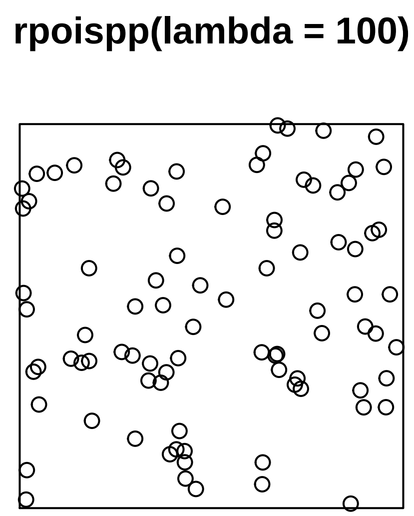
STAT 534 - Lecture 25: Key

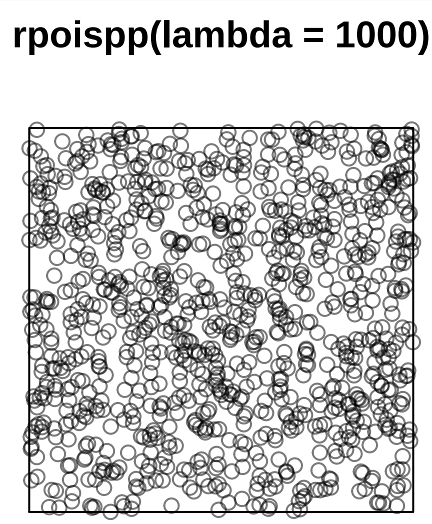
Point Process Simulation

- `spatstat` contains a set of functions for simulating point process data.

```r
plot(rpoispp(lambda = 100))
```



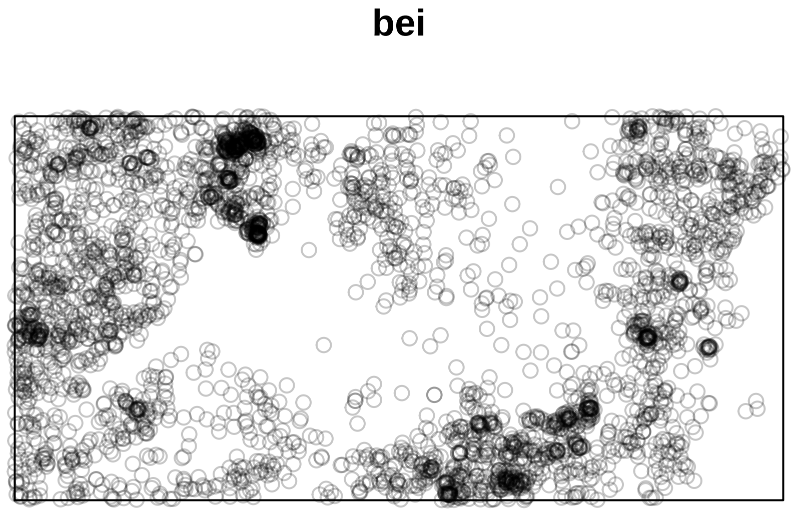

```r
plot(rpoispp(lambda = 1000))
```



Model Fitting

- The ppm function can be used for model fitting with a point process.

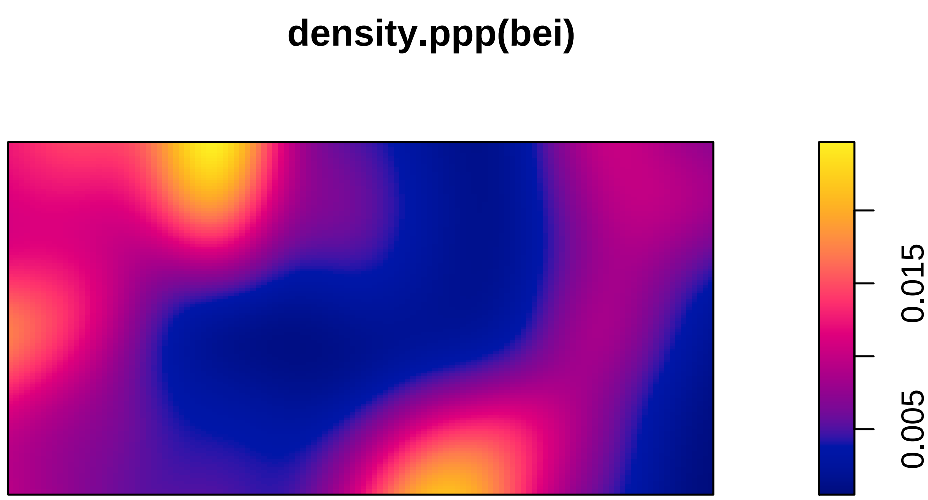
```r
plot(bei)
```



- The bei dataset contains locations of trees in a tropical rain forest.

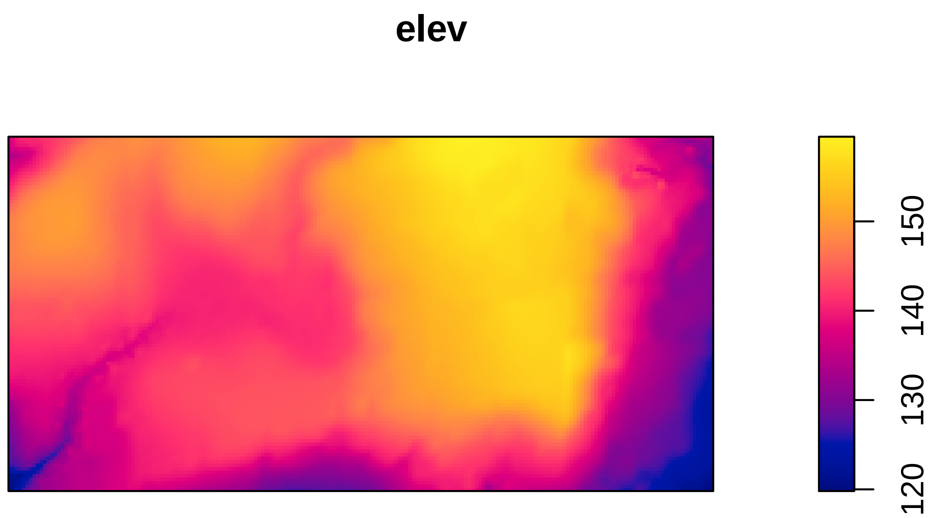
- The point pattern is clearly non-homogenous

```r
plot(density.ppp(bei))
```

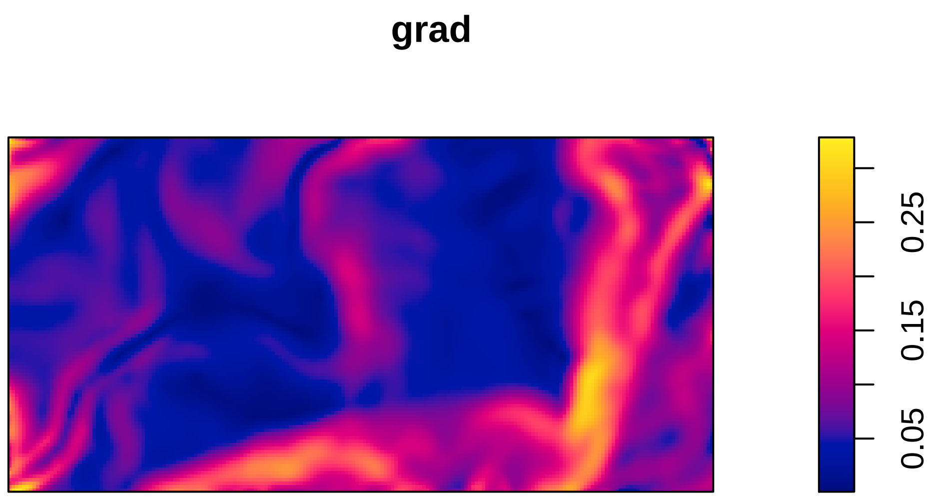


- The pattern in the intensity of the trees may be related to elevation and the elevation gradient.

```
elev <- bei.extra$elev
grad <- bei.extra$grad
plot(elev)
```




```
plot(grad)
```



- The elevation and gradient are stored as pixel image objects.

```
class(elev)
```

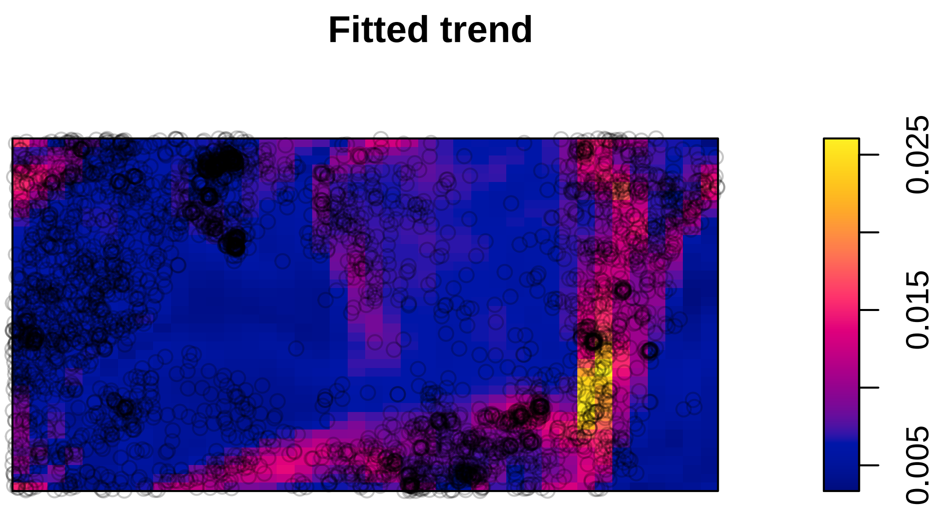
```
## [1] "im"
```

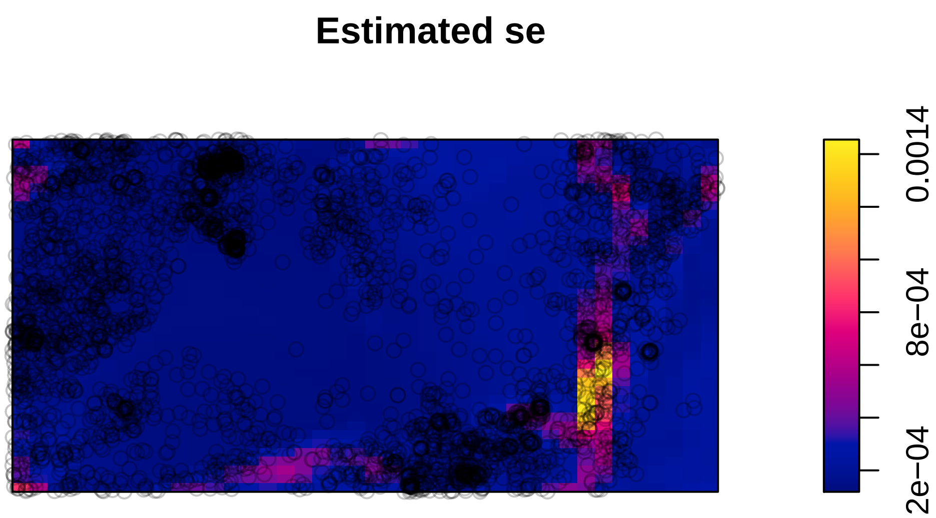
- The ppm function allows model fitting

```
tree.model <- ppm(bei ~ elev + grad);
tree.model
```

```
## Nonstationary Poisson process
##
## Log intensity:  ~elev + grad
##
## Fitted trend coefficients:
## (Intercept)        elev        grad
## -8.55862210  0.02140987  5.84104065
##
##                Estimate        S.E.     CI95.lo     CI95.hi Ztest
## (Intercept) -8.55862210 0.341100705 -9.22716720 -7.89007701   ***
## elev         0.02140987 0.002287773  0.01692592  0.02589383   ***
## grad         5.84104065 0.255860860  5.33956258  6.34251872   ***
##                   Zval
## (Intercept) -25.091189
## elev          9.358393
## grad         22.828973
```

```
plot(tree.model)
```



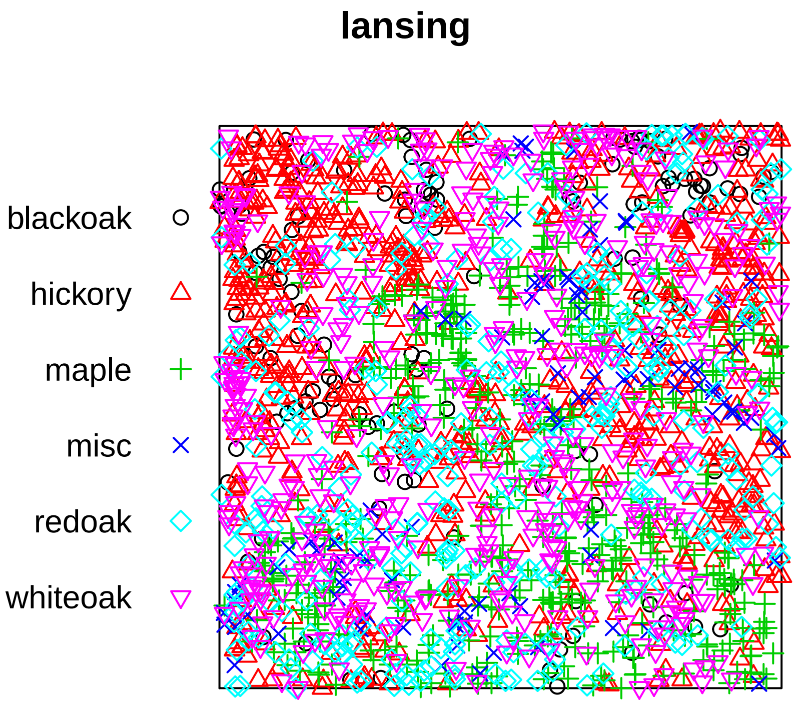


- For more complicated models, `kppm` can be used for clustering behavior.

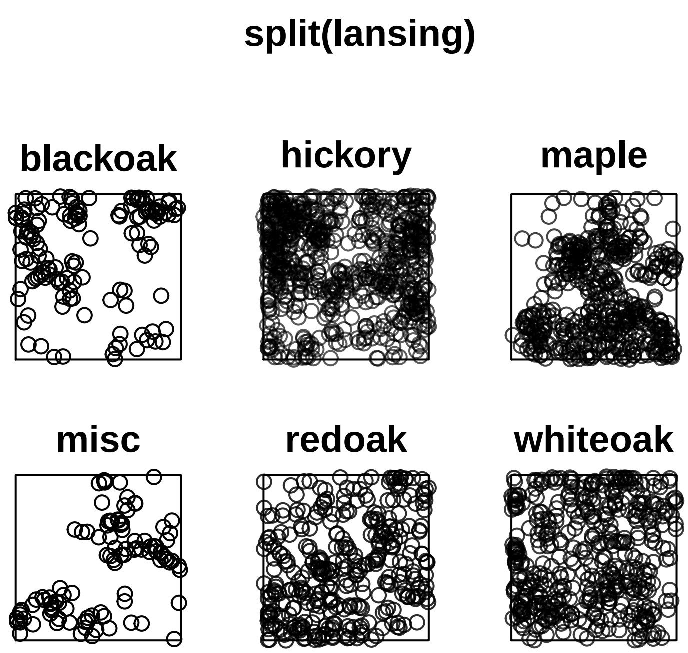
Marked Point Patterns

- Marked point process data contains meta data for each point. Rather than just $\boldsymbol{s}$, we have $(\boldsymbol{s}, m)$.
- The marked information can either be categorical (multi-type) or continuous.
- The `lansing` data set contains locations of six types of trees.

```
plot(lansing, cols = 1:6)
```




```
plot(split(lansing))
```



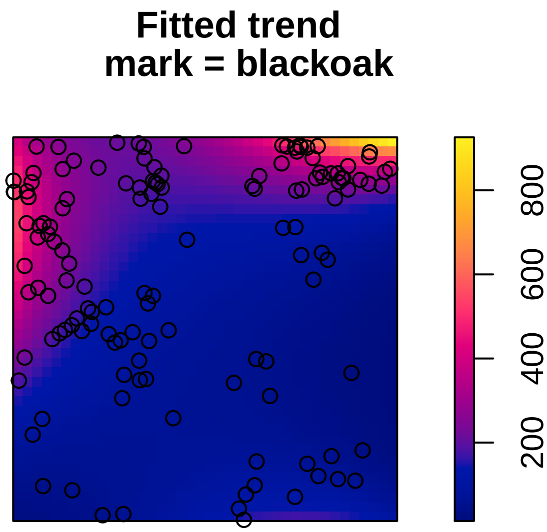
- To analyze this data, consider the following model.

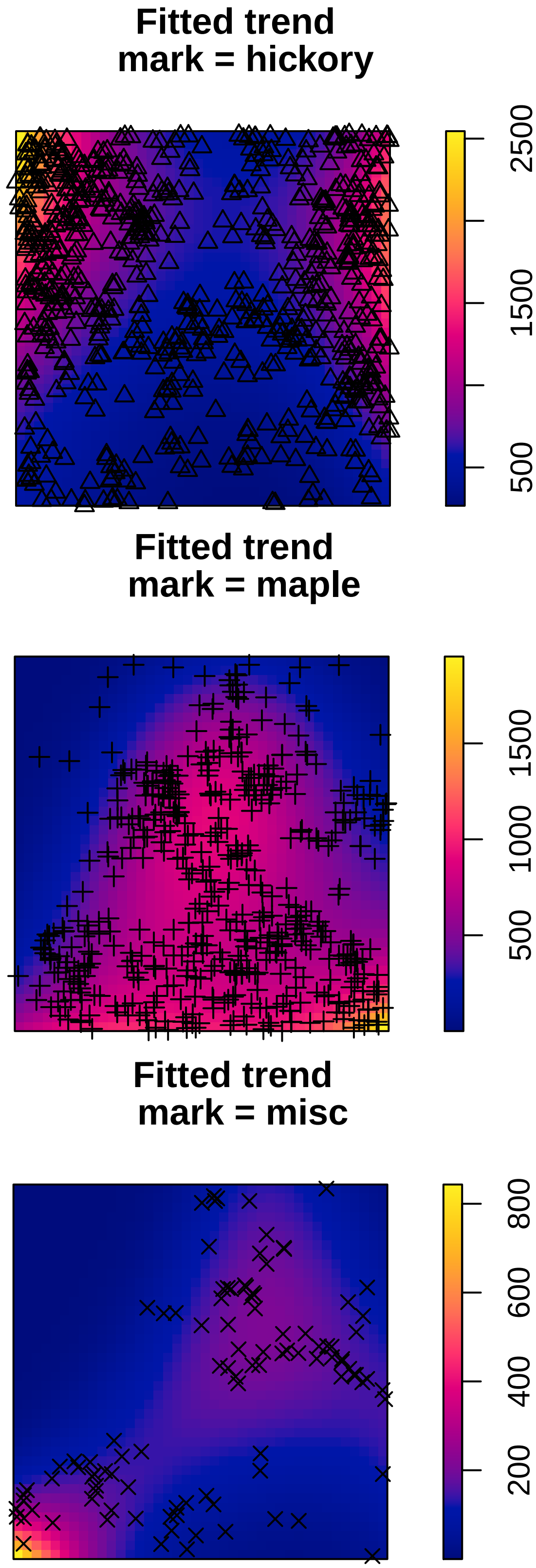
```
lansing.model <- ppm(lansing ~  marks - 1)
lansing.model
```

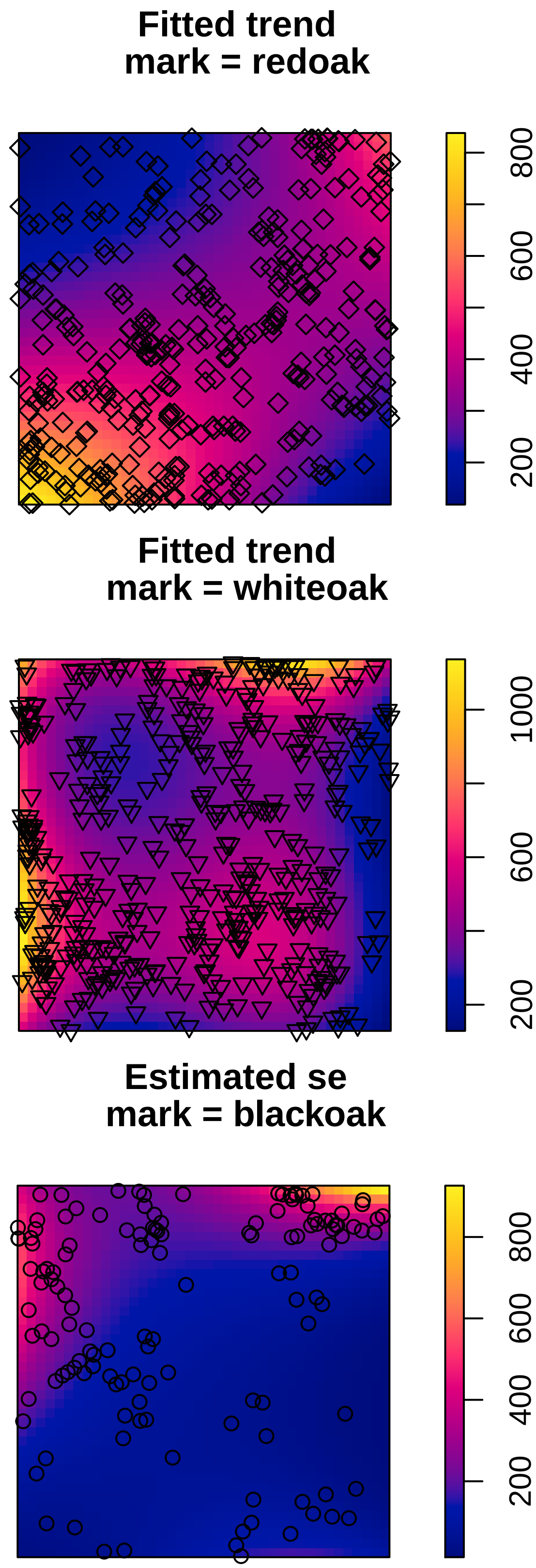
```
## Stationary multitype Poisson process
##
## Possible marks: 'blackoak', 'hickory', 'maple', 'misc', 'redoak' and
## 'whiteoak'
##
## Log intensity:  ~marks - 1
##
## Intensities:
## beta_blackoak  beta_hickory    beta_maple     beta_misc   beta_redoak
##           135           703           514           105           346
## beta_whiteoak
##           448
##
##                 Estimate       S.E.  CI95.lo  CI95.hi Ztest      Zval
## marksblackoak 4.905275 0.08606630 4.736588 5.073962   ***  56.99414
## markshickory  6.555357 0.03771571 6.481435 6.629278   *** 173.80970
## marksmaple    6.242223 0.04410811 6.155773 6.328674   *** 141.52099
## marksmisc     4.653960 0.09759001 4.462687 4.845233   ***  47.68890
## marksredoak   5.846439 0.05376033 5.741070 5.951807   *** 108.75005
## markswhiteoak 6.104793 0.04724556 6.012194 6.197393   *** 129.21412
```

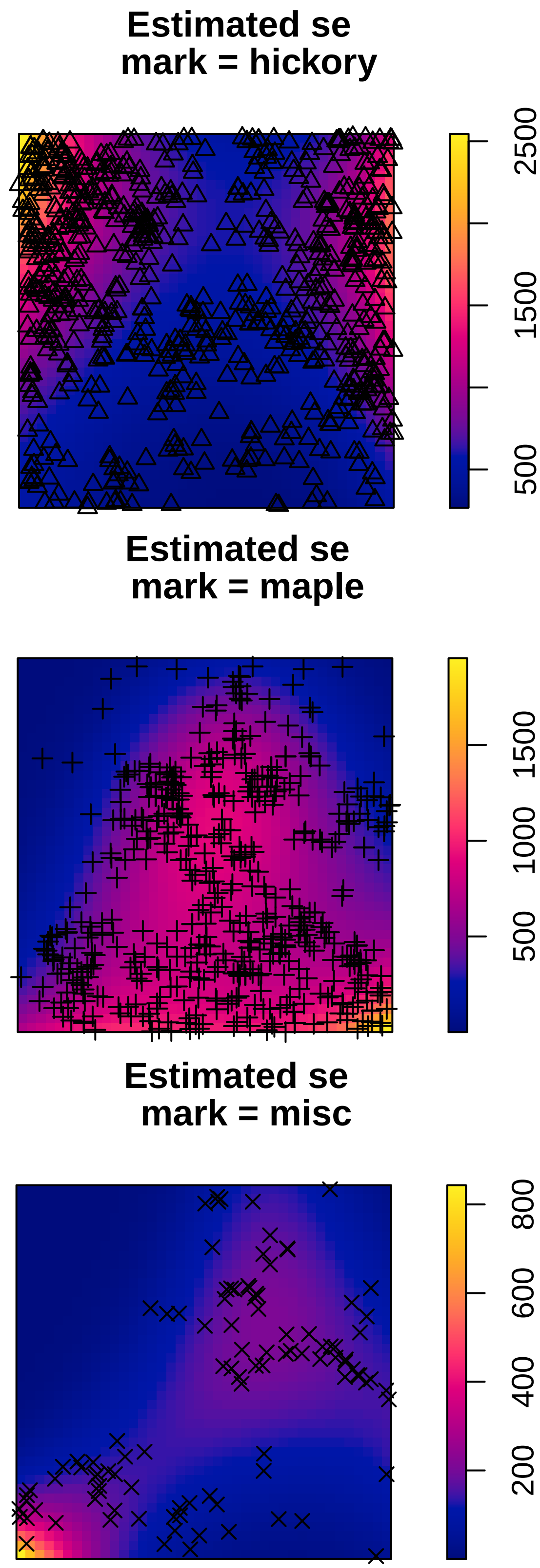
- In contrast with this model, we can also include

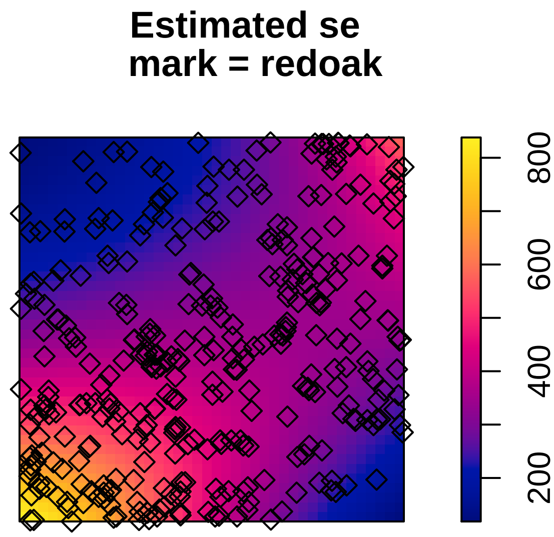
```
lansing.model2 <- ppm(lansing ~  marks * polynom(x,y,3))
#lansing.model2
plot(lansing.model2)
```

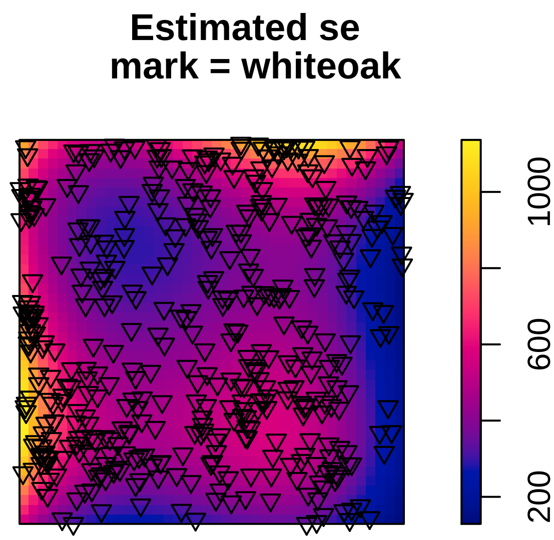



Fitted trend
mark = hickory
500
1500
2500
Fitted trend
mark = maple
500
1000
1500
Fitted trend
mark = misc
200
400
600
800


Fitted trend
mark = redoak
200
400
600
800
Fitted trend
mark = whiteoak
200
600
1000
Estimated se
mark = blackoak
200
400
600
800


Estimated se
mark = hickory
2500
1500
500
Estimated se
mark = maple
1500
1000
500
Estimated se
mark = misc
800
600
400
200





- Similarly continuous marked data can be included as a predictor i the `ppm` framework, potentially with interactions with spatially referenced data.

- Marked point process data can also be used for spatial-temporal point patterns, where the year corresponds to the mark.

More advanced point pattern models

Cluster processes

- Clustering is not well defined. In general the idea is that the point distances are shorter than expected. However, there "is a fundamental ambiguity between heterogeneity and clustering" (Diggle 2007).

- **Neyman-Scott Process**: This is a two stage process.

1. Generate parents

2. For each parent, generate a set of offspring

- **The shot noise processes** are variations on the Neyman-Scott process, also with a two stage process.

- **Strauss Process**: contains a term that allows repulsion by adjusting the intensity in a vicinity of an existing point. The "hardcore" process will make the intensity 0 for any pair of points less than a specified distance d_0.

- A good reference for additional point pattern code comes from a Spatstat Short Course