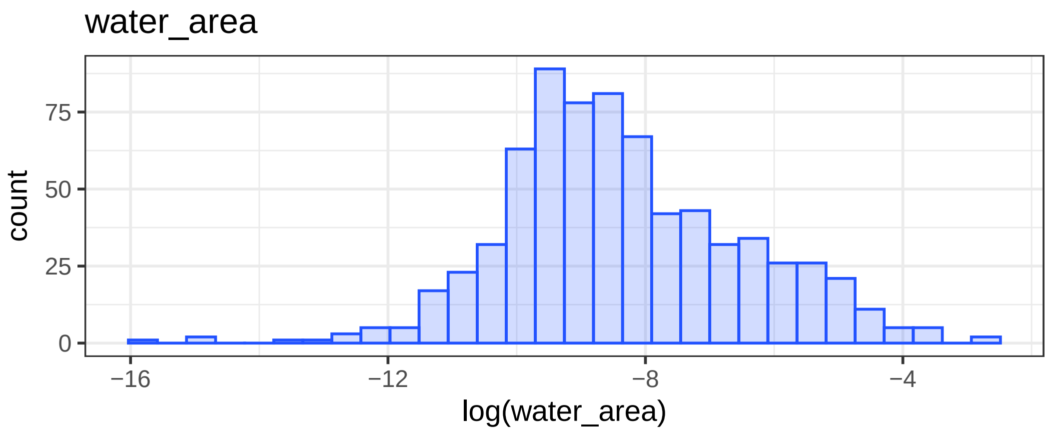

lst_day_mean
40
30
0.00
0.25
0.50
0.75
1.00
tree_area
year
2010
2012
2014
2016
2018
2020

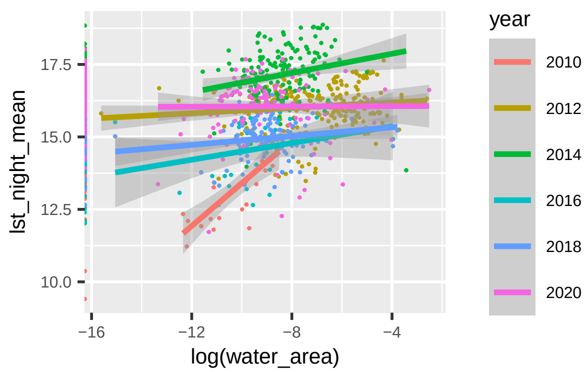

tree_areaSample Quantiles
1.0
0.5
0.0
−2
0
2
Normal Theoretical Quantiles

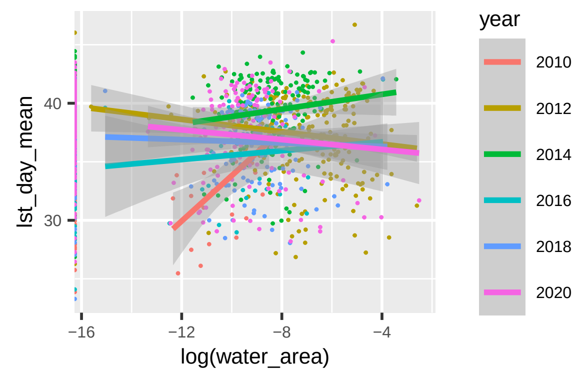

log(tree_area)Sample Quantiles
0.0
−2.5
−5.0
−7.5
−2
0
2
Normal Theoretical Quantiles

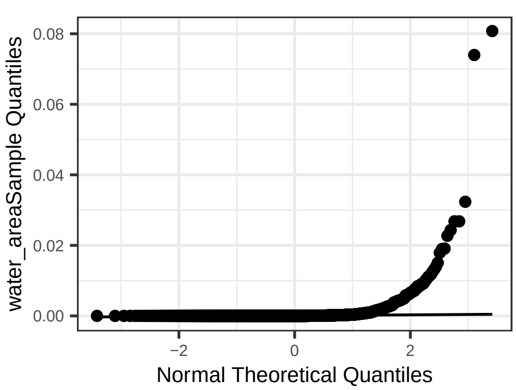

tree_area
1.00
0.75
0.50
0.25
0.00
2010
2012
2014
2016
2018
2020
year
year
2010
2012
2014
2016
2018
2020

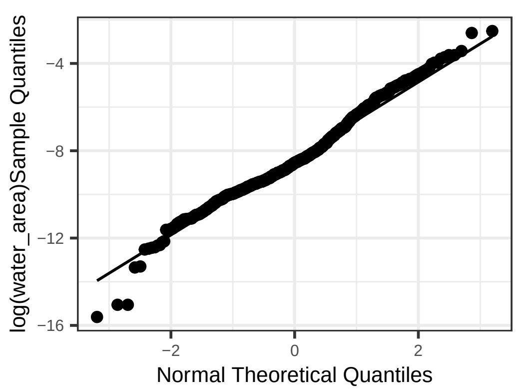
Water Area

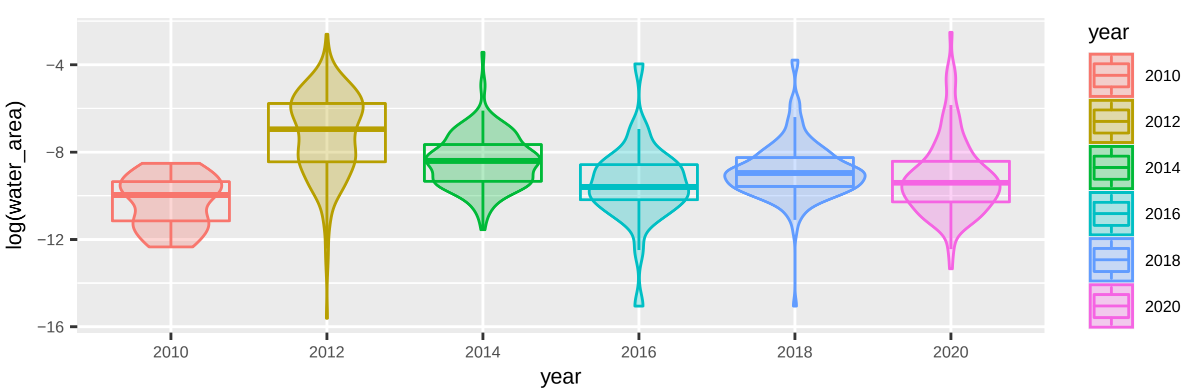

water_area
count
log(water_area)


lst_night_mean
log(water_area)
year
2010
2012
2014
2016
2018
2020

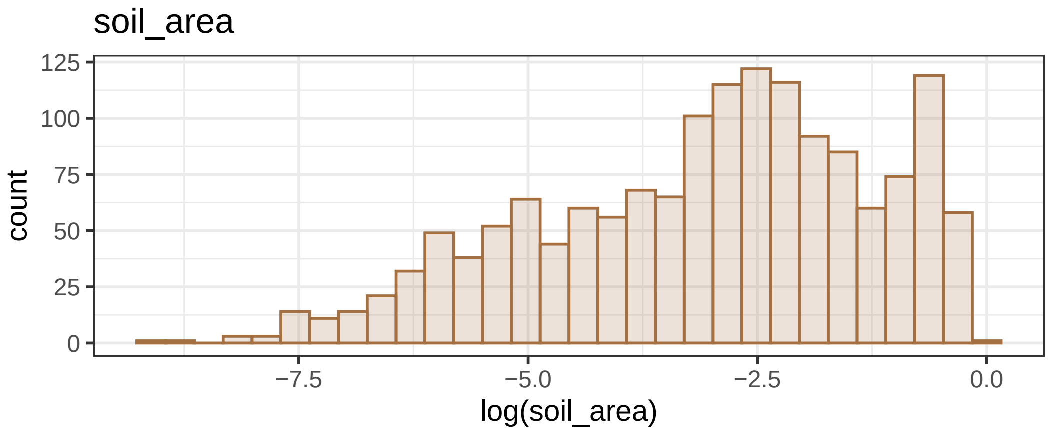

lst_day_mean
log(water_area)
year
2010
2012
2014
2016
2018
2020

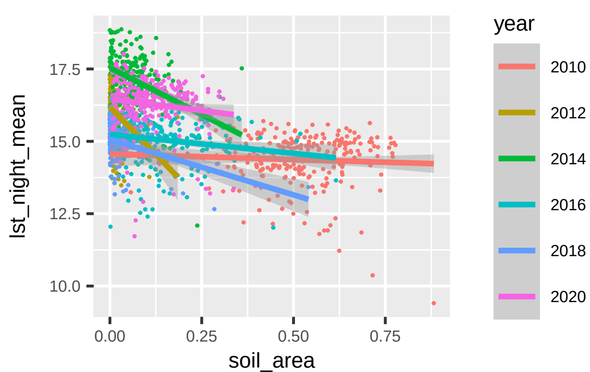

water_areaSample Quantiles
Normal Theoretical Quantiles

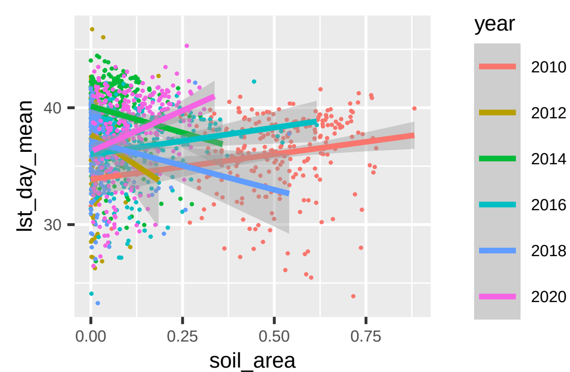

log(water_area)Sample Quantiles
Normal Theoretical Quantiles

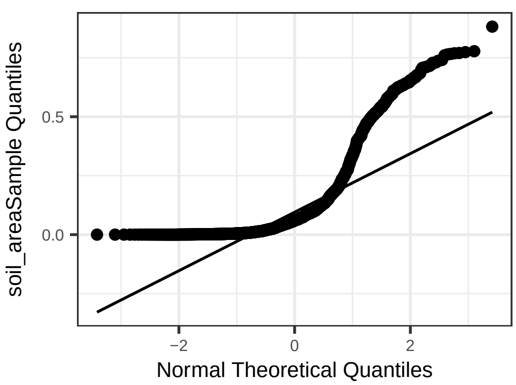

log(water_area)
year
2010
2012
2014
2016
2018
2020

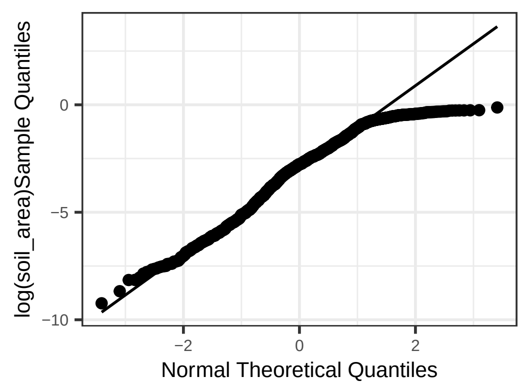
Soil Area

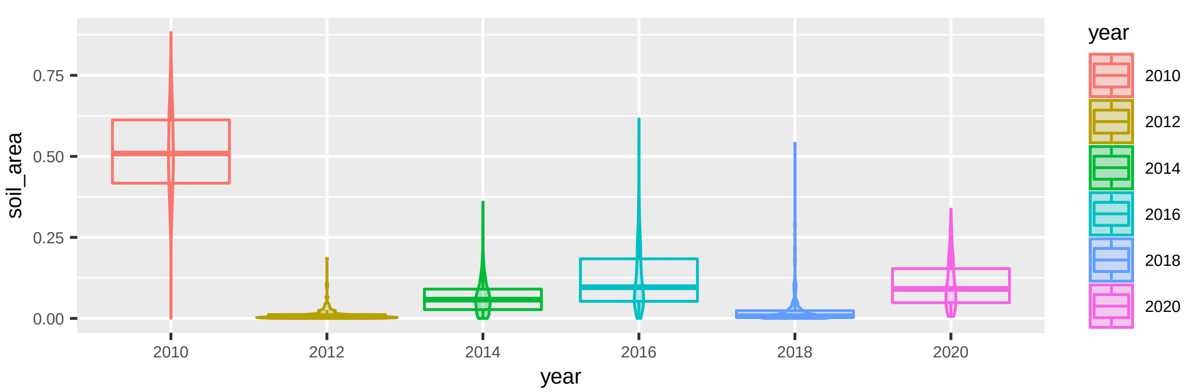

soil_area
count
log(soil_area)


lst_night_mean
soil_area
year
2010
2012
2014
2016
2018
2020

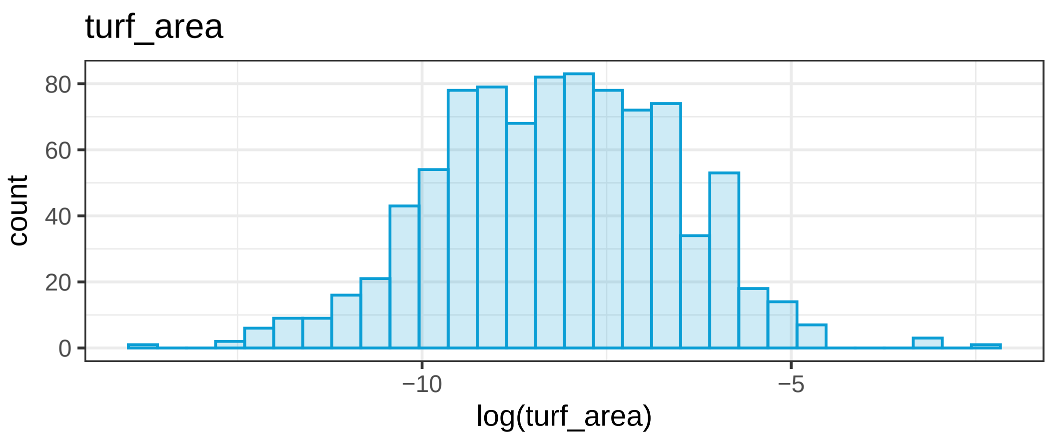

lst_day_mean
soil_area
year
2010
2012
2014
2016
2018
2020

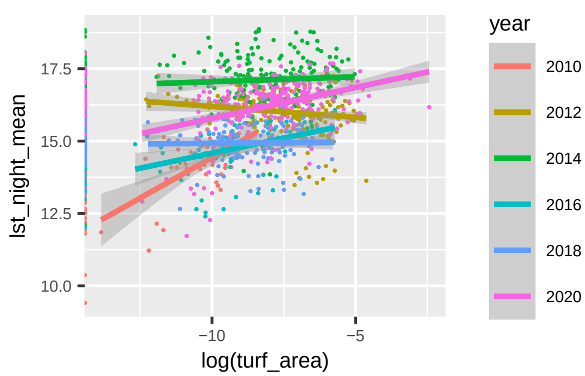

soil_areaSample Quantiles
Normal Theoretical Quantiles

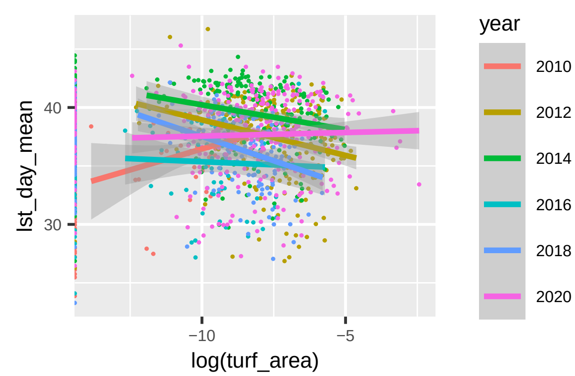

log(soil_area)Sample Quantiles
Normal Theoretical Quantiles

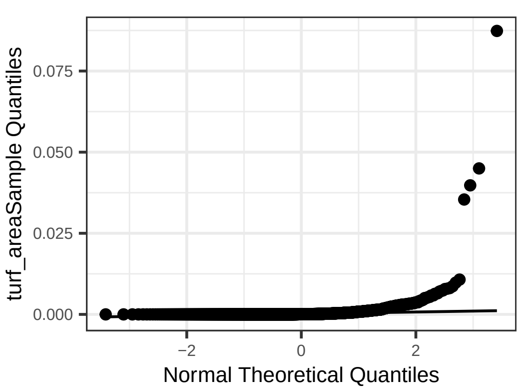

soil_area
year
2010
2012
2014
2016
2018
2020

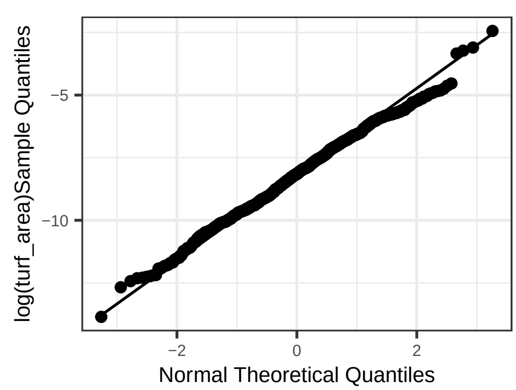
Turf Area


turf_area
count
0
20
40
60
80
−10
−5
log(turf_area)


lst_night_mean
10.0
12.5
15.0
17.5
−10
−5
log(turf_area)
year
2010
2012
2014
2016
2018
2020

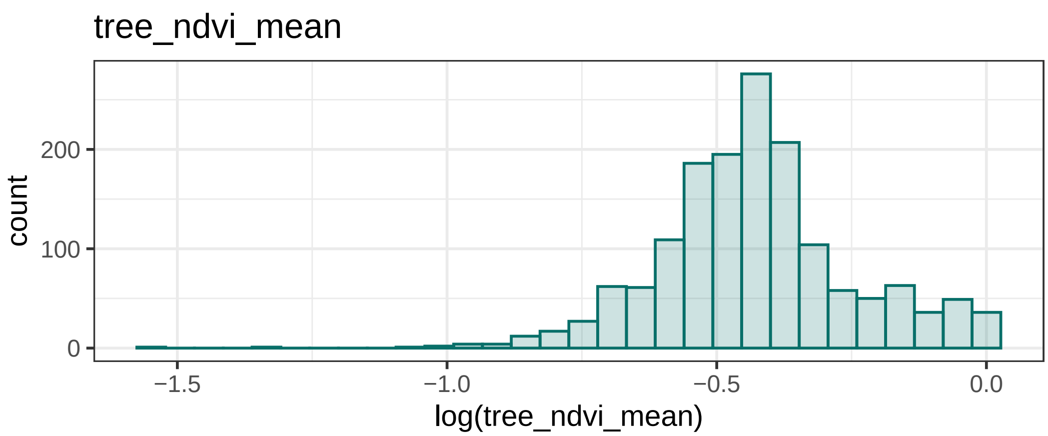

lst_day_mean
30
40
−10
−5
log(turf_area)
year
2010
2012
2014
2016
2018
2020

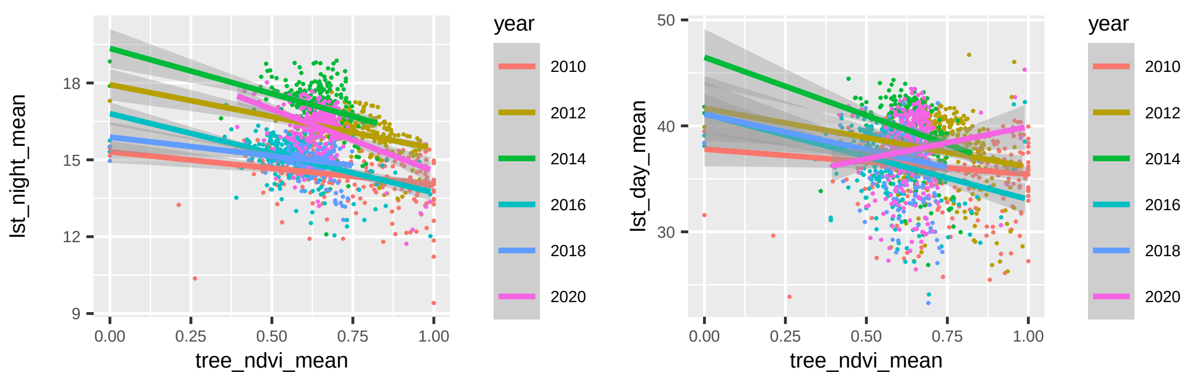

turf_areaSample Quantiles
0.000
0.025
0.050
0.075
−2
0
2
Normal Theoretical Quantiles

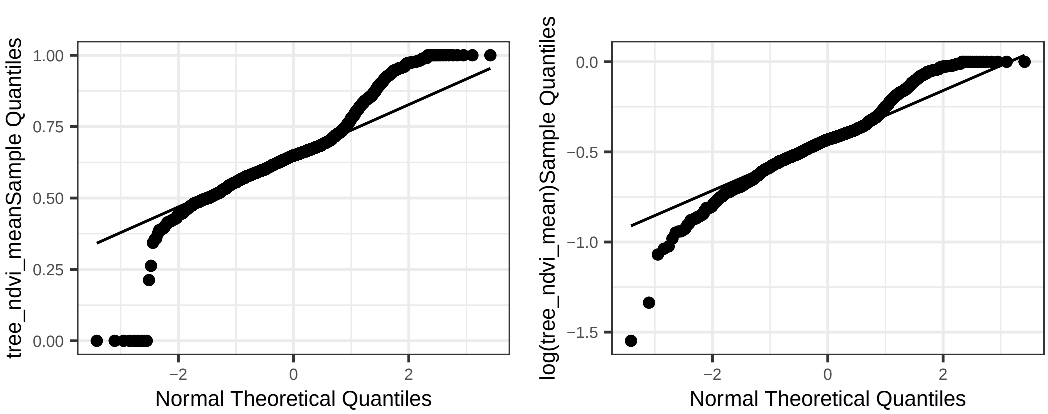

log(turf_area)Sample Quantiles
−10
−5
−2
0
2
Normal Theoretical Quantiles

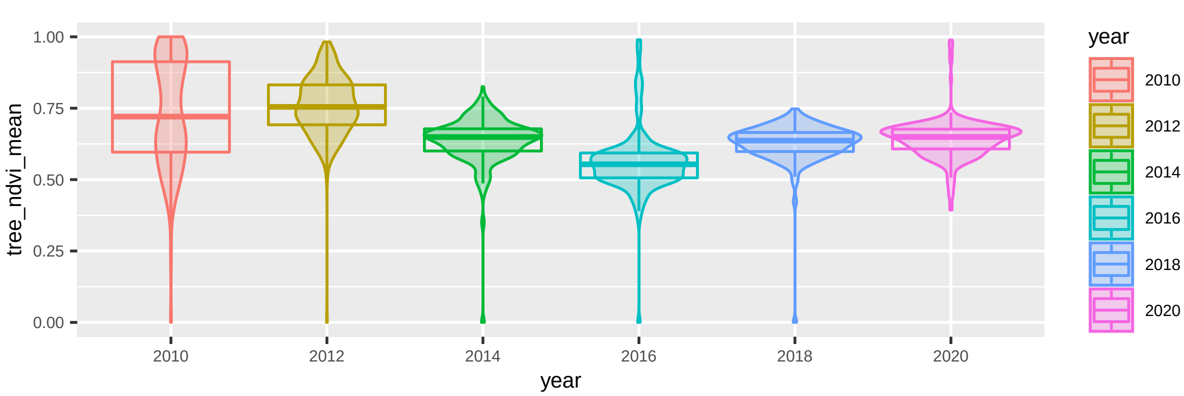

log(turf_area)
−10
−5
2010
2012
2014
2016
2018
2020
year
year
2010
2012
2014
2016
2018
2020

Tree NDVI Mean

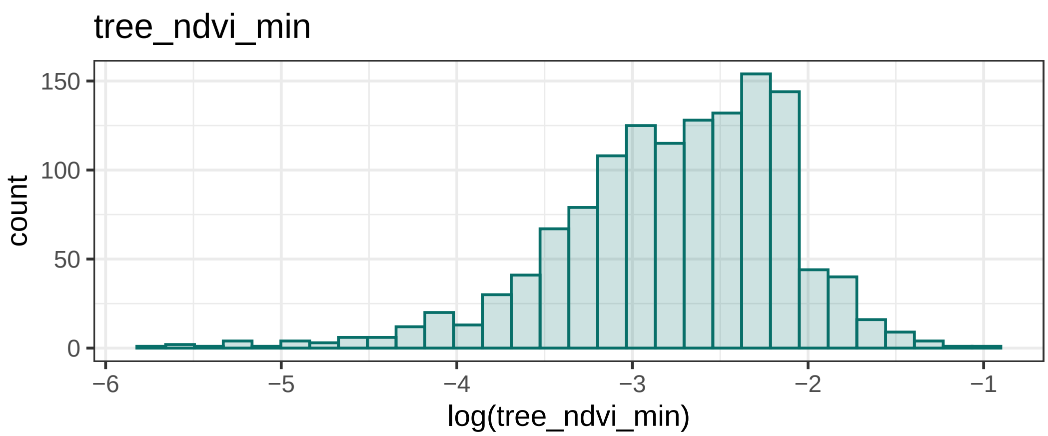


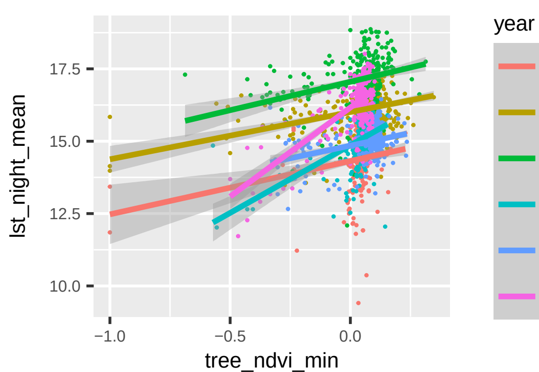


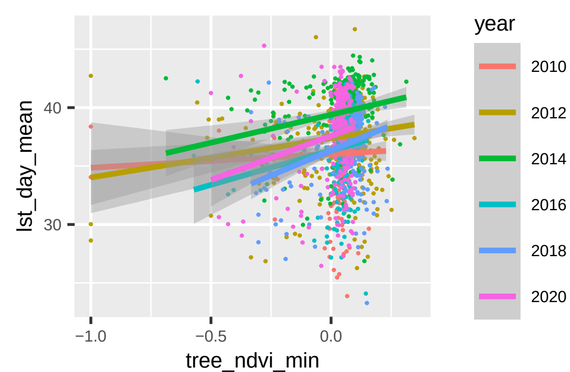


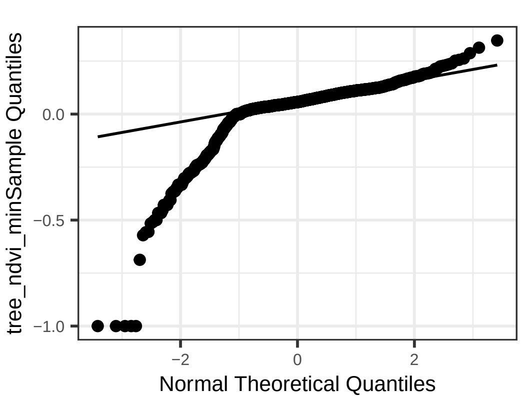


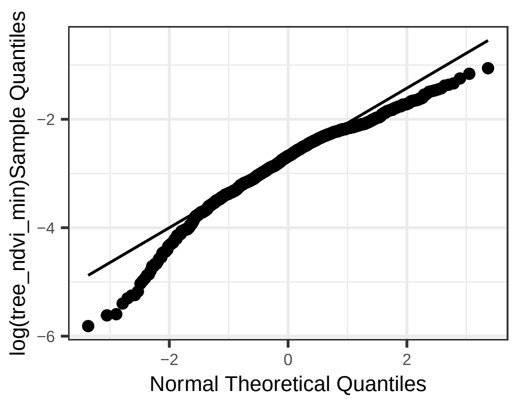
Tree NDVI Min

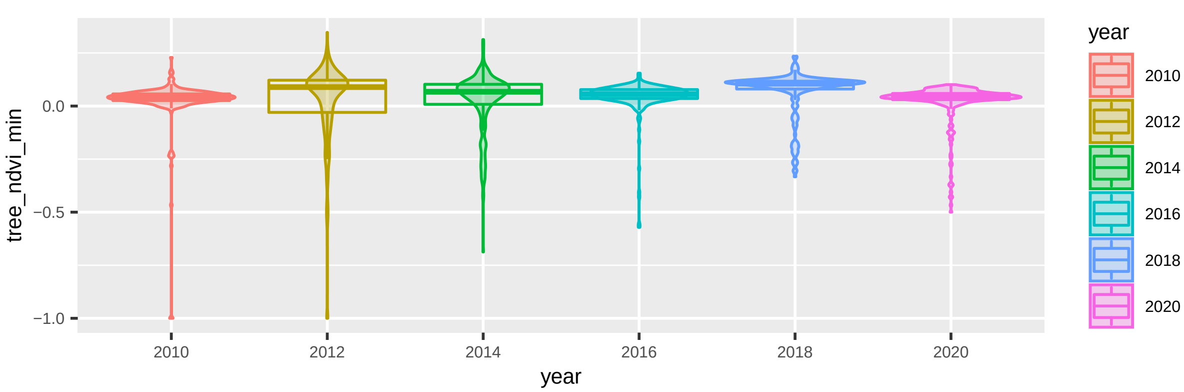




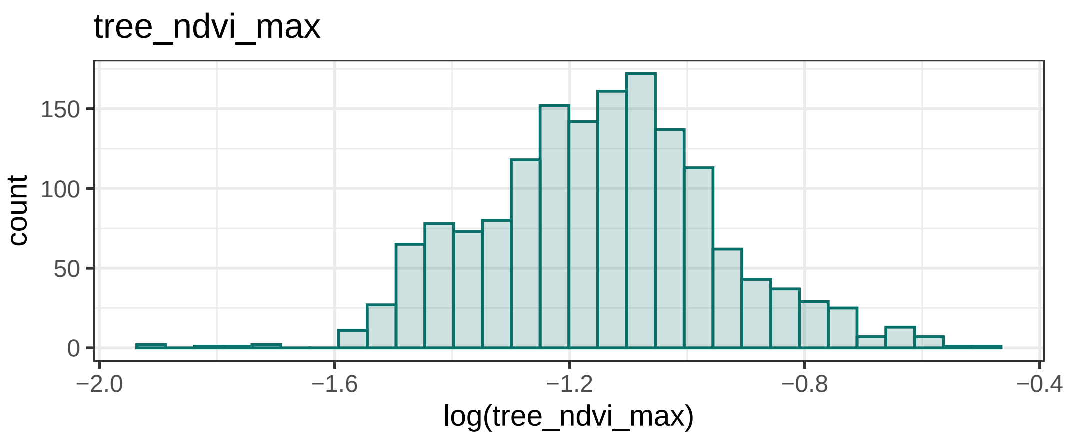


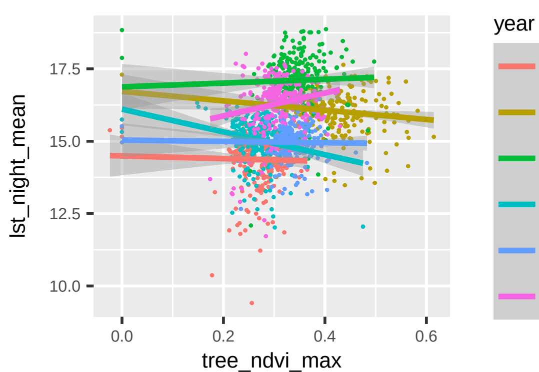


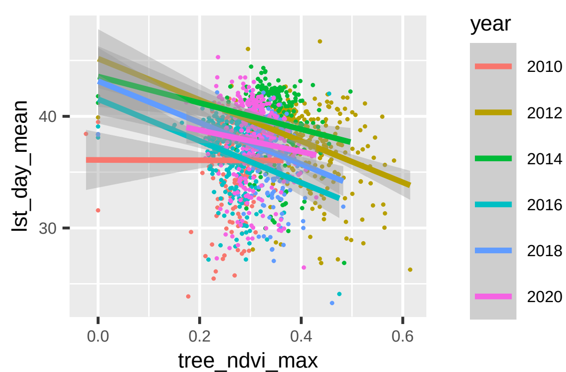


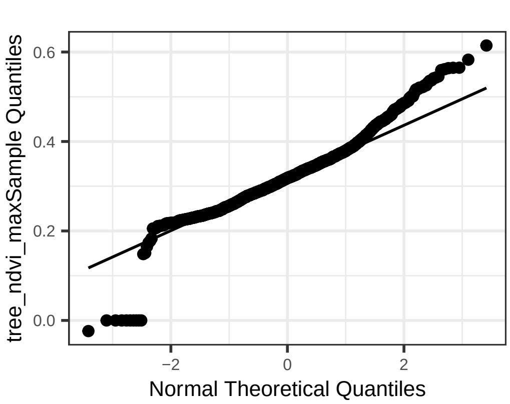


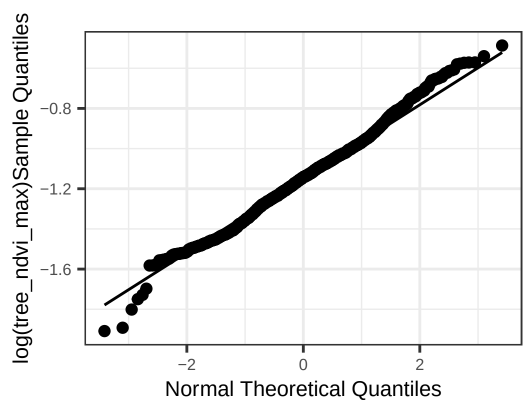
Tree NDVI Max

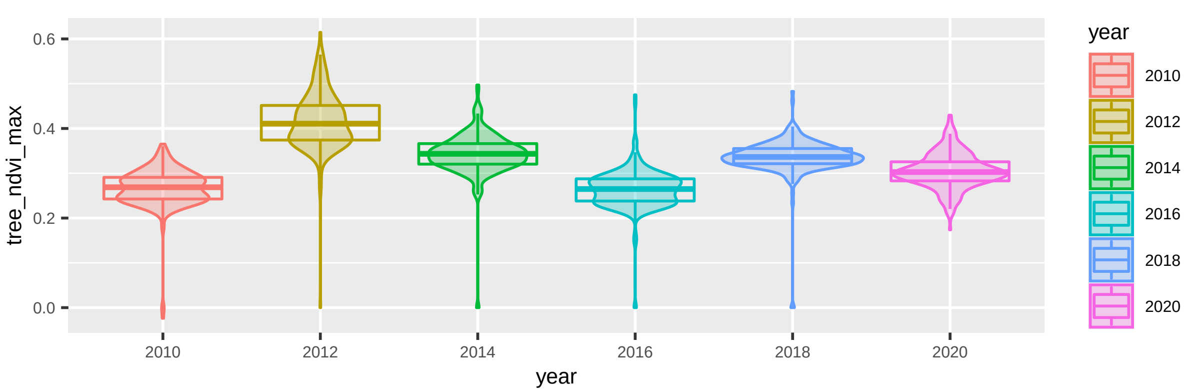




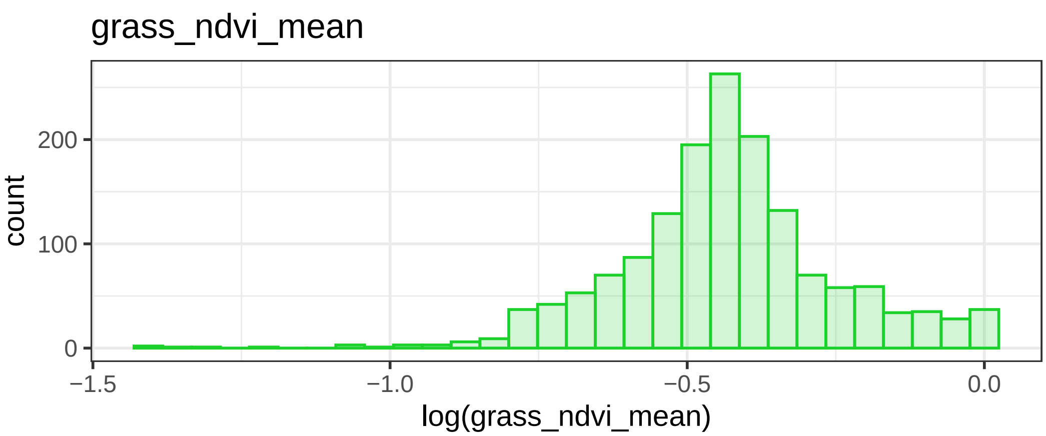


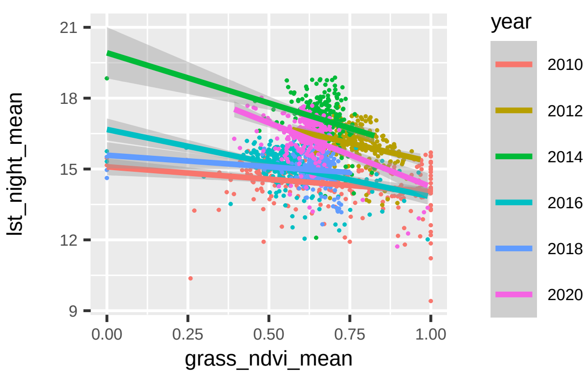


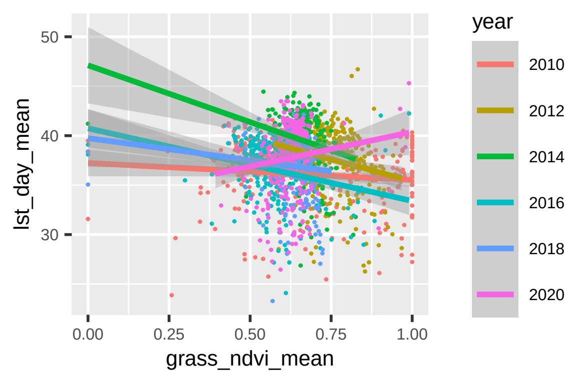


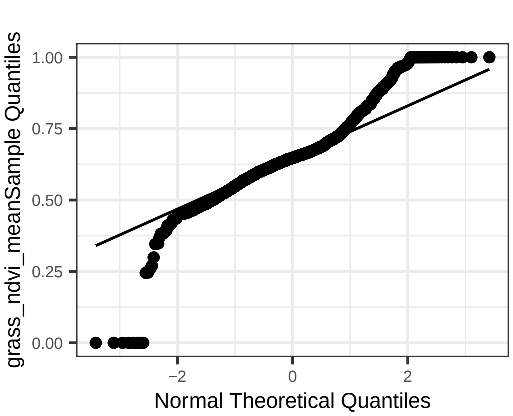


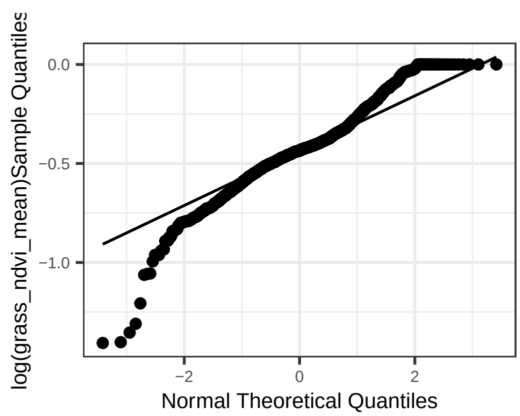
Lawn NDVI Mean

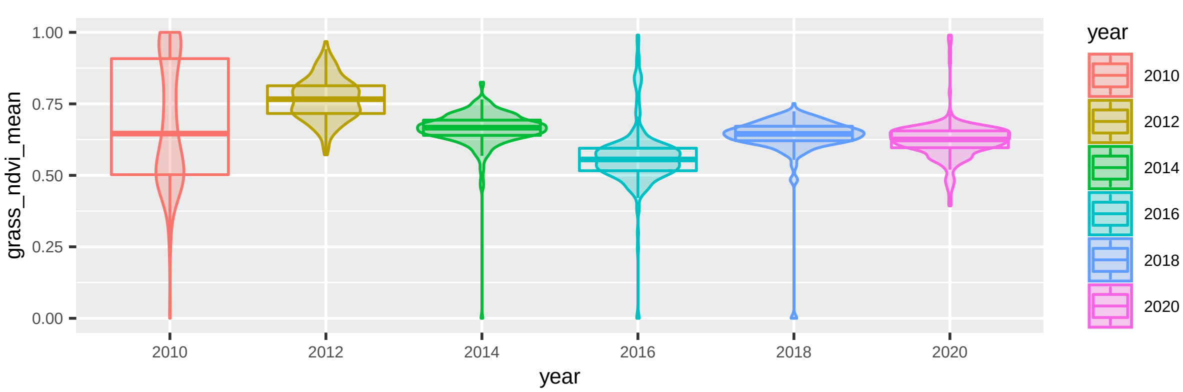






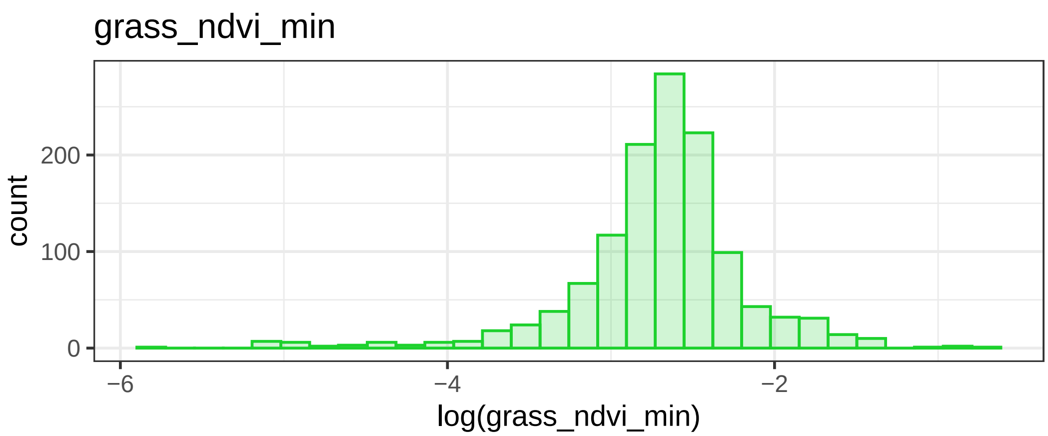


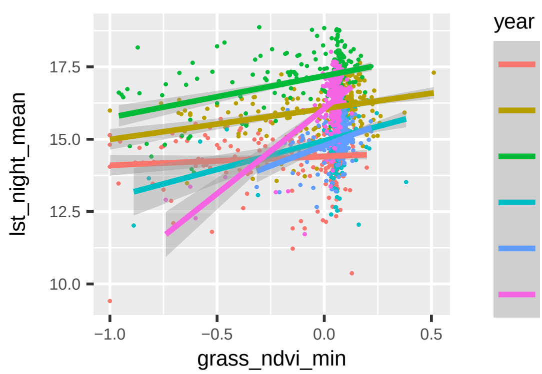


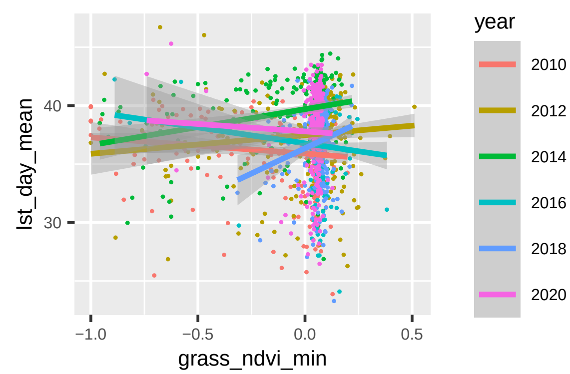


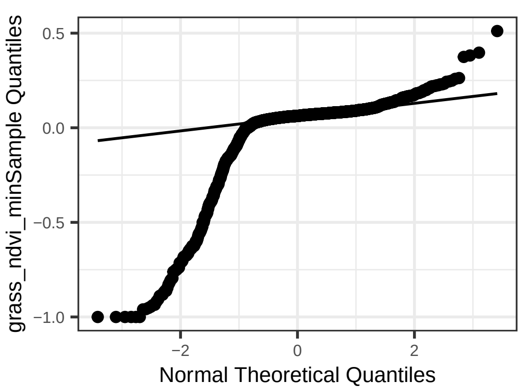
Google Earth: Tensor Flow Model

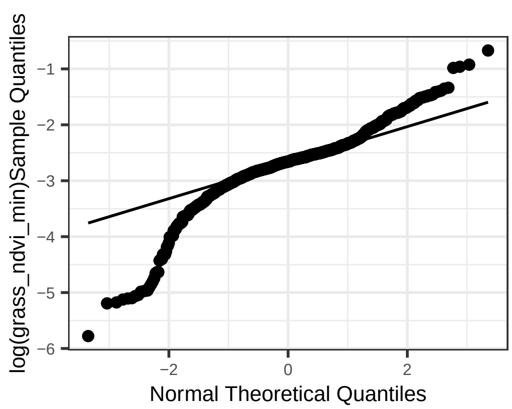
Lawn NDVI Min

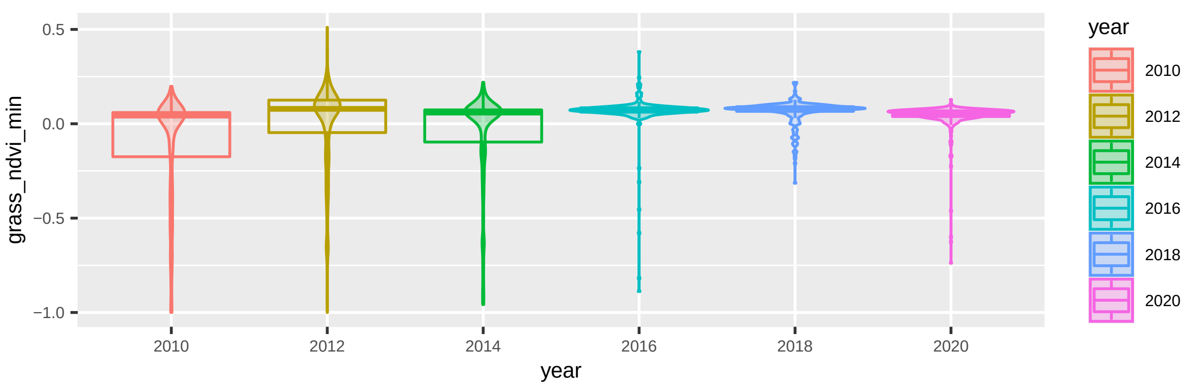




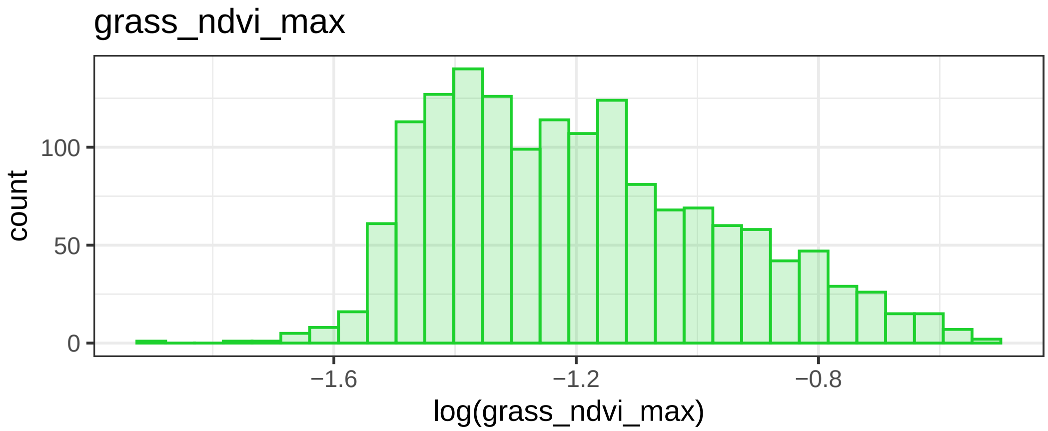


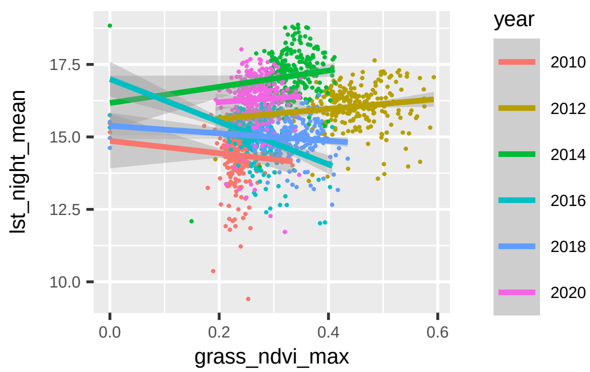


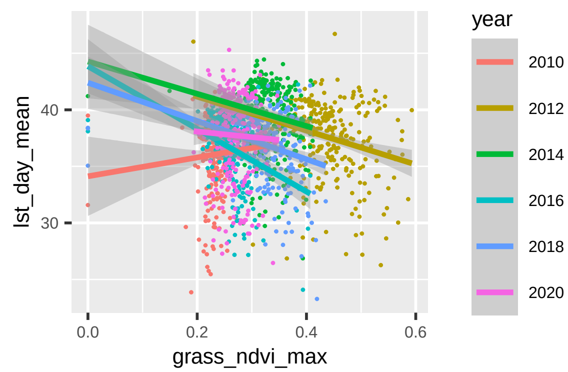


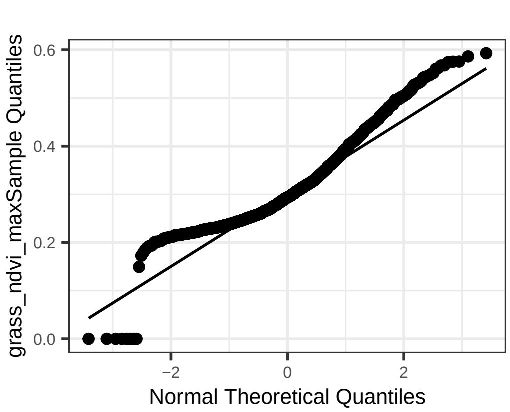


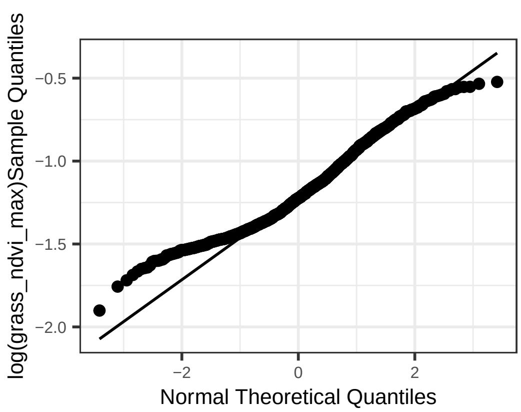
Lawn NDVI Max

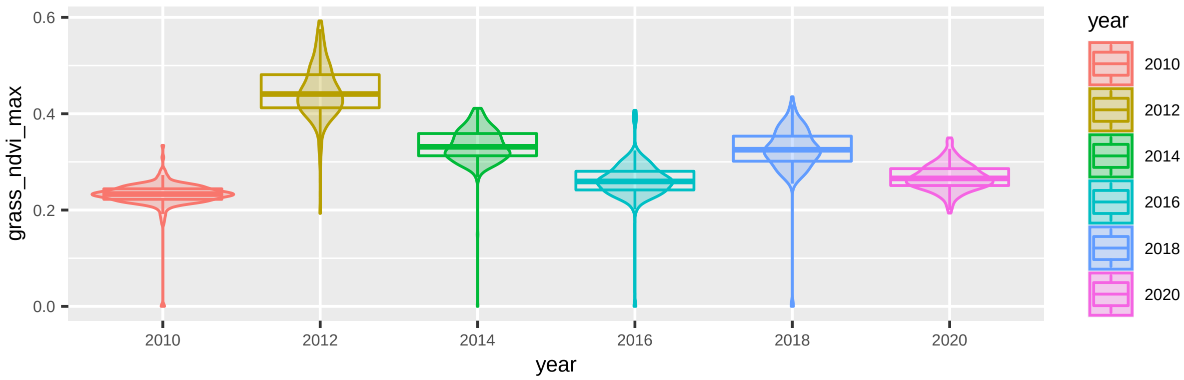




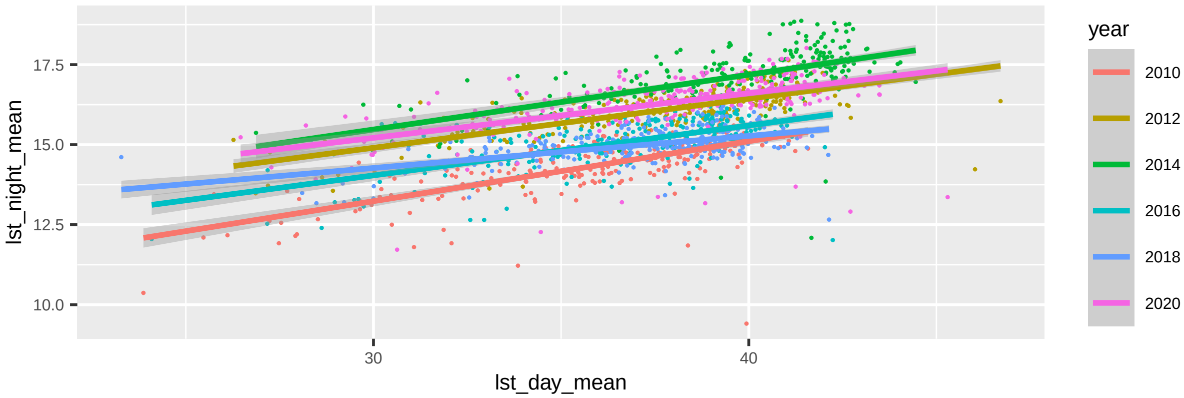


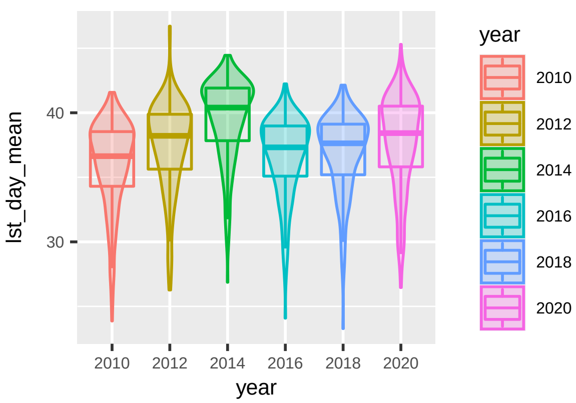


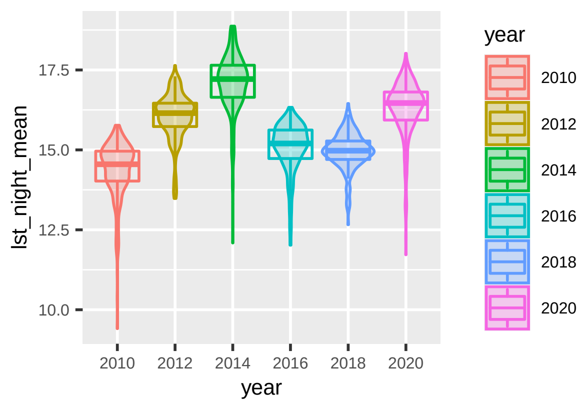


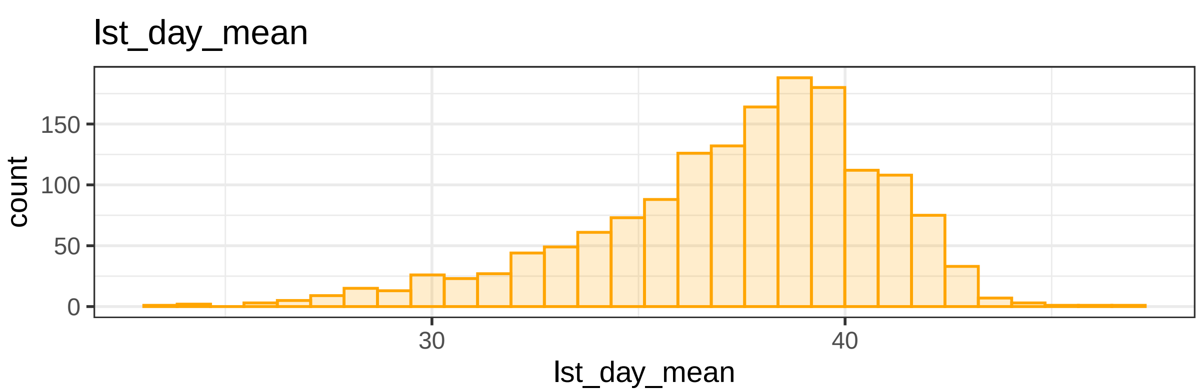


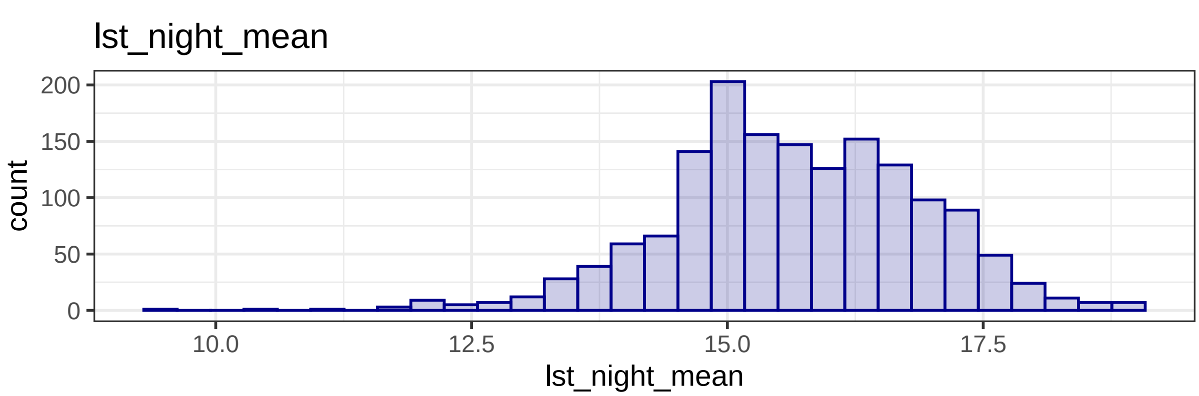
Mean Temperature











Create MicroClimate Panel Data Set

```
data <- subset(data, subset = year > 2012)

data$water_area <- data$water_area + 0.0000000001
data$soil_area <- data$soil_area + 0.0000000001
data$turf_area <- data$turf_area + 0.0000000001

# Create panel dataframe object
microClimatePanel <- pdata.frame(data, index=c("zipcode", "year"))
```

First Attempt with Traditional OLS Model

```
OLSM1 <- lm(
  log(lst_day_mean) ~ 0 + factor(year) + tree_area + lawn_area + log(water_area) + log(soil_are
    log(turf_area) + grass_ndvi_mean + tree_ndvi_mean,
  data = microClimatePanel)

OLSM2 <- lm(
  log(lst_night_mean) ~ 0 + factor(year) + tree_area + lawn_area + log(water_area) + log(soil_a
    log(turf_area) + grass_ndvi_mean + tree_ndvi_mean,
  data = microClimatePanel)

stargazer::stargazer(OLSM1,OLSM2, single.row = TRUE,
                     title = 'OLS Model',
                     column.labels = c("OLSModel Day Temp",
                                       "OLSModel Night Temp"))
```

% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Wed, Jul 27, 2022 - 7:58:11 AM

Second Attempt with a Mixed Effects Model

```
feM1 <- plm(
  log(lst_day_mean) ~ 0 + factor(year) + tree_area + lawn_area + log(water_area) + log(soil_are
    log(turf_area) + grass_ndvi_mean + tree_ndvi_mean,
  index = c(zipcode, year), data = microClimatePanel, model = 'within')

feM2 <- plm(
  log(lst_night_mean) ~ 0 + factor(year) + tree_area + lawn_area + log(water_area) + log(soil_a
    log(turf_area) + grass_ndvi_mean + tree_ndvi_mean,
```

Table 1: OLS Model

	Dependent variable:	
	log(lst_day_mean) OLSModel Day Temp	log(lst_night_mean) OLSModel Night Temp
	(1)	(2)
factor(year)2014	3.731^{***} (0.026)	2.973^{***} (0.016)
factor(year)2016	3.648^{***} (0.024)	2.837^{***} (0.015)
factor(year)2018	3.655^{***} (0.026)	2.836^{***} (0.016)
factor(year)2020	3.714^{***} (0.025)	2.932^{***} (0.015)
tree_area	-0.295^{***} (0.016)	-0.110^{***} (0.010)
lawn_area	-0.144^{**} (0.062)	-0.031 (0.038)
log(water_area)	-0.001^{***} (0.0004)	-0.0003 (0.0002)
log(soil_area)	0.001 (0.001)	-0.0004 (0.001)
log(turf_area)	0.0002 (0.0004)	0.001^{***} (0.0002)
grass_ndvi_mean	-0.086 (0.077)	-0.108^{**} (0.047)
tree_ndvi_mean	0.059 (0.075)	-0.069 (0.045)
Observations	1,057	1,057
R^2	1.000	1.000
Adjusted R^2	1.000	1.000
Residual Std. Error (df = 1046)	0.075	0.046
F Statistic (df = 11; 1046)	$222{,}248.400^{***}$	$349{,}475.500^{***}$
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

```r
  index = c(zipcode, year), data = microClimatePanel, model = 'within')

stargazer::stargazer(feM1,feM2, single.row = TRUE,
                     title = 'Fixed Effects Model',
                     column.labels = c("FixedEffects Day Temp",
                                       "FixedEffects Night Temp"))
```

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Table 2: Fixed Effects Model

	Dependent variable:	
	log(lst_day_mean) FixedEffects Day Temp	log(lst_night_mean) FixedEffects Night Temp
	(1)	(2)
factor(year)2014	0.038^{***} (0.002)	0.036^{***} (0.003)
factor(year)2016	-0.040^{***} (0.002)	-0.083^{***} (0.003)
factor(year)2018	-0.033^{***} (0.002)	-0.093^{***} (0.003)
tree_area	-0.017^{**} (0.008)	-0.022^{**} (0.010)
lawn_area	-0.048^{***} (0.018)	0.066^{***} (0.024)
log(water_area)	0.0001 (0.0001)	0.0002 (0.0001)
log(soil_area)	0.00002 (0.0002)	0.0003 (0.0003)
log(turf_area)	-0.00001 (0.0001)	0.0003^{*} (0.0001)
grass_ndvi_mean	0.012 (0.020)	0.014 (0.027)
tree_ndvi_mean	0.019 (0.018)	-0.026 (0.025)
Observations	1,057	1,057
R^2	0.848	0.914
Adjusted R^2	0.788	0.880
F Statistic (df = 10; 759)	422.384^{***}	804.984^{***}
Note:		*p<0.1; **p<0.05; ***p<0.01

Compare Performance of OLS vs Mixed Effects Models

```r
pFtest(feM1, OLSM1)
```

```
##
##  F test for individual effects
##
## data:  log(lst_day_mean) ~ 0 + factor(year) + tree_area + lawn_area +  ...
## F = 88.512, df1 = 287, df2 = 759, p-value < 2.2e-16
## alternative hypothesis: significant effects
```

```
## Fixed effects is a better choice than OLS
```

Fixed Effects is a Better Choice, Discard OLS Model

Try a Random Effects Model

```
reM1 <- plm(
  log(lst_day_mean) ~ 0 + factor(year) + tree_area + lawn_area + log(water_area) + log(soil_are
    log(turf_area) + grass_ndvi_mean + tree_ndvi_mean,
  index = c(zipcode, year), data = microClimatePanel, model = 'random')

reM2 <- plm(
  log(lst_night_mean) ~ 0 + factor(year) + tree_area + lawn_area + log(water_area) + log(soil_a
    log(turf_area) + grass_ndvi_mean + tree_ndvi_mean,
  index = c(zipcode, year), data = microClimatePanel, model = 'random')

stargazer::stargazer(reM1,reM2,
                     single.row = TRUE,
                     title = 'Random Effects Model',
                     column.labels = c("RandomEffects Day Temp",
                                       "RandomEffects Night Temp"))
```

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Compare Performance of Mixed Effects vs Random Effects Models

```
phtest(feM1, reM1)
```

```
##
##  Hausman Test
##
## data:  log(lst_day_mean) ~ 0 + factor(year) + tree_area + lawn_area +  ...
## chisq = 35196, df = 10, p-value < 2.2e-16
## alternative hypothesis: one model is inconsistent
```

```
## the p-value is significant so we choose fixed effects
## (since the unique errors are correlated with the regressors).
```

Table 3: Random Effects Model

	Dependent variable:	
	log(lst_day_mean) RandomEffects Day Temp	log(lst_night_mean) RandomEffects Night Temp
	(1)	(2)
factor(year)2014	3.658*** (0.009)	2.876*** (0.010)
factor(year)2016	3.580*** (0.008)	2.752*** (0.010)
factor(year)2018	3.586*** (0.009)	2.745*** (0.010)
factor(year)2020	3.622*** (0.009)	2.840*** (0.010)
tree_area	−0.046*** (0.008)	−0.063*** (0.009)
lawn_area	−0.065*** (0.019)	0.040 (0.025)
log(water_area)	−0.00001 (0.0001)	−0.00000 (0.0001)
log(soil_area)	0.00001 (0.0003)	0.0001 (0.0004)
log(turf_area)	−0.00002 (0.0001)	0.0003** (0.0001)
grass_ndvi_mean	0.002 (0.021)	−0.033 (0.029)
tree_ndvi_mean	0.026 (0.020)	−0.022 (0.027)
Observations	1,057	1,057
R^2	0.944	0.962
Adjusted R^2	0.944	0.961
F Statistic	623,338.300***	1,132,778.000***
Note:		*p<0.1; **p<0.05; ***p<0.01

the p-value is significant so we choose fixed effects (since the unique errors are correlated with the regressors). There is omitted variable bias at the higher level that the RE model has not accounted for (but the FE model has).

Try a Fixed Effects Model with Fixed Time

```
feM2FixedTime <- plm(
  log(lst_day_mean) ~ 0 + factor(year) + tree_area + lawn_area + log(water_area) + log(soil_are
    log(turf_area) + grass_ndvi_mean + tree_ndvi_mean,
  index = c(zipcode, year), data = microClimatePanel, model = 'within')

stargazer::stargazer(feM2FixedTime, single.row = TRUE)
```

% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Wed, Jul 27, 2022 - 7:58:14 AM

Table 4:

	Dependent variable:
	log(lst_day_mean)
factor(year)2014	0.038*** (0.002)
factor(year)2016	−0.040*** (0.002)
factor(year)2018	−0.033*** (0.002)
tree_area	−0.017** (0.008)
lawn_area	−0.048*** (0.018)
log(water_area)	0.0001 (0.0001)
log(soil_area)	0.00002 (0.0002)
log(turf_area)	−0.00001 (0.0001)
grass_ndvi_mean	0.012 (0.020)
tree_ndvi_mean	0.019 (0.018)
Observations	1,057
R^2	0.848
Adjusted R^2	0.788
F Statistic	422.384*** (df = 10; 759)
Note:	*p<0.1; **p<0.05; ***p<0.01

```
pFtest(feM1,feM2FixedTime)
```

```
##
##  F test for individual effects
##
## data:  log(lst_day_mean) ~ 0 + factor(year) + tree_area + lawn_area +  ...
## F = NaN, df1 = 0, df2 = 759, p-value = NA
## alternative hypothesis: significant effects
```

```r
plmtest(feM1, effect="time", type="bp")
```

```
##
##  Lagrange Multiplier Test - time effects (Breusch-Pagan) for unbalanced
##  panels
##
## data:  log(lst_day_mean) ~ 0 + factor(year) + tree_area + lawn_area +  ...
## chisq = 2.003, df = 1, p-value = 0.157
## alternative hypothesis: significant effects
```

```r
pbgtest(feM1)
```

```
##
##  Breusch-Godfrey/Wooldridge test for serial correlation in panel models
##
## data:  log(lst_day_mean) ~ 0 + factor(year) + tree_area + lawn_area +  ...
## chisq = 65.943, df = 1, p-value = 4.641e-16
## alternative hypothesis: serial correlation in idiosyncratic errors
```

```r
coeftest(feM1, vcovHC)
```

```
##
## t test of coefficients:
##
##                       Estimate  Std. Error  t value Pr(>|t|)
## factor(year)2014  3.7637e-02  2.2167e-03  16.9786  < 2e-16 ***
## factor(year)2016 -3.9754e-02  2.1335e-03 -18.6335  < 2e-16 ***
## factor(year)2018 -3.3418e-02  2.1174e-03 -15.7825  < 2e-16 ***
## tree_area        -1.6559e-02  8.4801e-03  -1.9527  0.05122 .
## lawn_area        -4.8498e-02  1.8836e-02  -2.5747  0.01022 *
## log(water_area)   5.7639e-05  9.1098e-05   0.6327  0.52712
## log(soil_area)    1.5724e-05  2.0004e-04   0.0786  0.93737
## log(turf_area)   -1.4409e-05  9.7065e-05  -0.1484  0.88203
## grass_ndvi_mean   1.1670e-02  1.8186e-02   0.6417  0.52127
## tree_ndvi_mean    1.8846e-02  1.7484e-02   1.0779  0.28142
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
coeftest(feM1, vcovHC(feM1, method = "arellano"))
```

```
##
## t test of coefficients:
##
##                       Estimate  Std. Error  t value Pr(>|t|)
```

```
## factor(year)2014  3.7637e-02  2.2167e-03  16.9786  < 2e-16 ***
## factor(year)2016 -3.9754e-02  2.1335e-03 -18.6335  < 2e-16 ***
## factor(year)2018 -3.3418e-02  2.1174e-03 -15.7825  < 2e-16 ***
## tree_area        -1.6559e-02  8.4801e-03  -1.9527  0.05122 .
## lawn_area        -4.8498e-02  1.8836e-02  -2.5747  0.01022 *
## log(water_area)   5.7639e-05  9.1098e-05   0.6327  0.52712
## log(soil_area)    1.5724e-05  2.0004e-04   0.0786  0.93737
## log(turf_area)   -1.4409e-05  9.7065e-05  -0.1484  0.88203
## grass_ndvi_mean   1.1670e-02  1.8186e-02   0.6417  0.52127
## tree_ndvi_mean    1.8846e-02  1.7484e-02   1.0779  0.28142
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
t(sapply(c("HC0", "HC1", "HC2", "HC3", "HC4"), function(x) sqrt(diag(vcovHC(feM1, method = "ar
```

```
##     factor(year)2014 factor(year)2016 factor(year)2018   tree_area  lawn_area
## HC0      0.002216722      0.002133486      0.002117418 0.008480110 0.01883616
## HC1      0.002227283      0.002143650      0.002127506 0.008520511 0.01892590
## HC2      0.002239820      0.002149481      0.002135953 0.008598112 0.01904156
## HC3      0.002264050      0.002165774      0.002155249 0.008720369 0.01925110
## HC4      0.002288379      0.002169726      0.002170617 0.008890239 0.01943844
##     log(water_area) log(soil_area) log(turf_area) grass_ndvi_mean
## HC0    9.109829e-05   0.0002000430   9.706478e-05      0.01818635
## HC1    9.153230e-05   0.0002009961   9.752722e-05      0.01827300
## HC2    9.164299e-05   0.0002041261   9.769445e-05      0.01844363
## HC3    9.219607e-05   0.0002083641   9.833642e-05      0.01872569
## HC4    9.215027e-05   0.0002159333   9.838242e-05      0.01916683
##     tree_ndvi_mean
## HC0      0.01748404
## HC1      0.01756734
## HC2      0.01768413
## HC3      0.01790124
## HC4      0.01818965
```

```
totalRobust <- coeftest(feM1, vcov = vcovHC(feM1, type = 'HC0'))
cInterval <- coefci(feM1, vcov. = vcovHC(feM1, type = 'HC0'))
```

```
print(totalRobust)
```

```
##
## t test of coefficients:
##
##                     Estimate  Std. Error  t value Pr(>|t|)
## factor(year)2014  3.7637e-02  2.2167e-03  16.9786  < 2e-16 ***
## factor(year)2016 -3.9754e-02  2.1335e-03 -18.6335  < 2e-16 ***
## factor(year)2018 -3.3418e-02  2.1174e-03 -15.7825  < 2e-16 ***
```

```
## tree_area        -1.6559e-02  8.4801e-03  -1.9527  0.05122 .
## lawn_area        -4.8498e-02  1.8836e-02  -2.5747  0.01022 *
## log(water_area)   5.7639e-05  9.1098e-05   0.6327  0.52712
## log(soil_area)    1.5724e-05  2.0004e-04   0.0786  0.93737
## log(turf_area)   -1.4409e-05  9.7065e-05  -0.1484  0.88203
## grass_ndvi_mean   1.1670e-02  1.8186e-02   0.6417  0.52127
## tree_ndvi_mean    1.8846e-02  1.7484e-02   1.0779  0.28142
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
print(cInterval)
```

```
##                          2.5 %        97.5 %
## factor(year)2014  0.0332852113  4.198848e-02
## factor(year)2016 -0.0439424594 -3.556599e-02
## factor(year)2018 -0.0375747900 -2.926141e-02
## tree_area        -0.0332066033  8.790881e-05
## lawn_area        -0.0854749189 -1.152059e-02
## log(water_area)  -0.0001211960  2.364731e-04
## log(soil_area)   -0.0003769789  4.084278e-04
## log(turf_area)   -0.0002049560  1.761387e-04
## grass_ndvi_mean  -0.0240315858  4.737147e-02
## tree_ndvi_mean   -0.0154767832  5.316887e-02
```

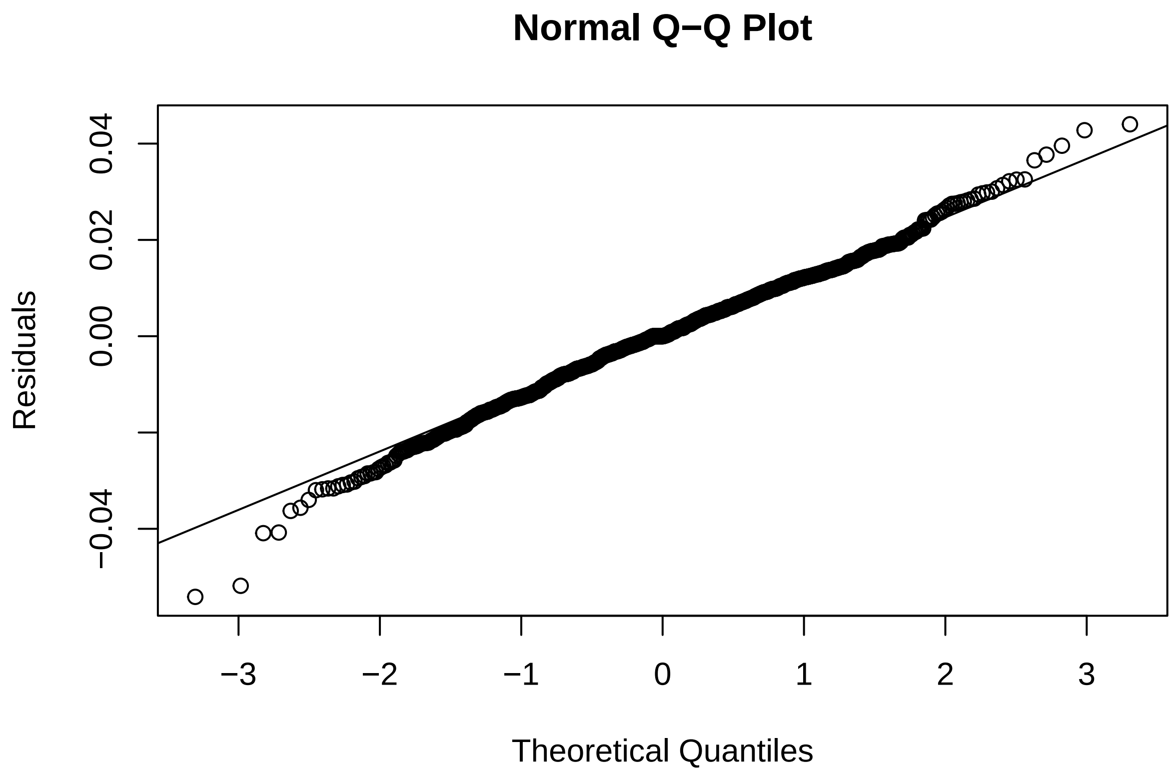
```
stargazer::stargazer(OLSM1,feM1,reM1,feM2FixedTime,
                     font.size = 'tiny',
                     title = 'Regression Models Sumamry',
                     column.labels = c("OLS", "FixedEffects",
                                       "RandomEffects",
                                       "FixedEffectsFixedTime"))
```

% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Wed, Jul 27, 2022 - 7:58:15 AM

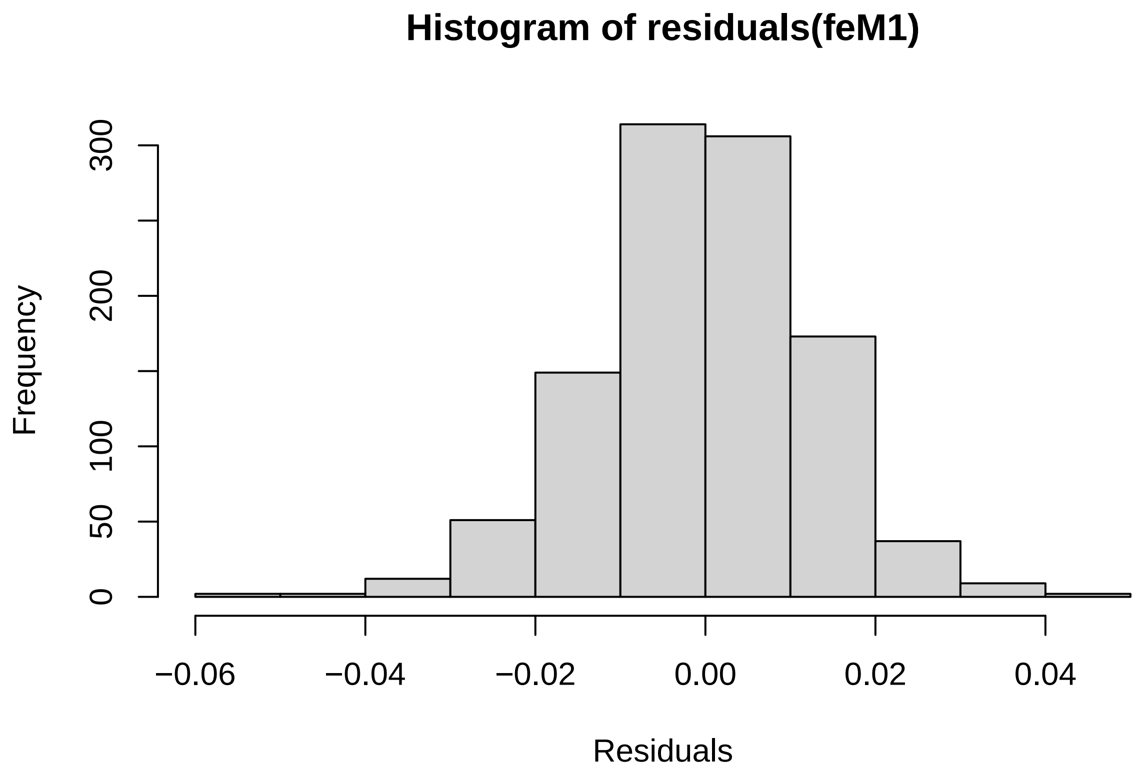
```
qqnorm(residuals(feM1), ylab = 'Residuals')
qqline(residuals(feM1))
```

Table 5: Regression Models Sumamry

	Dependent variable:			
	log(lst_day_mean)			
	OLS		*panel linear*	
	OLS	FixedEffects	RandomEffects	FixedEffectsFixedTime
	(1)	(2)	(3)	(4)
factor(year)2014	3.731^{***}	0.038^{***}	3.658^{***}	0.038^{***}
	(0.026)	(0.002)	(0.009)	(0.002)
factor(year)2016	3.648^{***}	-0.040^{***}	3.580^{***}	-0.040^{***}
	(0.024)	(0.002)	(0.008)	(0.002)
factor(year)2018	3.655^{***}	-0.033^{***}	3.586^{***}	-0.033^{***}
	(0.026)	(0.002)	(0.009)	(0.002)
factor(year)2020	3.714^{***}		3.622^{***}	
	(0.025)		(0.009)	
tree_area	-0.295^{***}	-0.017^{**}	-0.046^{***}	-0.017^{**}
	(0.016)	(0.008)	(0.008)	(0.008)
lawn_area	-0.144^{**}	-0.048^{***}	-0.065^{***}	-0.048^{***}
	(0.062)	(0.018)	(0.019)	(0.018)
log(water_area)	-0.001^{***}	0.0001	−0.00001	0.0001
	(0.0004)	(0.0001)	(0.0001)	(0.0001)
log(soil_area)	0.001	0.00002	0.00001	0.00002
	(0.001)	(0.0002)	(0.0003)	(0.0002)
log(turf_area)	0.0002	−0.00001	−0.00002	−0.00001
	(0.0004)	(0.0001)	(0.0001)	(0.0001)
grass_ndvi_mean	−0.086	0.012	0.002	0.012
	(0.077)	(0.020)	(0.021)	(0.020)
tree_ndvi_mean	0.059	0.019	0.026	0.019
	(0.075)	(0.018)	(0.020)	(0.018)
Observations	1,057	1,057	1,057	1,057
R^2	1.000	0.848	0.944	0.848
Adjusted R^2	1.000	0.788	0.944	0.788
Residual Std. Error	0.075 (df = 1046)			
F Statistic	$222{,}248.400^{***}$ (df = 11; 1046)	422.384^{***} (df = 10; 759)	$623{,}338.300^{***}$	422.384^{***} (df = 10; 759)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$




```
hist(residuals(feM1), xlab = 'Residuals')
```


Histogram of residuals(feM1)
Frequency
0
50
100
200
300
−0.06
−0.04
−0.02
0.00
0.02
0.04
Residuals