Final Report

Spatial Analysis Ponderosa Pine Tree Point Pattern

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14 pages

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Introduction:

Motivation: Ponderosa pine forests are crucial because they are important for lumber/wood, especially in the Southwest USA (Kolb et al, 2019). Meanwhile, ponderosa pine trees are crucial for the grazing of livestock, and recreation. Numerous other wildlife species as deer and elk find food and refuge in the forests (UCLA,2022)

Unfortunately, this precious tree is endangered because of cutting for lumber, climate changes, wildfire (Owen et al,2017), droughts, and insects (Reich et al,1991). Study Franklin et al (1985) applied the Poisson model in finding locations, distribution patterns, and relationships in Ponderosa pine forests. All analyses revealed that the pattern was regular at the scale of the average inter-plant distance in the denser stands, while the second order and spectral analysis failed to detect any indication of a distinct clumped pattern at any scale. For the sparser stands, a mixed Poisson model representing the aggregated pattern fits the counts in big quadrats better than a Poisson distribution (Franklin et al,1985).

Getis & Franklin (1987) used second-order neighborhood analysis to quantify clustering at different spatial scales for a sample of ponderosa and present that heterogeneity within the forest is a function of the scale of analysis. They demonstrate that the overall pattern can not be distinguished from a spatial Poisson process, but a deeper look at the spatial interactions between specific trees and their neighbors reveals interesting differences (Getis&Franklin,1987).

Statement of research: The aim of this study is to understand and find the distribution patterns of Ponderosa pine trees in the Klamath National Forest.

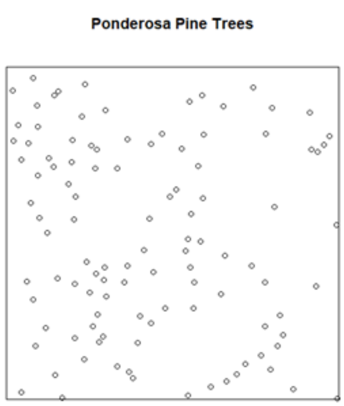
Image: Ponderosa Pine Tree and the map of the Klamath National Forest

Information on Data set

Ponderosa data set

Data description: The spatial point pattern (object of class ppp) known as "the dataset ponderosa" displays the positional point pattern of trees. In the Klamath National Forest in northern California, the data depicts the locations of 108 Ponderosa Pine (Pinus ponderosa) trees in a 120-meter square area. (RStudio Team,2022).

Plotting data:



Statistical Methods, Model & Results:

The purpose of statistical analysis is to learn about the true/underlying process that generated the data, and not just the particular data that you have (Horrocks,2022)

first-order property:

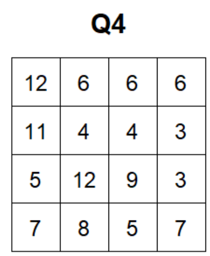
Intensity and Unit of Measurement:The intensity in a homogeneous process equal: n/a

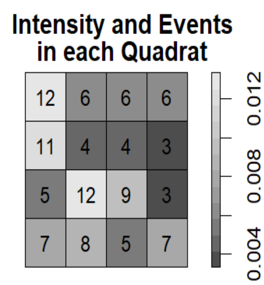
Intensity = 108

Unit of measurement: 108/120*120 = 0.0075 points per square metre

Quadrats:

The number of events in each of 4 quadrats





Quadrat Test:
Chi-squared test of CSR using quadrat counts

data: ponderosa

X2 = 19, df = 15, p-value = 0.4

alternative hypothesis: two. sided

Quadrats: 4 by 4 grid of tiles

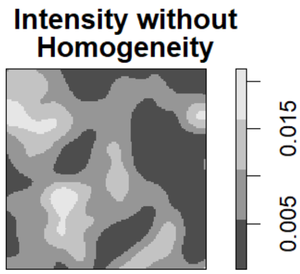
H0: The ponderosa pine trees distribution is complete spatial randomness (CSR)

Ha: The ponderosa pine trees distribution is not complete spatial randomness

H0 is not rejected because P-value is not small. It seems that process is homogeneous pp or CSR.

Intensity without Homogeneity:

Intensity is highest near the clusters and lowest near the empty spaces.



#G Function

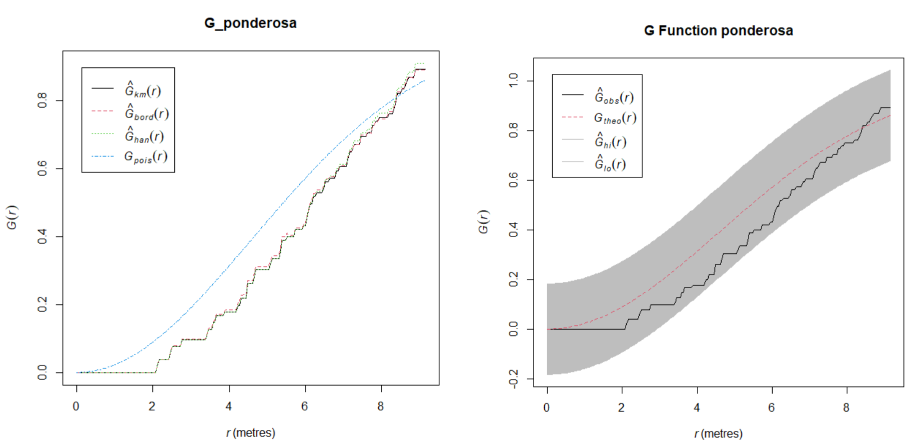
The G function calculates the distribution of the separation between an arbitrarily selected event and its closest occurrence. If we show distances with d_i = minj{ d_{ij}, ∀ i≠j} then the G function is estimated as

$\hat{G}(r) = \frac{\neq\{di: di \leq r\}}{n}$ (S.Bivand et al, 2013).

Under CSR, the value of the G function is:

$G(r) = 1 - \exp\{-\lambda\pi r^2\}$.(S.Bivand et al, 2013).

Ho: Underlying process is CSR Ha: Underlying process is not CSR



H0 is not rejected therefore it is CSR, because the stepped line (G function for the data) falls inside the envelope, then the null hypothesis of CSR is not rejected.

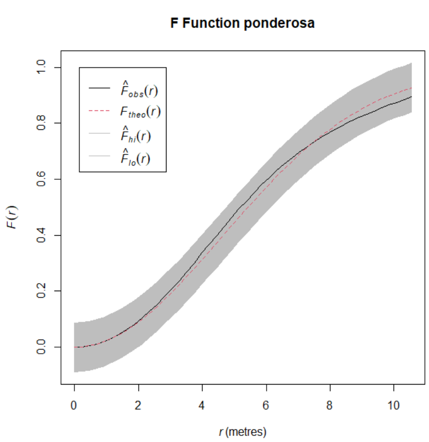
#F Function

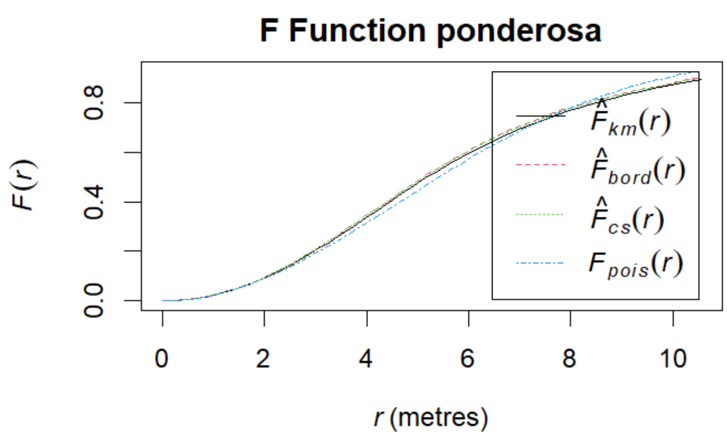
The distribution of all distances from every location on the plane to its nearest event is measured by the F function. Because it calculates the typical amount of time between events, this function is frequently referred to as the "empty space function."(S.Bivand et al, 2013).

Under CSR, the expected value of the F function is

F(r)= 1 – exp{-$\lambda\pi r^2$}(S.Bivand et al, 2013).

Ho: Underlying process is CSR Ha: Underlying process is not CSR





Fest looks is CSR (H0 is not rejected) because the black curve is in the enveloped area.

Second-Order Properties:

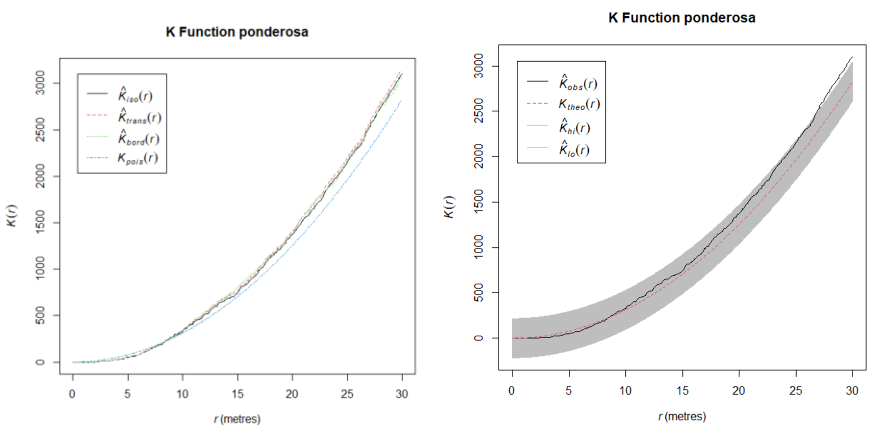
The strength and nature of the interactions between the events in the point process are measured by second-order characteristics. They are therefore especially intriguing if we are interested in researching event clustering or competition (S.Bivand et al, 2013).

K Function

K-function can also be used to measure second-order qualities when the spatial process is HPP. The K-function is defined as, counting the number of events that can be located within a certain distance of each given event. (S.Bivand et al, 2013).

$K(s) = \lambda^{-1} E[N_0(s)]$ (S.Bivand et al, 2013).

Ho: Underlying process is CSR Ha: Underlying process is not CSR



CSR is supported except at large scales.

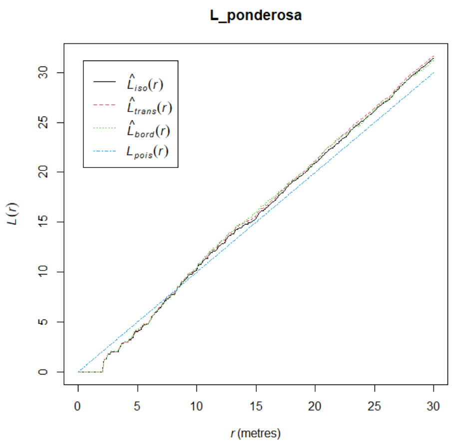
L Function

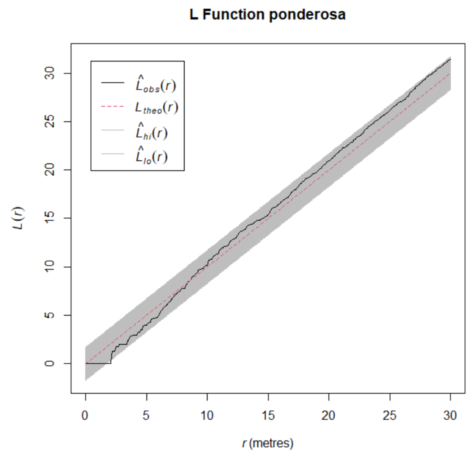
This is a simple transformation of the K function which

• is more linear, so marginally easier to interpret graphs

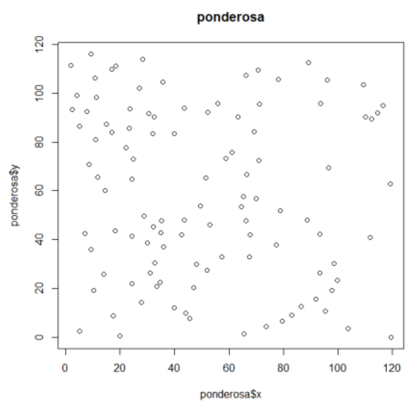
• stabilizes variance, so works better than K for envelopes

For CSR, $L(r) = r$ (Horrocks,2022)





L test, H0 is not rejected (It is CSR), because the black line is located in the enveloped area



Model:

Nonstationary Poisson process

Log intensity: ~x + y + I(x^2) + I(y^2) + I(x * y)

```
Fitted trend coefficients:

(Intercept)           x           y      I(x^2)      I(y^2)
I(x * y)

  -4.91e+00    6.08e-03    6.67e-03   -6.21e-05   -1.83e-05   -
1.15e-04


                Estimate     S.E.   CI95.lo   CI95.hi Ztest   Zval

(Intercept) -4.91e+00 4.92e-01 -5.873922 -3.95e+00    *** -9.987
```

x	6.08e-03	1.25e-02	-0.018475	3.06e-02	0.486
y	6.67e-03	1.24e-02	-0.017674	3.10e-02	0.537
I(x^2)	-6.21e-05	9.40e-05	-0.000246	1.22e-04	-0.661
I(y^2)	-1.83e-05	9.08e-05	-0.000196	1.60e-04	-0.201
I(x * y)	-1.15e-04	8.63e-05	-0.000284	5.46e-05	-1.327

The result does not show any trend.

Parsimonious Model:

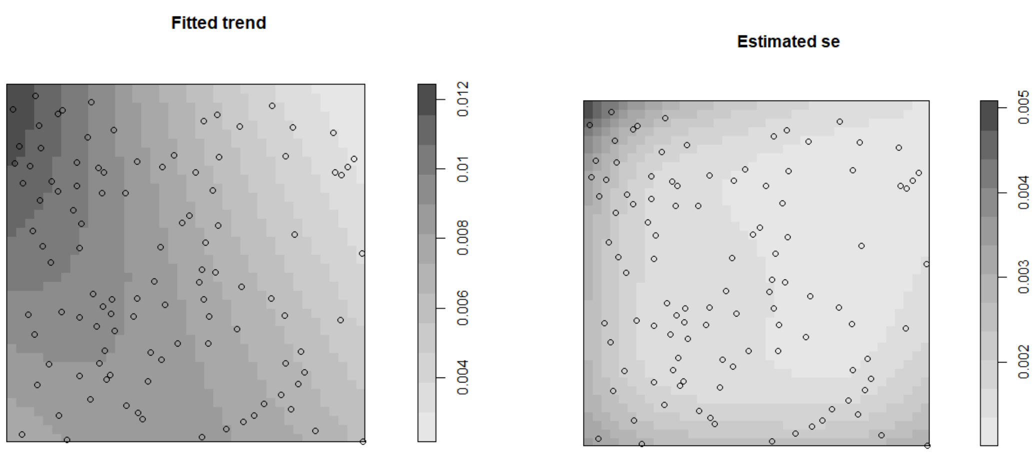
Nonstationary Poisson process

Log intensity: ~x + y + I (x * y)

Fitted trend coefficients:

(Intercept)	x	y	I(x * y)
-4.716299	-0.001398	0.004069	-0.000106

	Estimate	S.E.	CI95.lo	CI95.hi	Ztest	Zval
(Intercept)	-4.716299	3.53e-01	-5.409128	-4.02e+00	***	-13.342
x	-0.001398	5.47e-03	-0.012121	9.32e-03		-0.256
y	0.004069	5.01e-03	-0.005744	1.39e-02		0.813
I(x * y)	-0.000106	8.19e-05	-0.000266	5.45e-05		-1.294

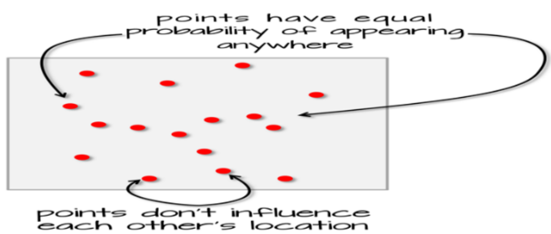


The result does not show any trend.

Conclusion and Future Work:

The results reveal that the underlying process of the distribution of the Ponderosa tree is Complete spatial randomness (CSR) .CSR/IRP satisfies two conditions:

The first-order effect of CSR/IRP is that every event has an equal chance of happening somewhere.A second-order effect is one in which the location of one event is unrelated to the location of another event (Gimond ,2022).



(Gimond ,2022)

Quadrat Test shows the process is homogenous. With assuming homogenity , the estimated intensity equals to 0.0075 points per square meter. The ppm model does not show any trend for the distribution of the Ponderosa tree in the Klamath National Forest.

For future researches, I suggest that spatial analysis studies will be done on ponderosa pine trees that are infected with insects, wildfires, and droughts.

Reference

Bivand, R. S., Pebesma, E. J., Gómez-Rubio, V., & Pebesma, E. J. (2008). *Applied spatial data analysis with R* (Vol. 747248717, pp. 237-268). New York: Springer.

Franklin, J., Michaelsen, J., & Strahler, A. (1985). Spatial analysis of density dependent pattern in coniferous forest stands. *Vegetatio,64(1),* 29–36. https://doi.org/10.1007/BF000334516.

Getis, A. and Franklin, J. (1987) Second-order neighbourhood analysis of mapped point patterns. *Ecology 68*, 473–477.

Gimond,M(2022) Intro to GIS and Spatial analysis https://mgimond.github.io/Spatial/index.html

Horrocks, J. (2022) Analyse of Spatial-Temporal Data [Course notes]. Retrieved from https://courselink.uoguelph.ca/d2l/home/758284

Kolb, T., Dixit, A., & Burney, O. (2019). Challenges and opportunities for maintaining ponderosa pine forests in the southwestern United States. *Tree Planters' Notes,62(1&2)*, 104-112

Owen, S. M., Sieg, C. H., Meador, A. J. S., Fulé, P. Z., Iniguez, J. M., Baggett, L. S & Battaglia, M. A. (2017). Spatial patterns of ponderosa pine regeneration in high-severity burn patches. *Forest Ecology and Management, 405, 134-149.*

Reich, R. M., Mielke Jr, P. W., & Hawksworth, F. G. (1991). Spatial analysis of ponderosa pine trees infected with dwarf mistletoe. *Canadian Journal of Forest Research, 21(12), 1808-1815.*

RStudio Team (2022). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/.

UCLA(2022). Forest Research and Outreach:Ponderosa Pine. https://ucanr.edu/sites/forestry/California_forests/http___ucanrorg_sites_forestry_California_forests_Tree_Identification_/Ponderosa_Pine_Pinus_ponderosa/

Appendix

```
install.packages("spatstat")
library(spatstat)
data = data(ponderosa)
??ponderosa
View(ponderosa)
plot(ponderosa)
npoints(X)
print(X)
Window(X)
intensity(X)
summary(X)
plot(ponderosa, main = "ponderosa")
G_ponderosa = Gest(ponderosa)
plot(G_ponderosa)
set.seed(10)
Env_ponderosa = envelope(ponderosa,fun=Gest, global=T,nrank=5, nsim=99)
plot(Env_ponderosa, main = "G Function ponderosa")
par(mfrow=c(1,1))
F_ponderosa = Fest(ponderosa)
plot(F_ponderosa, main = "F Function ponderosa")
F_ponderosa_Env = envelope(ponderosa,fun=Fest, global=T,nrank=5, nsim=99)
plot(F_ponderosa_Env, main = "F Function ponderosa")
K_ponderosa = Kest(ponderosa)
plot(K_ponderosa, main = "K Function ponderosa")
K_ponderosa_Env = envelope(ponderosa,fun=Kest, global=T,nrank=5, nsim=99)
plot(K_ponderosa_Env, main = "K Function ponderosa")
L_ponderosa = Lest(ponderosa)
plot(L_ponderosa)
```

```
L_ponderosa_Env = envelope(ponderosa,fun=Lest, global=T,nrank=5, nsim=99)
plot(L_ponderosa_Env, main = "L Function ponderosa")
install.packages("spatstat")
library(spatstat)
ponderosa
plot(ponderosa$x, ponderosa$y, main = "ponderosa")
hold=ppm(ponderosa~x+y+I(x^2)+I(y^2)+I(x*y))
options(digits=3)
hold
plot(hold,col=gray.colors(12,rev=T ))
hold2=ppm(ponderosa~x+y+I(x*y))
hold2
install.packages("spatstat")
library(spatstat)
Q4 <- quadratcount(ponderosa,4,4)
Q4=quadratcount(ponderosa,nx=4,ny=4)
Q4
plot(Q4)
plot(intensity(Q4,image=T),col=gray.colors(12),main="Intensity and Events
in each Quadrat")
plot(Q4, add=T) #add counts
#Quadrat test
install.packages("spatstat")
library(spatstat)
quadrat.test(ponderosa,4,4)
install.packages("spatstat")
library(spatstat)
bw.diggle(ponderosa)
intponderosa = density(ponderosa,sigma=bw.diggle(ponderosa))
```

```
plot(intponderosa,col=gray.colors(4,rev=F), main="Intensity without Homogeneity")
install.packages("spatstat")
```