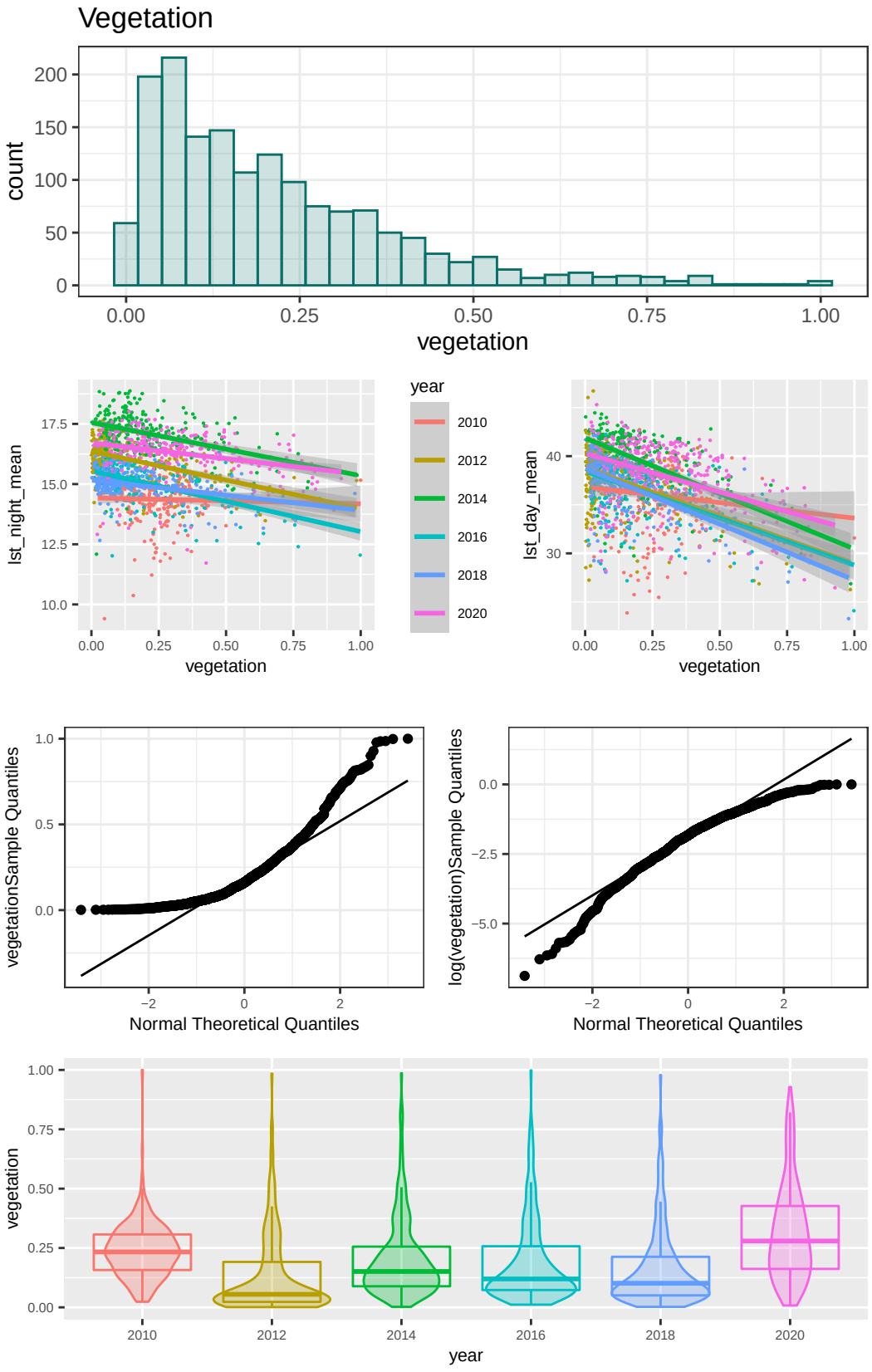
LawnProject Panel Data Analysis / Tensor Flow Data

LawnProject Team

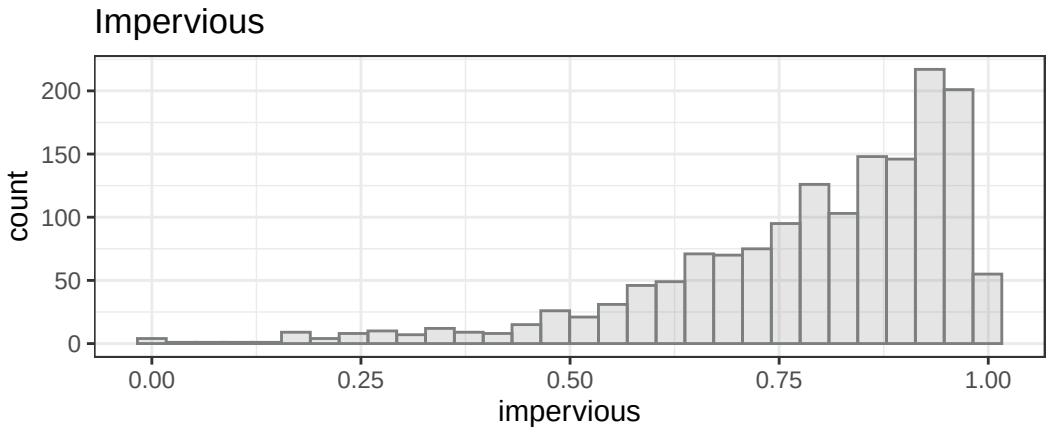
Intro

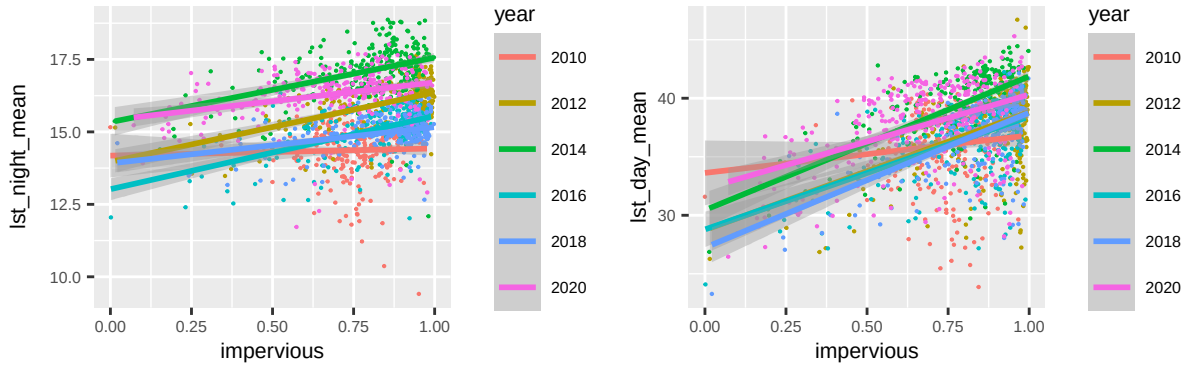
Aggregate Vegetation Area (Trees + Lawn)

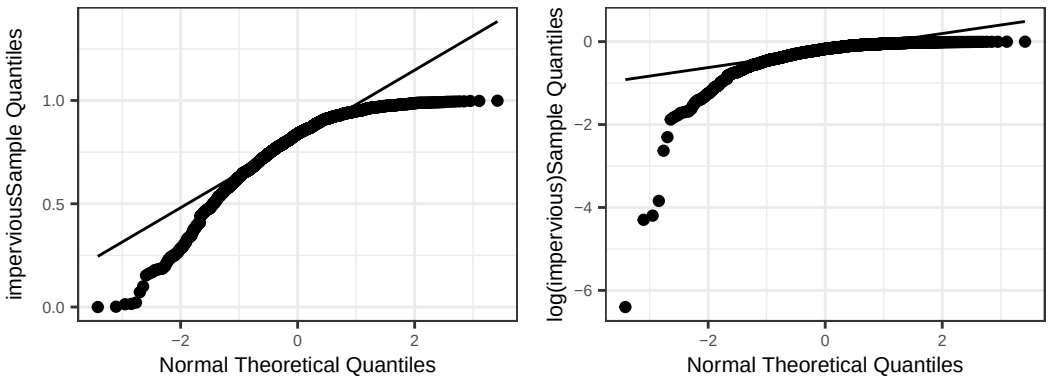


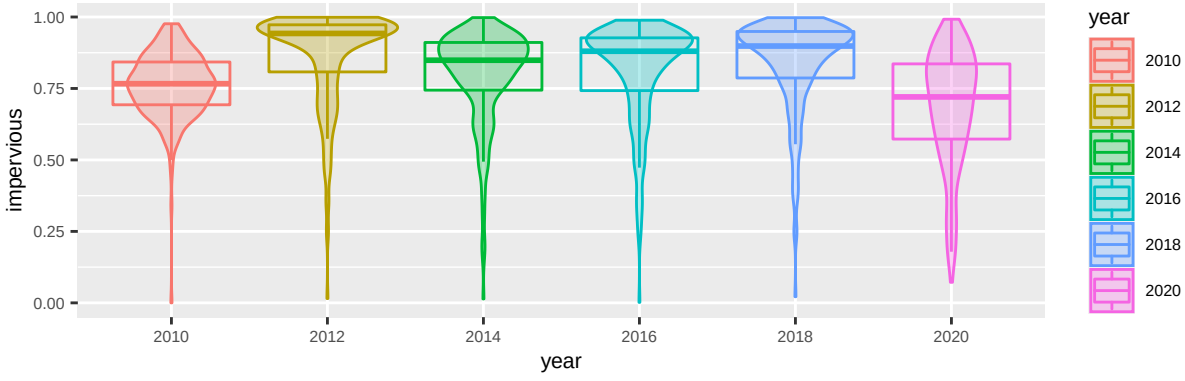
Google Earth: Tensor Flow Model

Aggregate Impervious Area (Soil + Turf + Impervious)



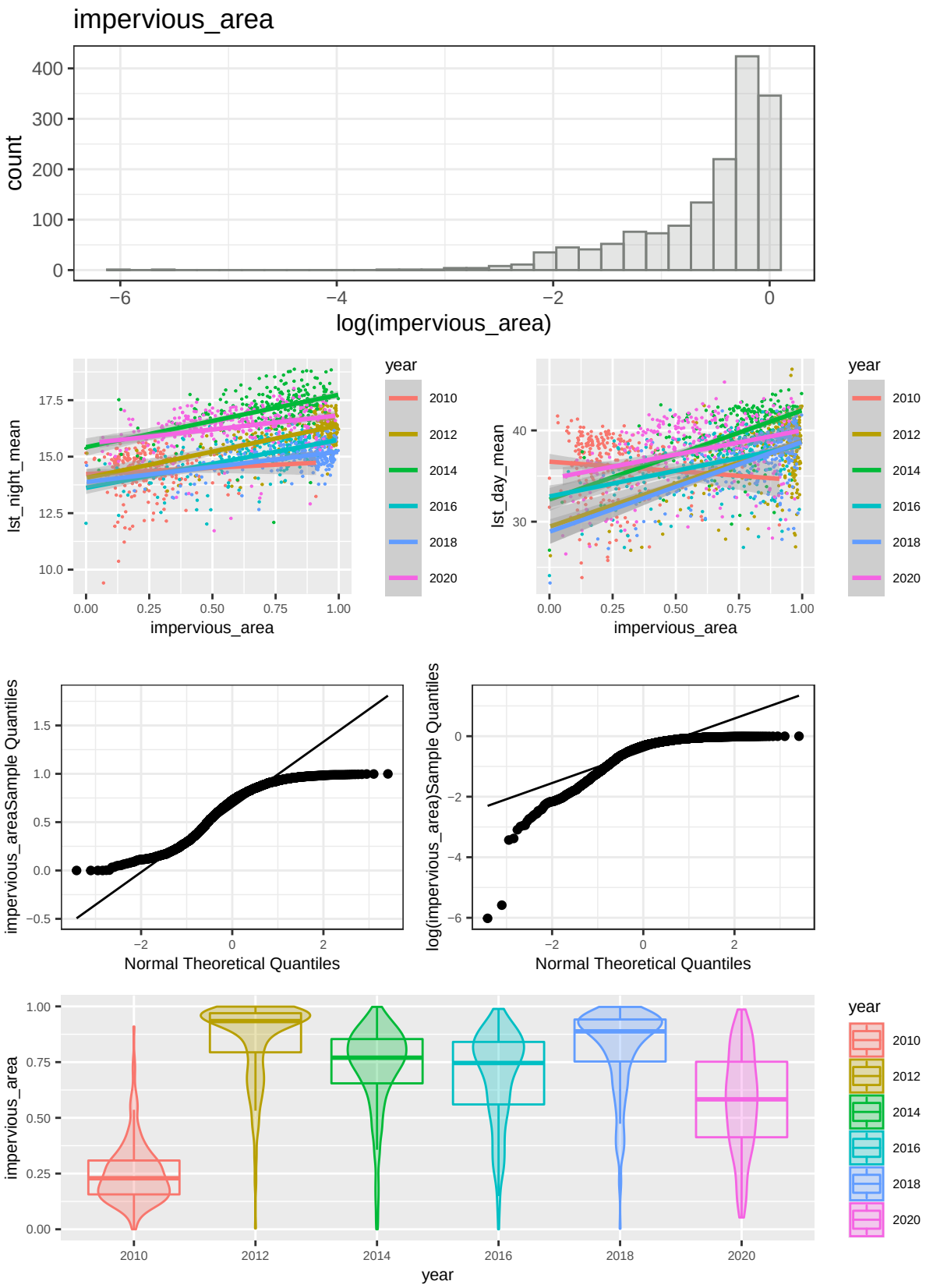






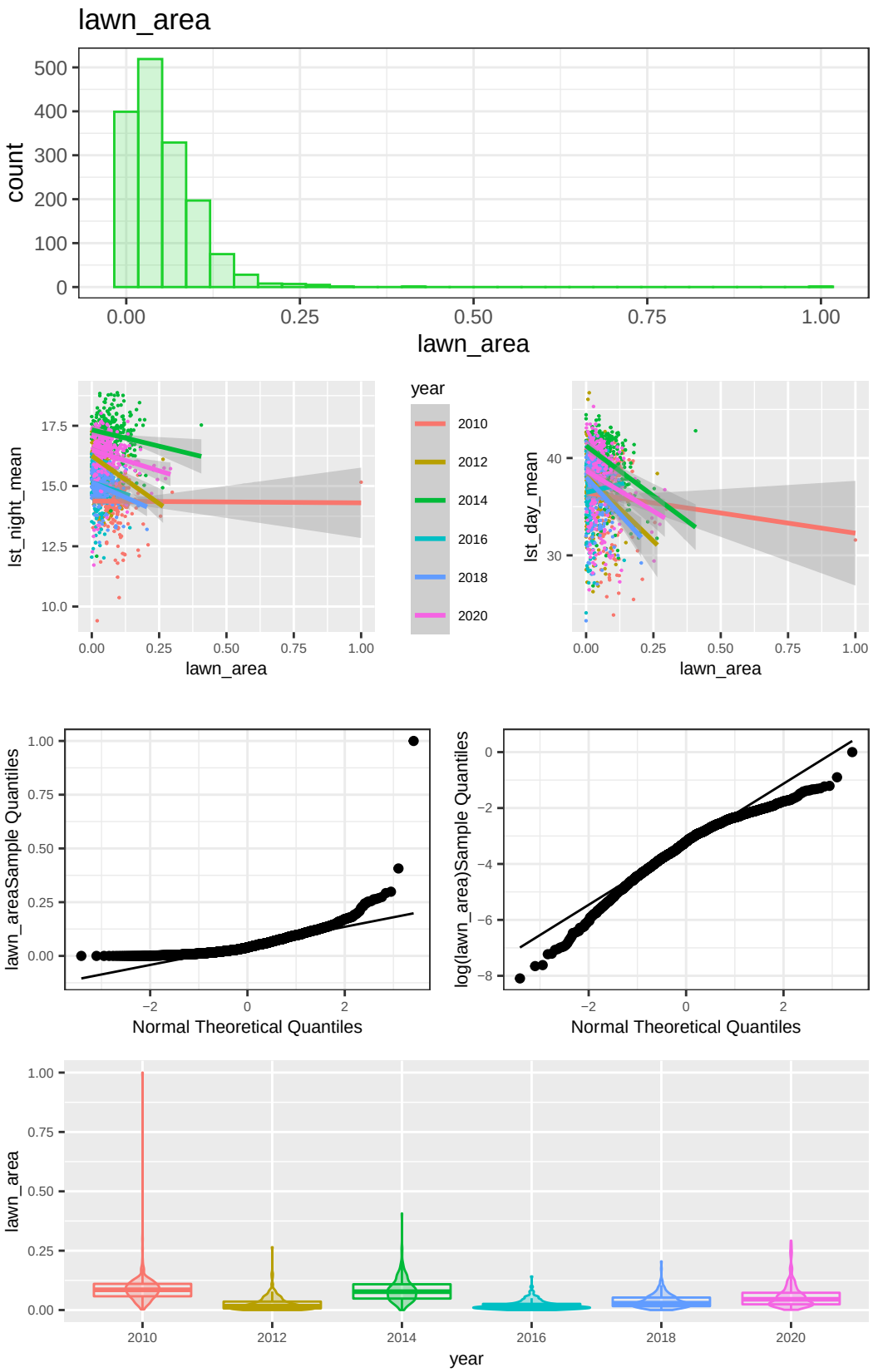
Google Earth: Tensor Flow Model

Impervious Area



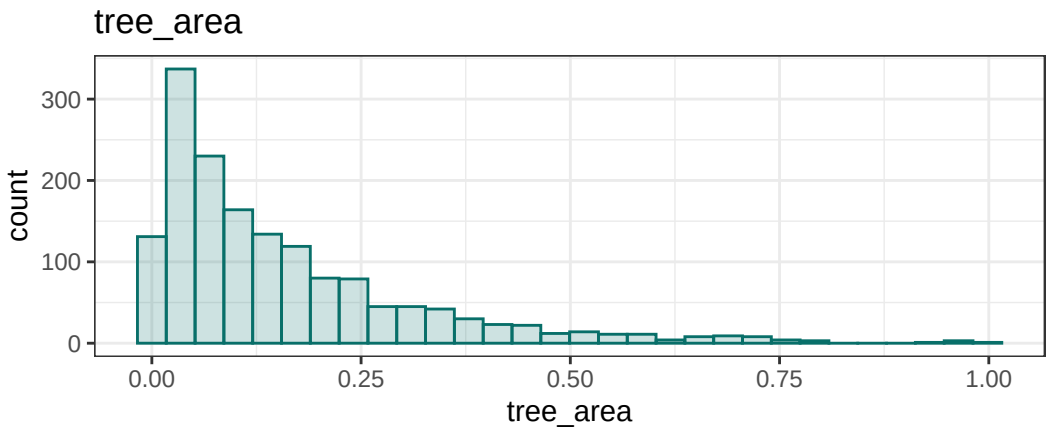
Google Earth: Tensor Flow Model

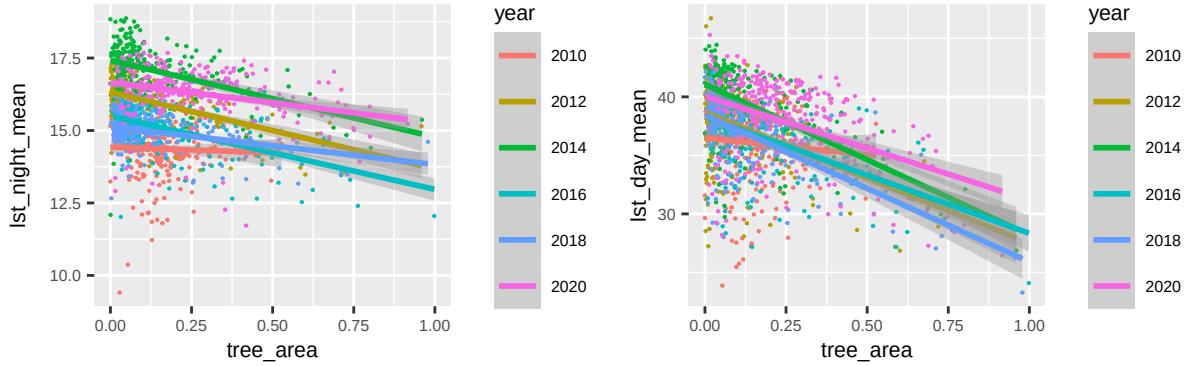
Lawn Area

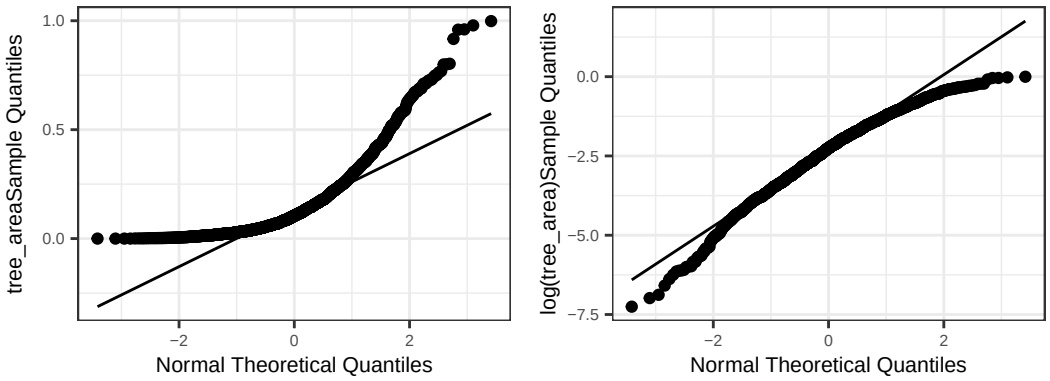


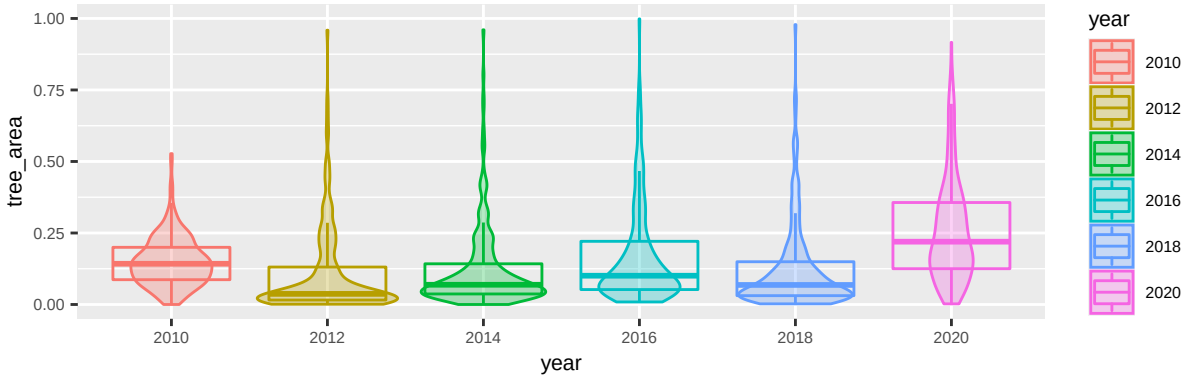
Google Earth: Tensor Flow Model

Tree Area



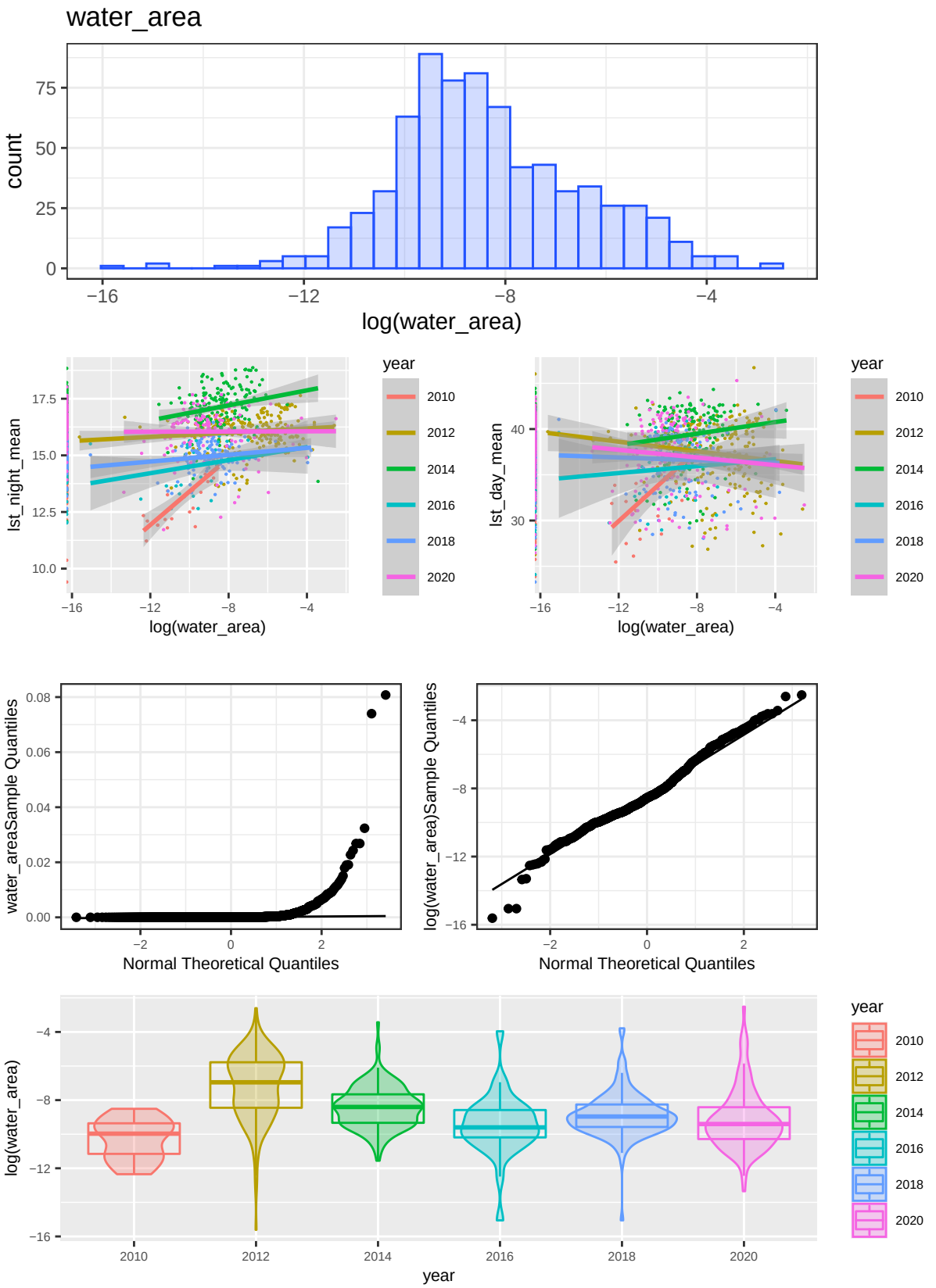






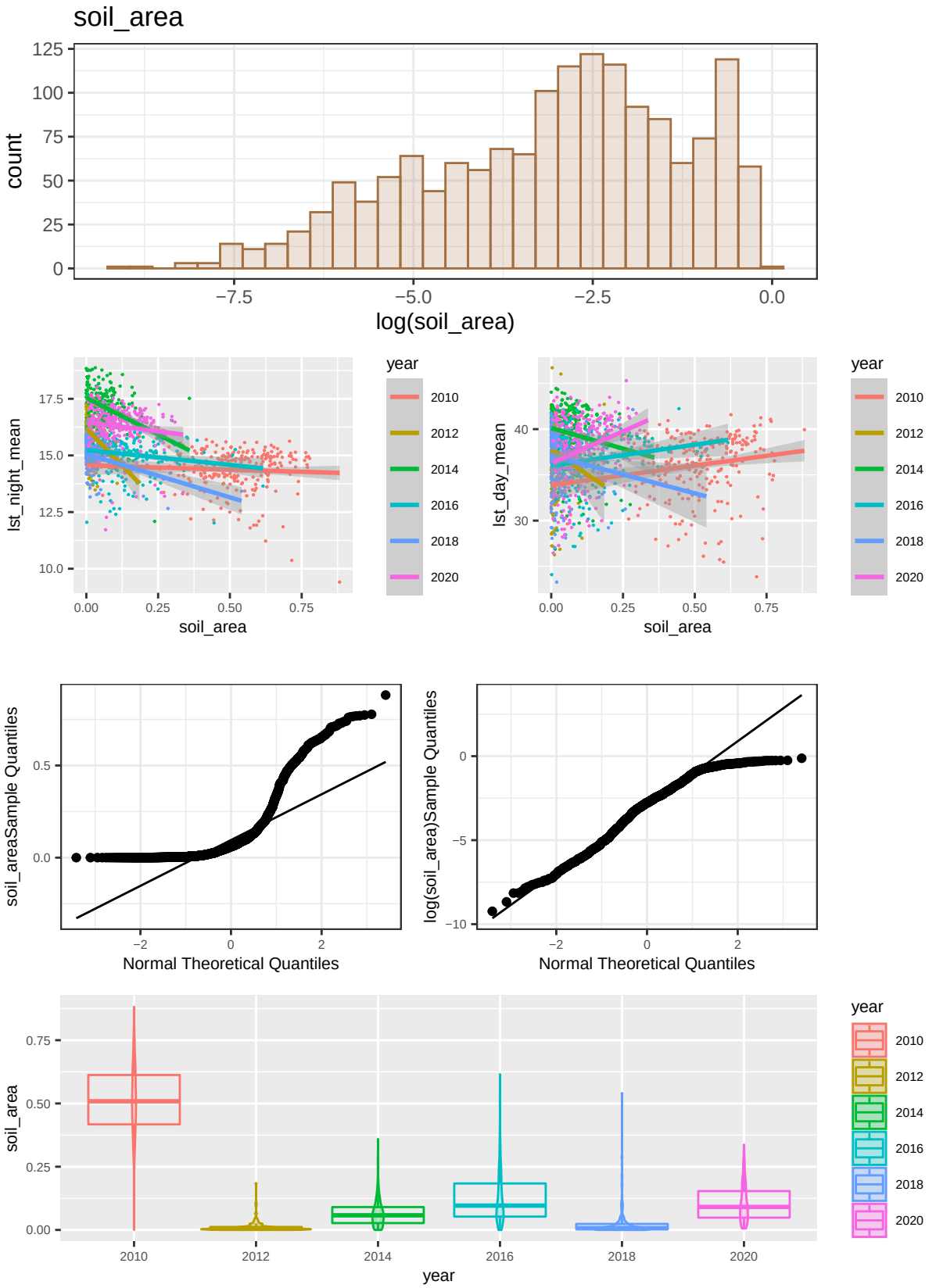
Google Earth: Tensor Flow Model

Water Area



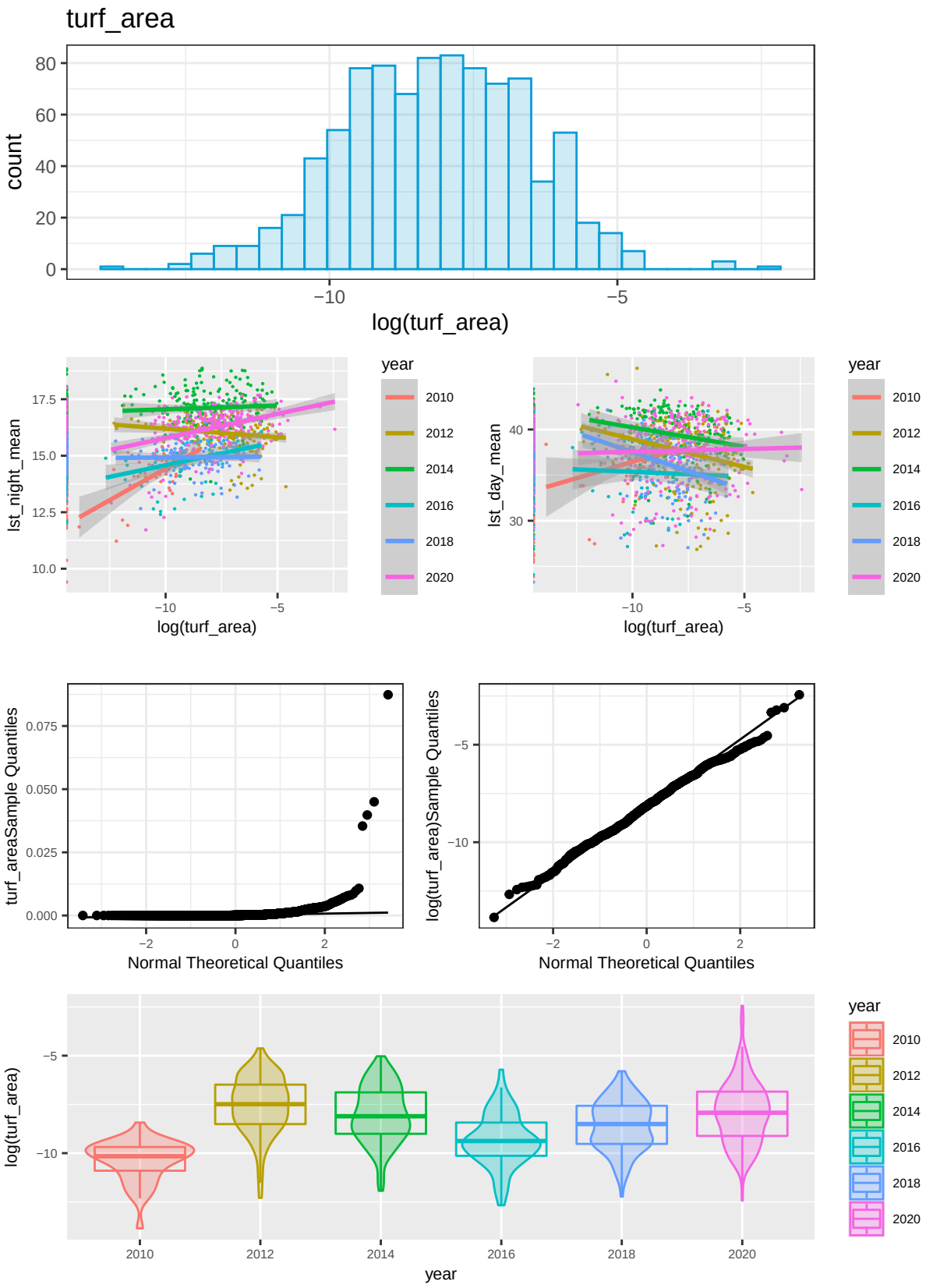
Google Earth: Tensor Flow Model

Soil Area



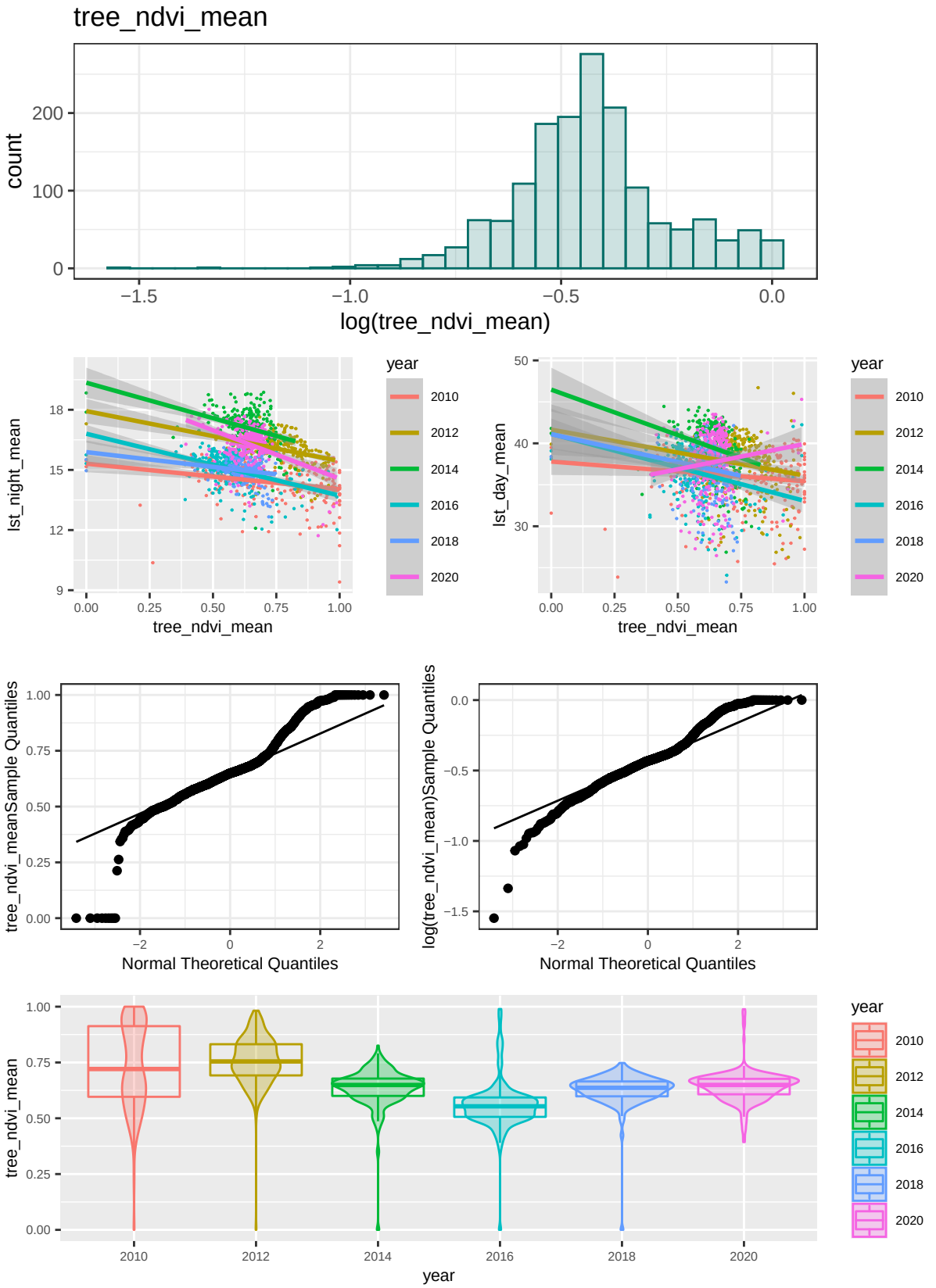
Google Earth: Tensor Flow Model

Turf Area



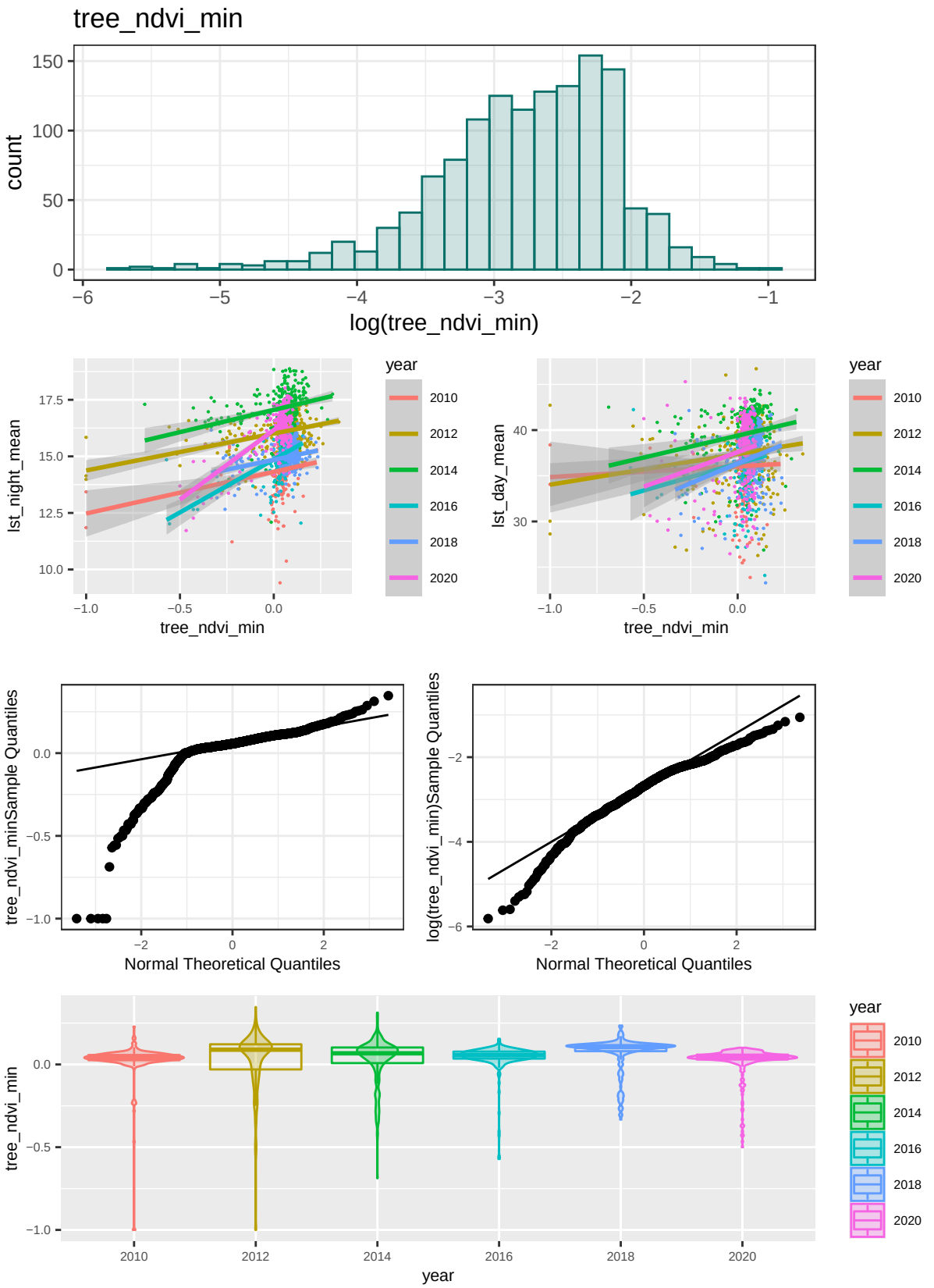
Google Earth: Tensor Flow Model

Tree NDVI Mean



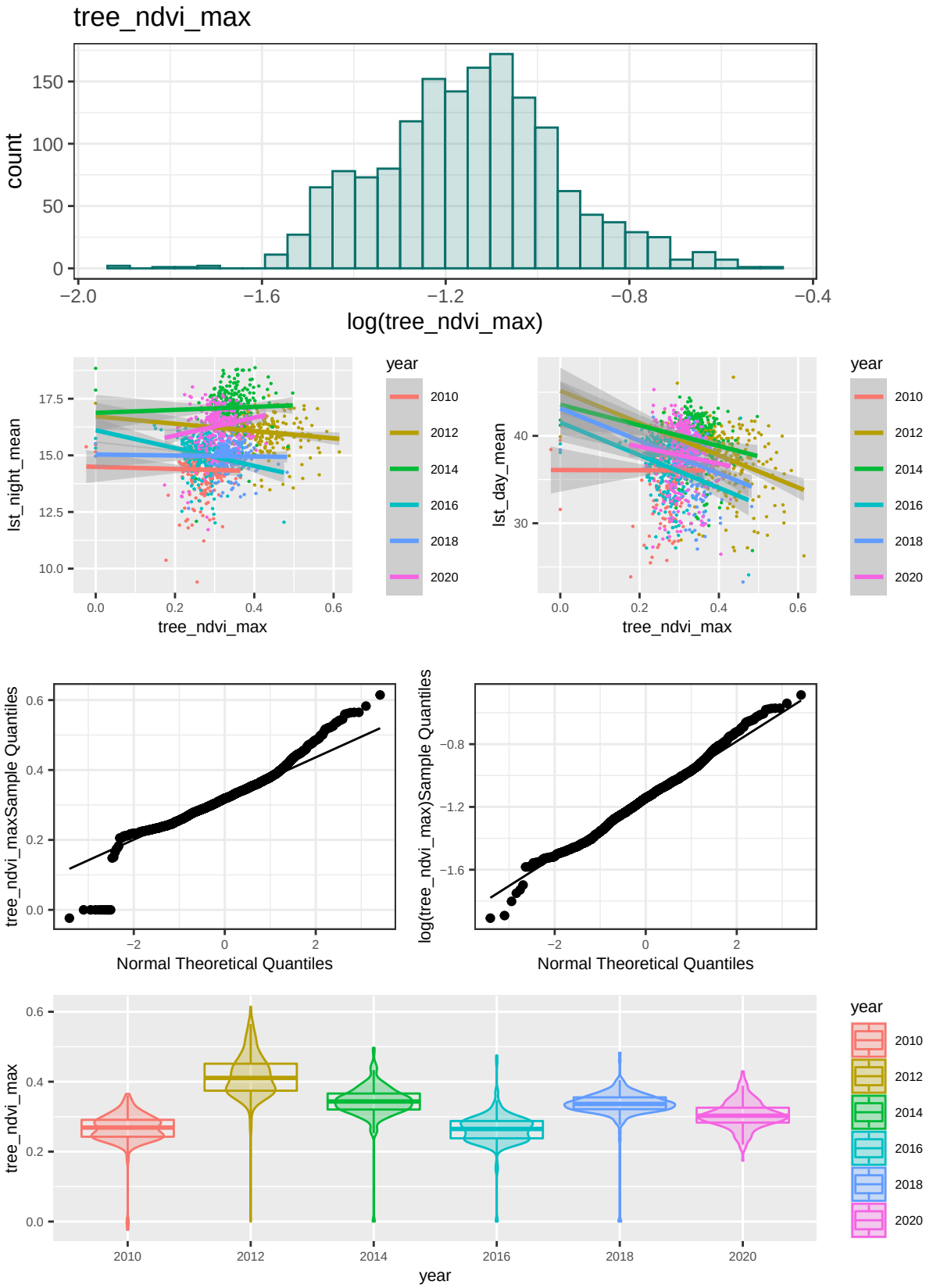
Google Earth: Tensor Flow Model

Tree NDVI Min



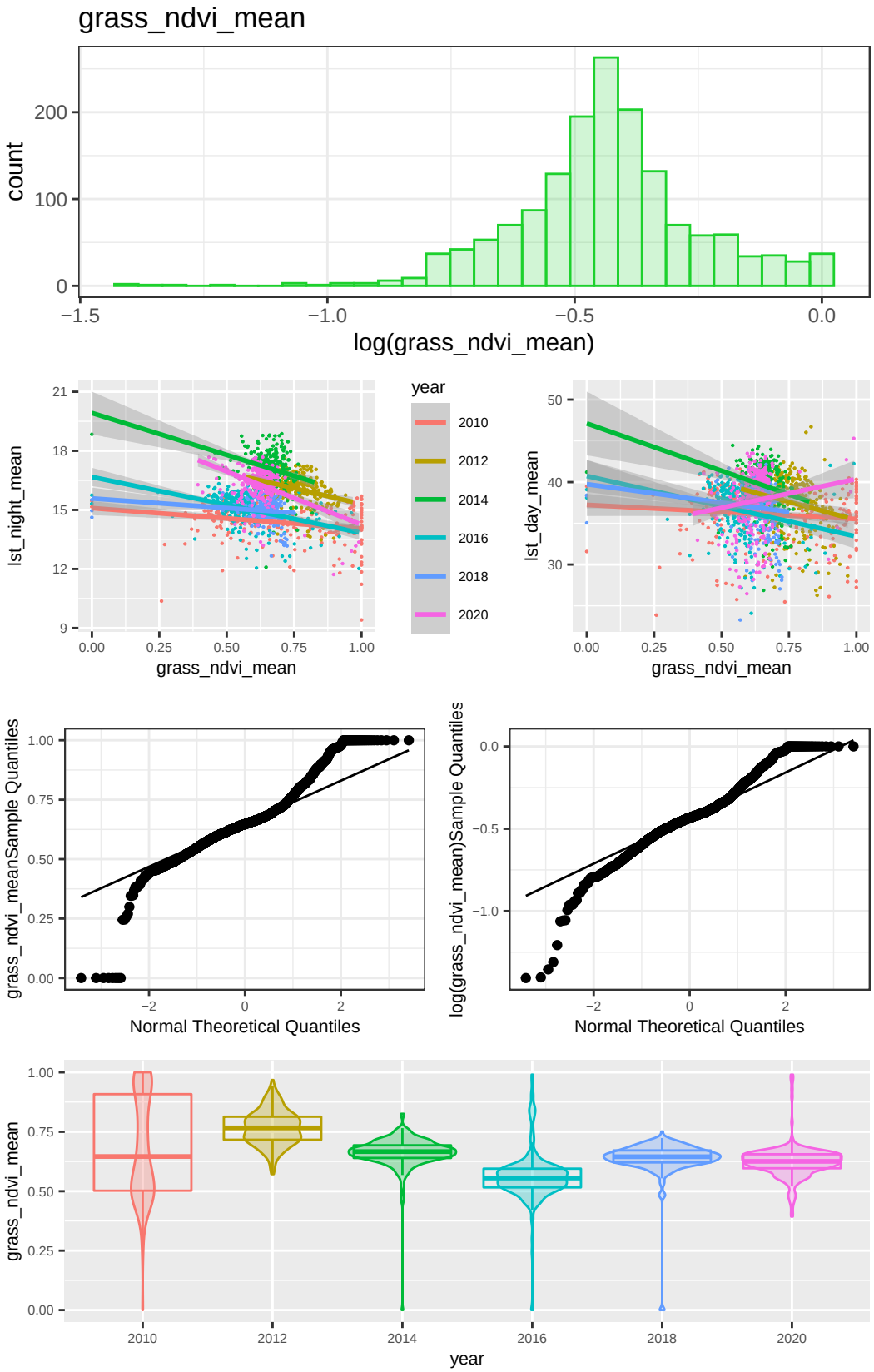
Google Earth: Tensor Flow Model

Tree NDVI Max



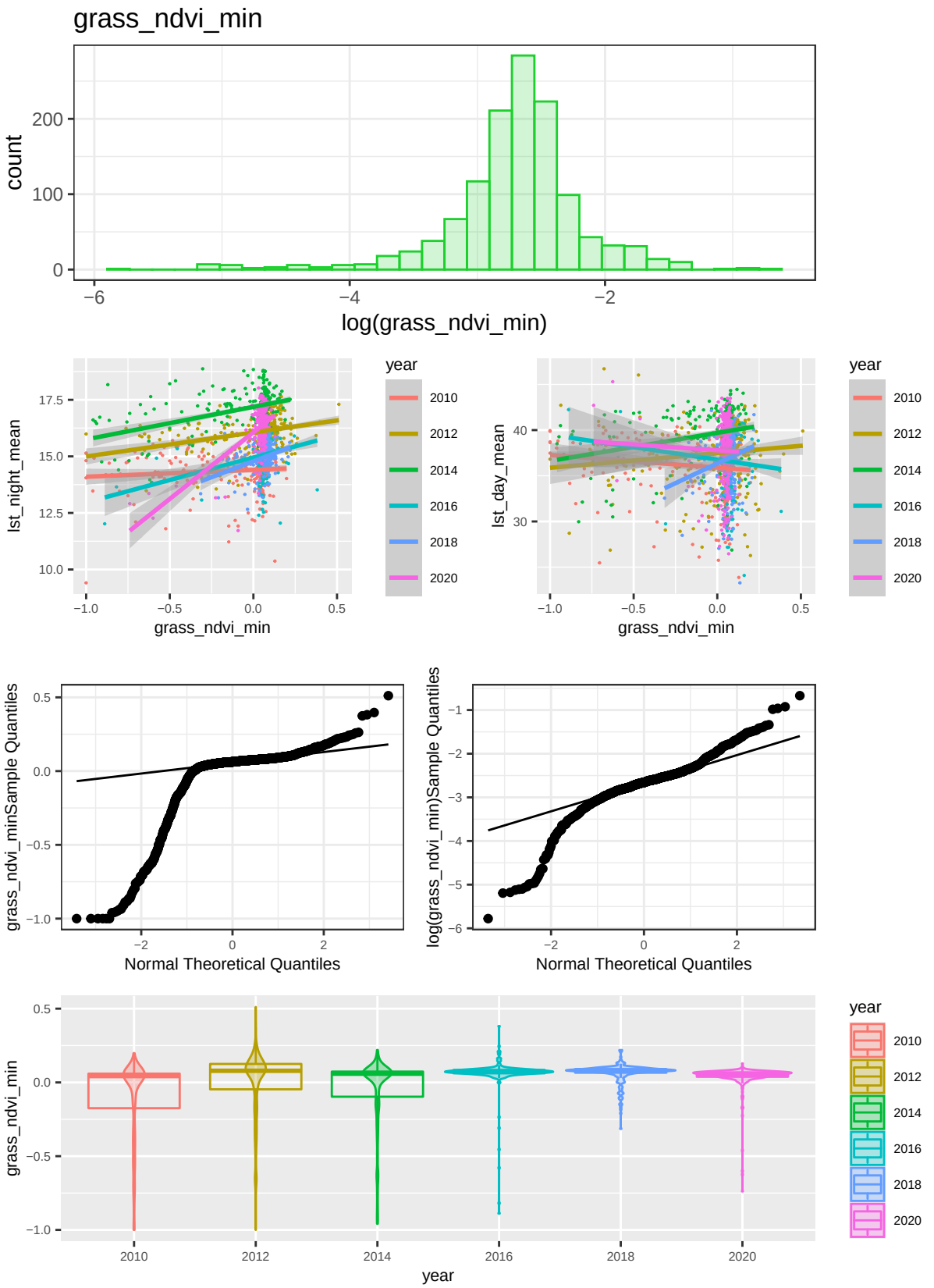
Google Earth: Tensor Flow Model

Lawn NDVI Mean



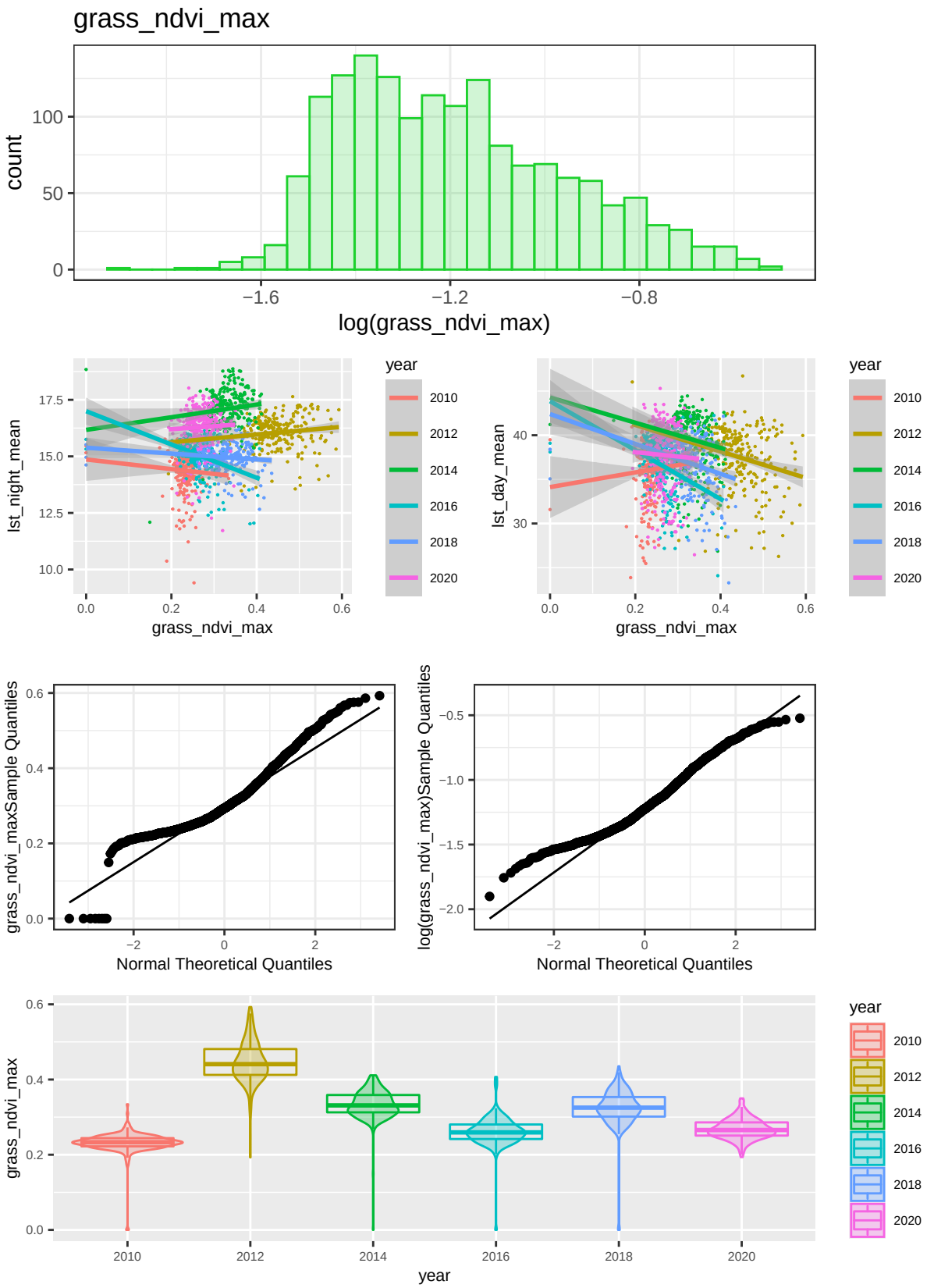
Google Earth: Tensor Flow Model

Lawn NDVI Min



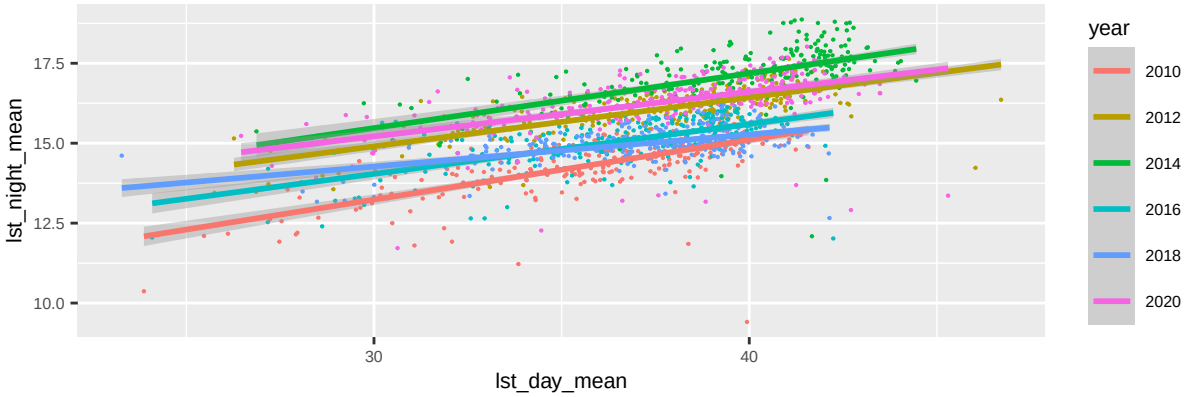
Google Earth: Tensor Flow Model

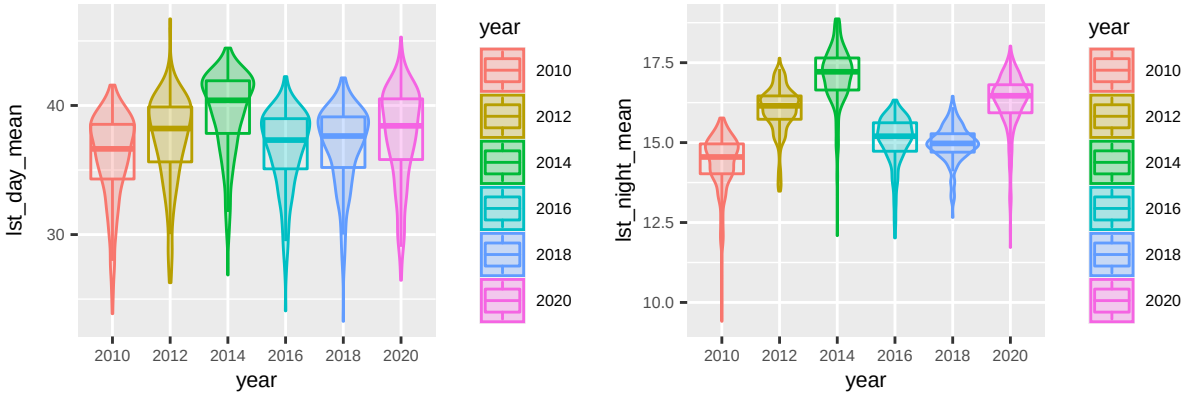
Lawn NDVI Max

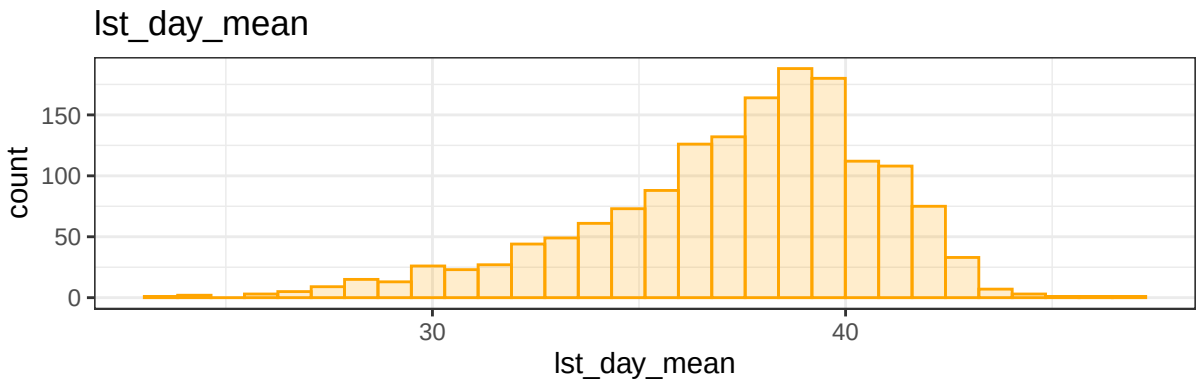


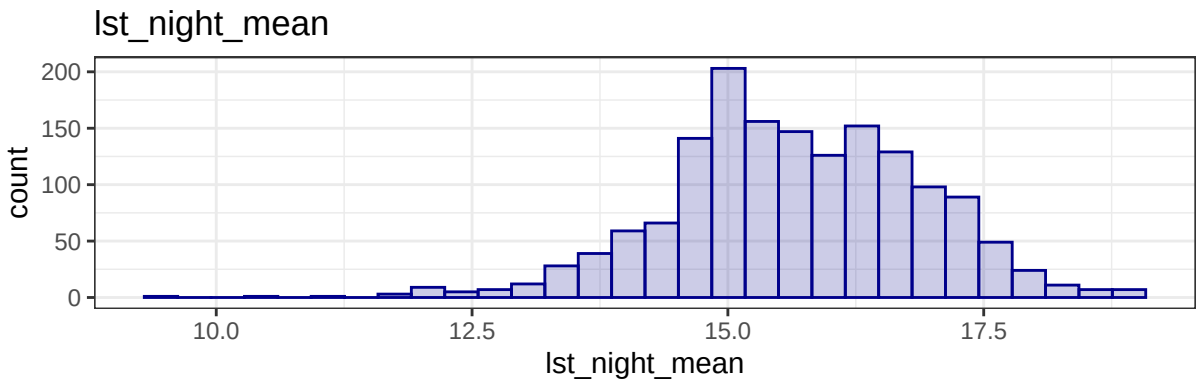
Google Earth: Tensor Flow Model

Mean Temperature









Google Earth: Tensor Flow Model

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: Thu, Jul 28, 2022 - 8:20:30 PM

Second Attempt with a Mixed Effects Model

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

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

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

```
                                        "FixedEffects Night Temp"))
```

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Table 2: Fixed Effects Model

	Dependent variable:	
	lst_day_mean FixedEffects Day Temp	lst_night_mean FixedEffects Night Temp
	(1)	(2)
factor(year)2014	1.446*** (0.070)	0.616*** (0.040)
factor(year)2016	−1.489*** (0.071)	−1.303*** (0.041)
factor(year)2018	−1.267*** (0.072)	−1.460*** (0.041)
tree_area	−0.470 (0.286)	−0.332** (0.164)
lawn_area	−2.424*** (0.657)	0.720* (0.377)
log(water_area)	0.002 (0.004)	0.004* (0.002)
log(soil_area)	0.001 (0.009)	0.003 (0.005)
log(turf_area)	0.002 (0.004)	0.005** (0.002)
grass_ndvi_mean	0.952 (0.729)	0.377 (0.418)
tree_ndvi_mean	0.301 (0.671)	−0.491 (0.385)
Observations	1,057	1,057
R^2	0.855	0.917
Adjusted R^2	0.799	0.884
F Statistic (df = 10; 759)	448.774***	836.577***
Note:		*p<0.1; **p<0.05; ***p<0.01

Compare Performance of OLS vs Mixed Effects Models

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

```
##
##  F test for individual effects
##
## data:  lst_day_mean ~ 0 + factor(year) + tree_area + lawn_area + log(water_area) +  ...
## F = -2.5772, df1 = 287, df2 = 759, p-value = 1
## 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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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

Compare Performance of Mixed Effects vs Random Effects Models

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

```
##
##  Hausman Test
##
## data:  lst_day_mean ~ 0 + factor(year) + tree_area + lawn_area + log(water_area) +  ...
## chisq = 14601, 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).
```

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_ar
    log(turf_area) + grass_ndvi_mean + tree_ndvi_mean,
  index = c(zipcode, year), data = microClimatePanel, model = 'within')

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

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

```
## Warning in pf(stat, df1, df2, lower.tail = FALSE): NaNs produced
```

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

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

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

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

```
pbgtest(feM1)
```

```
##
##  Breusch-Godfrey/Wooldridge test for serial correlation in panel models
##
## data:  lst_day_mean ~ 0 + factor(year) + tree_area + lawn_area + log(water_area) +  ...
## chisq = 63.96, df = 1, p-value = 1.269e-15
## alternative hypothesis: serial correlation in idiosyncratic errors
```

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

```
##
## t test of coefficients:
##
##                      Estimate  Std. Error  t value  Pr(>|t|)
## factor(year)2014  1.44554180  0.07522295  19.2168 < 2.2e-16 ***
## factor(year)2016 -1.48852424  0.07962260 -18.6947 < 2.2e-16 ***
## factor(year)2018 -1.26725732  0.07330603 -17.2872 < 2.2e-16 ***
## tree_area        -0.47047382  0.29350404  -1.6030 0.1093606
## lawn_area        -2.42438974  0.66414662  -3.6504 0.0002798 ***
## log(water_area)   0.00228291  0.00333302   0.6849 0.4935934
## log(soil_area)    0.00088539  0.00732982   0.1208 0.9038876
## log(turf_area)    0.00170148  0.00368336   0.4619 0.6442589
## grass_ndvi_mean   0.95245403  0.62772823   1.5173 0.1296065
## tree_ndvi_mean    0.30131761  0.59217533   0.5088 0.6110180
## ---
```

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

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

```
##
## t test of coefficients:
##
##                      Estimate  Std. Error  t value  Pr(>|t|)
## factor(year)2014  1.44554180  0.07522295  19.2168 < 2.2e-16 ***
## factor(year)2016 -1.48852424  0.07962260 -18.6947 < 2.2e-16 ***
## factor(year)2018 -1.26725732  0.07330603 -17.2872 < 2.2e-16 ***
## tree_area        -0.47047382  0.29350404  -1.6030 0.1093606
## lawn_area        -2.42438974  0.66414662  -3.6504 0.0002798 ***
## log(water_area)   0.00228291  0.00333302   0.6849 0.4935934
## log(soil_area)    0.00088539  0.00732982   0.1208 0.9038876
## log(turf_area)    0.00170148  0.00368336   0.4619 0.6442589
## grass_ndvi_mean   0.95245403  0.62772823   1.5173 0.1296065
## tree_ndvi_mean    0.30131761  0.59217533   0.5088 0.6110180
## ---
## 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 = "are
```

```
##     factor(year)2014 factor(year)2016 factor(year)2018 tree_area lawn_area
## HC0       0.07522295       0.07962260       0.07330603 0.2935040 0.6641466
## HC1       0.07558133       0.08000194       0.07365528 0.2949023 0.6673107
## HC2       0.07598188       0.08023038       0.07392496 0.2976493 0.6722953
## HC3       0.07676684       0.08084975       0.07456335 0.3019512 0.6806513
## HC4       0.07748397       0.08102597       0.07502642 0.3080608 0.6897522
##     log(water_area) log(soil_area) log(turf_area) grass_ndvi_mean
## HC0     0.003333023    0.007329821    0.003683361       0.6277282
## HC1     0.003348902    0.007364742    0.003700909       0.6307188
## HC2     0.003352529    0.007491388    0.003705880       0.6345154
## HC3     0.003372337    0.007659104    0.003728814       0.6415432
## HC4     0.003369895    0.007972571    0.003727963       0.6488436
##     tree_ndvi_mean
## HC0      0.5921753
## HC1      0.5949966
## HC2      0.5974213
## HC3      0.6028150
## HC4      0.6068934
```

```
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  1.44554180  0.07522295  19.2168 < 2.2e-16 ***
## factor(year)2016 -1.48852424  0.07962260 -18.6947 < 2.2e-16 ***
## factor(year)2018 -1.26725732  0.07330603 -17.2872 < 2.2e-16 ***
## tree_area        -0.47047382  0.29350404  -1.6030 0.1093606
## lawn_area        -2.42438974  0.66414662  -3.6504 0.0002798 ***
## log(water_area)   0.00228291  0.00333302   0.6849 0.4935934
## log(soil_area)    0.00088539  0.00732982   0.1208 0.9038876
## log(turf_area)    0.00170148  0.00368336   0.4619 0.6442589
## grass_ndvi_mean   0.95245403  0.62772823   1.5173 0.1296065
## tree_ndvi_mean    0.30131761  0.59217533   0.5088 0.6110180
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
print(cInterval)
```

```
##                           2.5 %       97.5 %
## factor(year)2014  1.297872041  1.593211562
## factor(year)2016 -1.644830921 -1.332217550
## factor(year)2018 -1.411163981 -1.123350653
## tree_area        -1.046649950  0.105702315
## lawn_area        -3.728172253 -1.120607230
## log(water_area)  -0.004260132  0.008825946
## log(soil_area)   -0.013503746  0.015274516
## log(turf_area)   -0.005529305  0.008932266
## grass_ndvi_mean  -0.279835746  2.184743802
## tree_ndvi_mean   -0.861178472  1.463813687
```

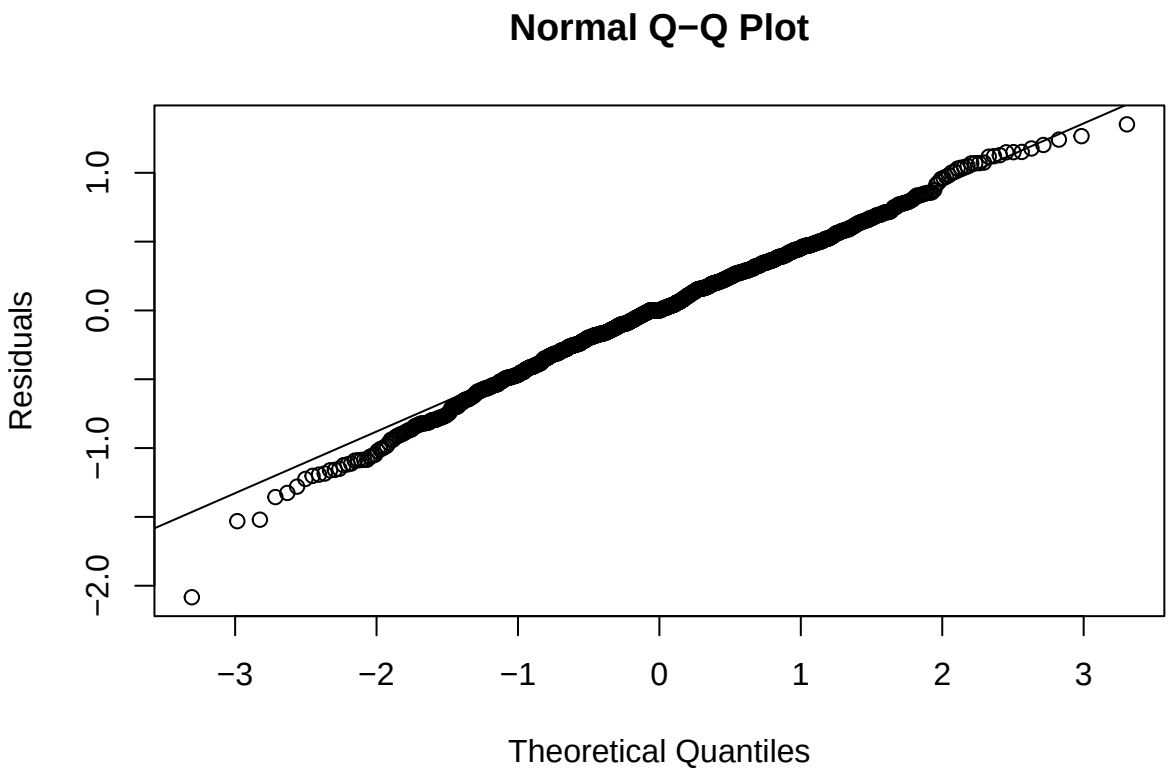
```
stargazer::stargazer(OLSM1,feM1,reM1,feM2FixedTime,
                     font.size = 'tiny',
                     title = 'Regression Models Sumamry',
                     column.labels = c("OLS", "FixedEffects",
                                       "RandomEffects",
                                       "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: Thu, Jul 28, 2022 - 8:20:34 PM

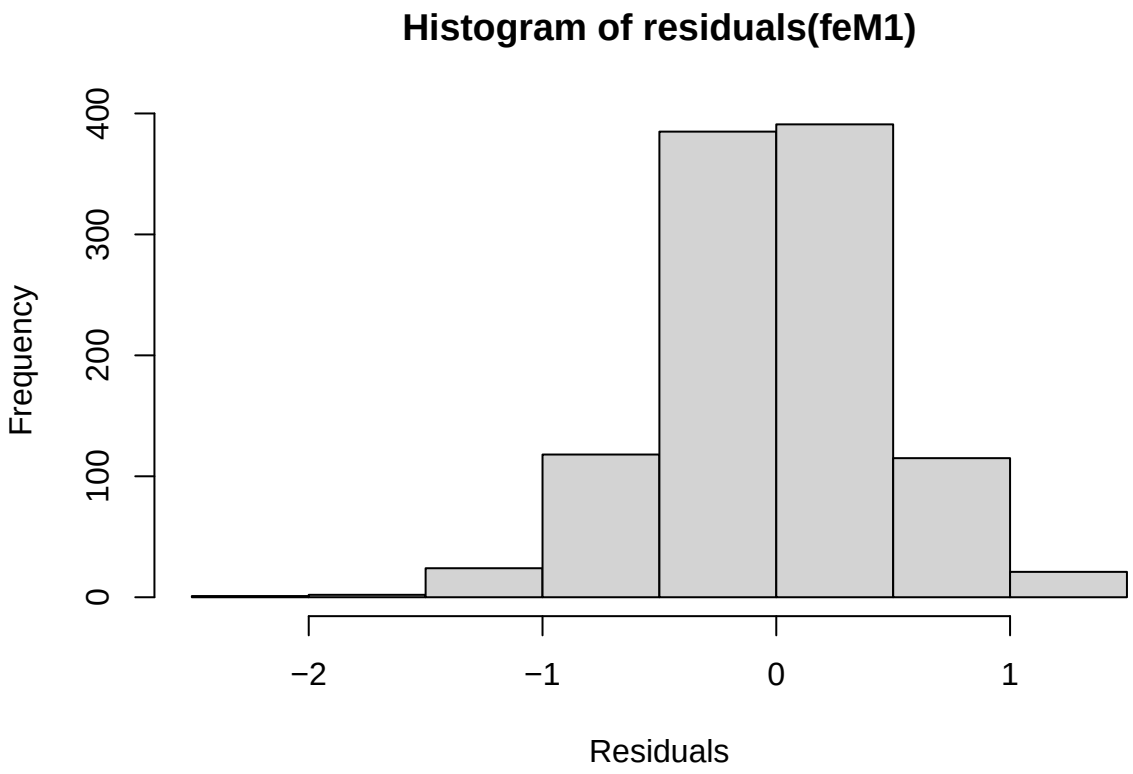
```
qqnorm(residuals(feM1), ylab = 'Residuals')
qqline(residuals(feM1))
```

Table 5: Regression Models Sumamry

	Dependent variable:			
	log(lst_day_mean)	lst_day_mean	log(lst_day_mean)	
	OLS	*panel linear*		*panel linear*
	OLS	FixedEffects	RandomEffects	FixedEffectsFixedTime
	(1)	(2)	(3)	(4)
factor(year)2014	3.731***	1.446***	3.658***	0.038***
	(0.026)	(0.070)	(0.009)	(0.002)
factor(year)2016	3.648***	−1.489***	3.580***	−0.040***
	(0.024)	(0.071)	(0.008)	(0.002)
factor(year)2018	3.655***	−1.267***	3.586***	−0.033***
	(0.026)	(0.072)	(0.009)	(0.002)
factor(year)2020	3.714***		3.622***	
	(0.025)		(0.009)	
tree_area	−0.295***	−0.470	−0.046***	−0.017**
	(0.016)	(0.286)	(0.008)	(0.008)
lawn_area	−0.144**	−2.424***	−0.065***	−0.048***
	(0.062)	(0.657)	(0.019)	(0.018)
log(water_area)	−0.001***	0.002	−0.00001	0.0001
	(0.0004)	(0.004)	(0.0001)	(0.0001)
log(soil_area)	0.001	0.001	0.00001	0.00002
	(0.001)	(0.009)	(0.0003)	(0.0002)
log(turf_area)	0.0002	0.002	−0.00002	−0.00001
	(0.0004)	(0.004)	(0.0001)	(0.0001)
grass_ndvi_mean	−0.086	0.952	0.002	0.012
	(0.077)	(0.729)	(0.021)	(0.020)
tree_ndvi_mean	0.059	0.301	0.026	0.019
	(0.075)	(0.671)	(0.020)	(0.018)
Observations	1,057	1,057	1,057	1,057
R^2	1.000	0.855	0.944	0.848
Adjusted R^2	1.000	0.799	0.944	0.788
Residual Std. Error	0.075 (df = 1046)			
F Statistic	222,248.400*** (df = 11; 1046)	448.774*** (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
100
200
300
400
−2
−1
0
1
Residuals