

# Overlays

HES 505 Fall 2022: Session 18

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# Objectives

By the end of today you should be able to:

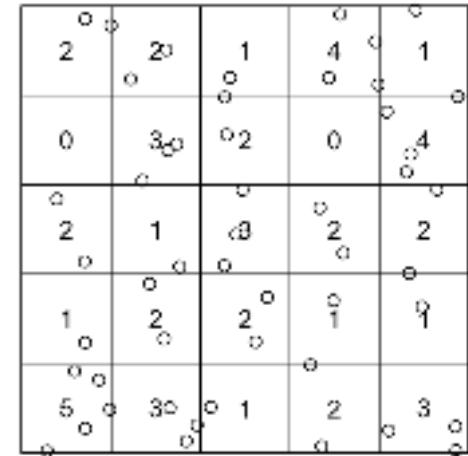
- integrate a covariate into KDE's
- Describe the utility and shortcomings of overlay analysis
- Describe and implement different overlay approaches

# Re-visiting Density Methods

- The overall *intensity* of a point pattern is a crude density estimate

$$\hat{\lambda} = \frac{\#(S \in A)}{a}$$

- Local density = quadrat counts



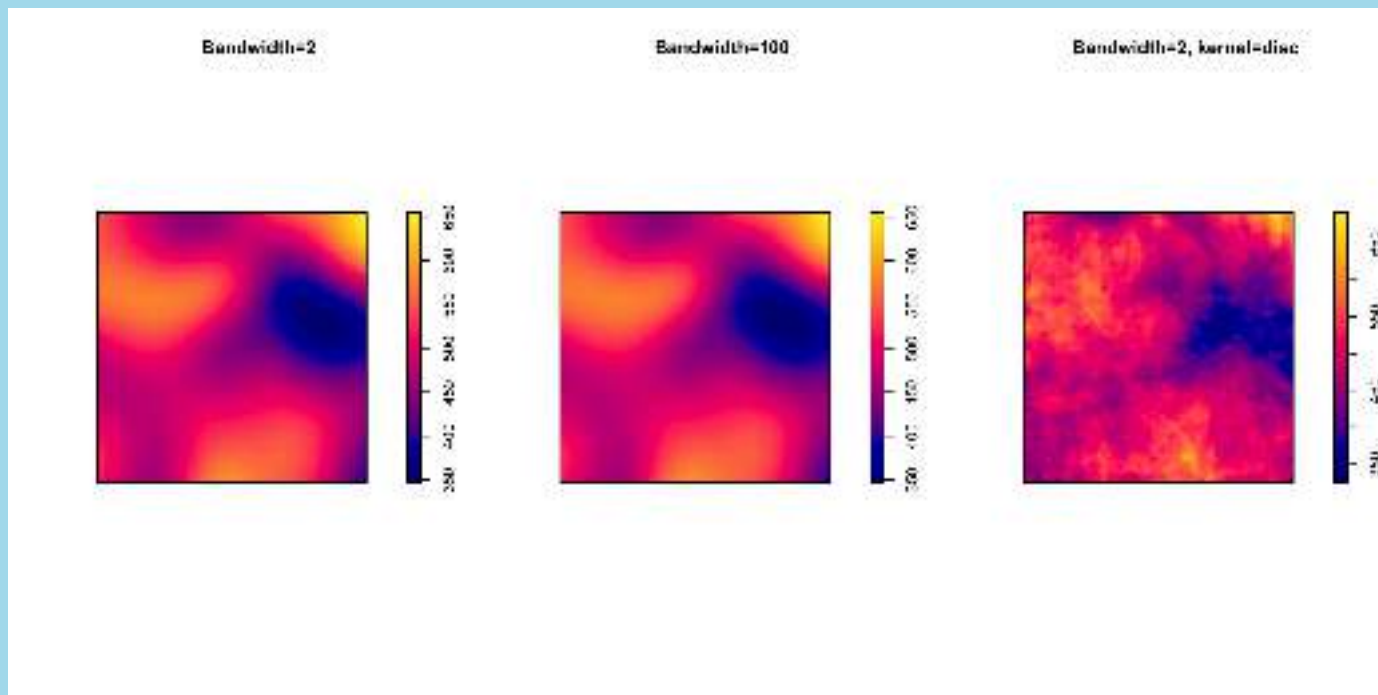
# Kernel Density Estimates (KDE)

$$\hat{f}(\mathbf{x}) = \frac{1}{nh_x h_y} \sum_{i=1}^n k\left(\frac{x - x_i}{h_x}, \frac{y - y_i}{h_y}\right)$$

::: {style="font-size: 0.7em"} \* Assume each location in  $\mathbf{s}_i$  drawn from unknown distribution

# Kernel Density Estimates (KDE)

- $h$  is the bandwidth and  $k$  is the kernel
- We can use `stats::density` to explore
- **kernel**: defines the shape, size, and weight assigned to observations in the window
- **bandwidth** often assigned based on distance from the window center



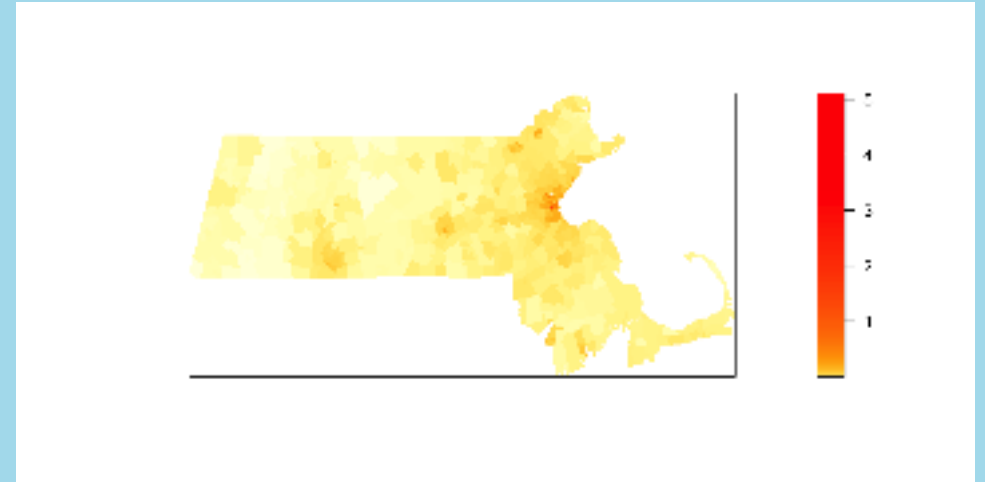
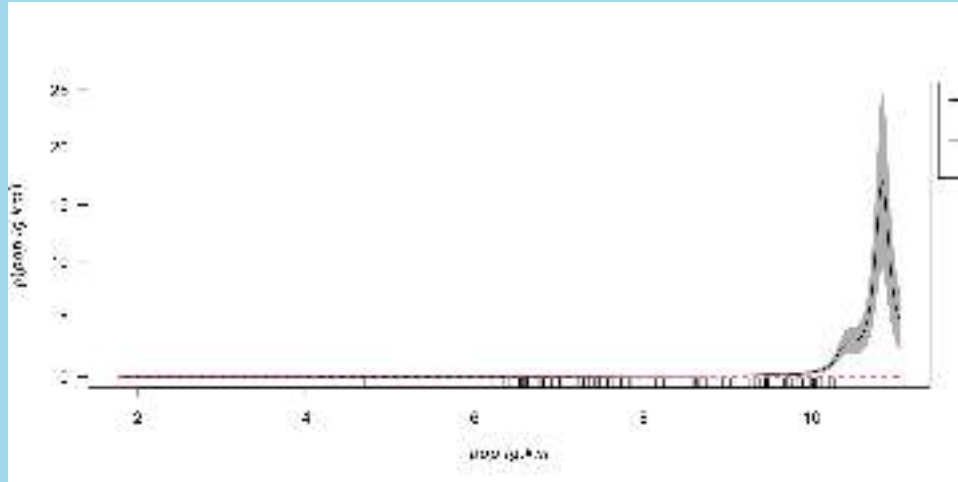
# Kernel Density Estimates (KDE)

# Adding a Covariate to KDE

- **rhohat** computes nonparametric intensity  $\rho$  as a function of a covariate

$$\lambda(u) = \rho(Z(u))$$

# Adding a Covariate to KDE





# Adding a Covariate to KDE

- We can also think more generatively
- Model explicitly as a Poisson Point Process using **ppm**

$$\lambda(u) = \exp^{\text{Int} + \beta X}$$

```
1 # Create the Poisson point process model
2 PPM1 <- ppm(starbucks.km ~ pop.lg.km)
3 # Plot the relationship
```

# Adding a Covariate to KDE

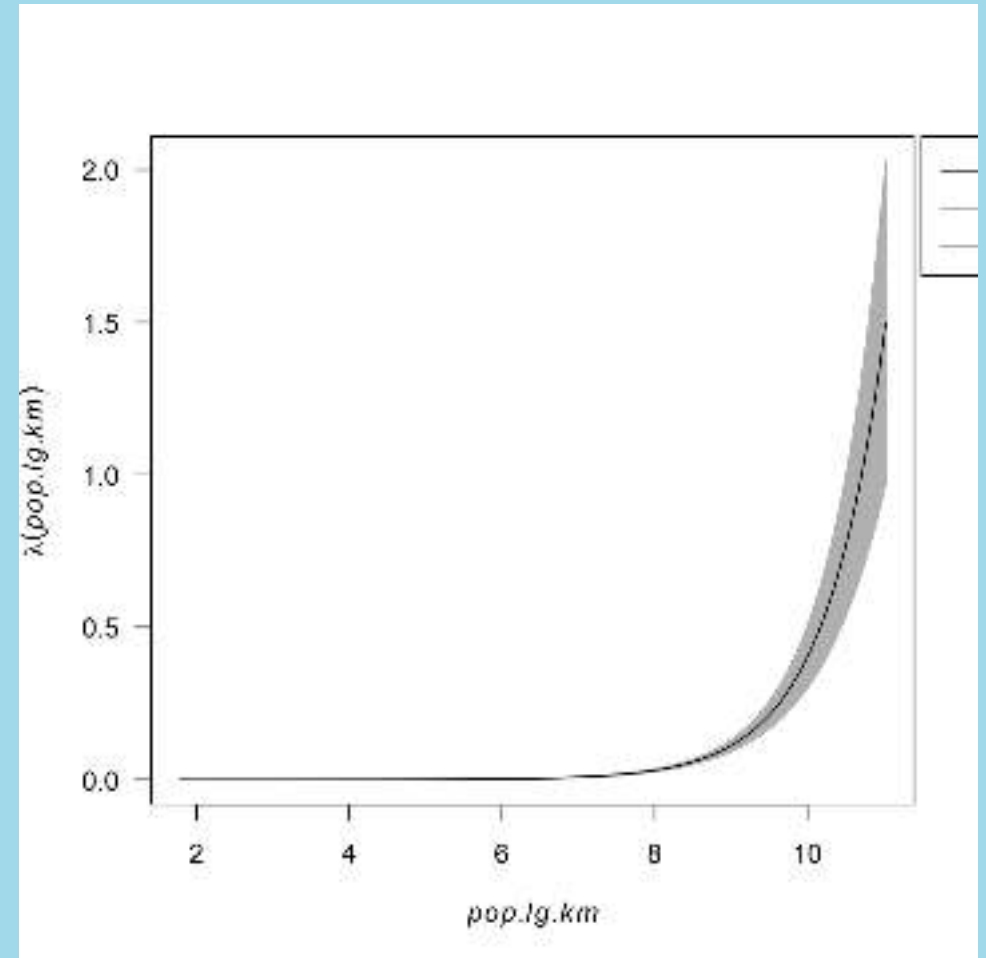
Nonstationary Poisson process  
Fitted to point pattern dataset  
'starbucks.km'

Log intensity:  $\sim \text{pop.lg.km}$

Fitted trend coefficients:

(Intercept)	pop.lg.km
-13.710551	1.279928

	Estimate	S.E.
CI95.lo	CI95.hi	Ztest
(Intercept)	-13.710551	0.46745489
	-14.626746	-12.794356
	***	-29.33021
pop.lg.km	1.279928	0.05626785
	1.166645	1.399811
	***	22.74705



# Overlays

# Overlays

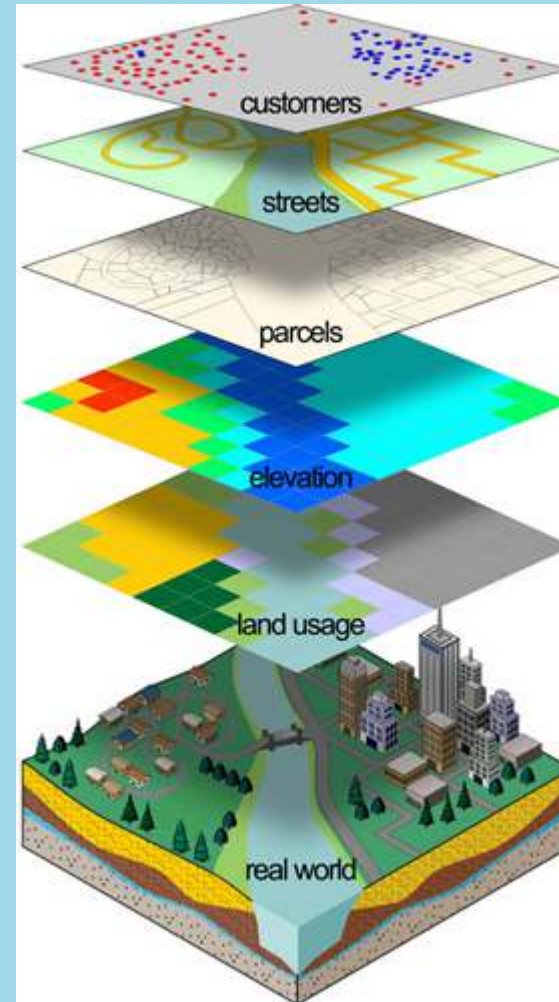
- Methods for identifying optimal site selection or suitability
- Apply a common scale to diverse or dissimilar outputs

# Getting Started

1. Define the problem.
2. Break the problem into submodels.
3. Determine significant layers.
4. Reclassify or transform the data within a layer.
5. Add or combine the layers.
6. Verify

# Boolean Overlays

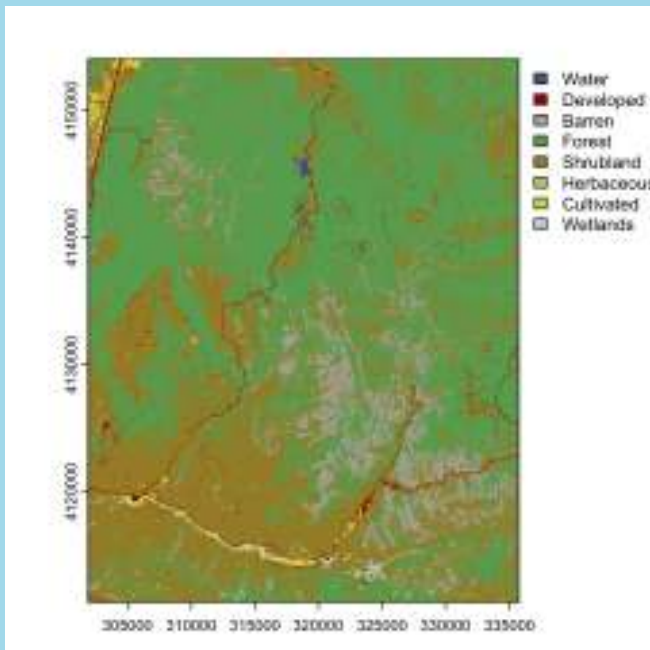
- Successive disqualification of areas
- Series of “yes/no” questions
- “Sieve” mapping



# Boolean Overlays

- Reclassifying
- Which types of land are appropriate

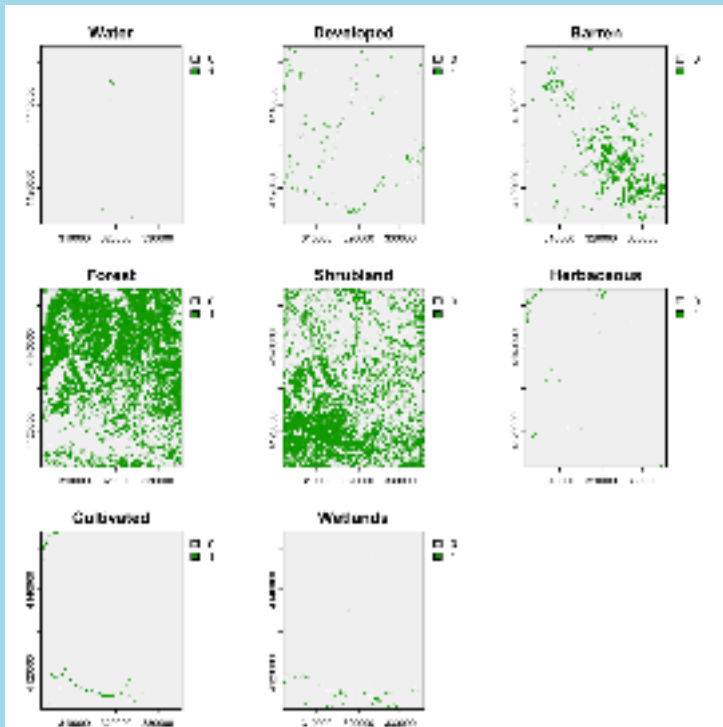
```
1 nlcd <- rast(system.file("raster/nlcd.tif", package = "spDataLarge"))  
2 plot(nlcd)
```



# Boolean Overlays

- Which types of land are appropriate?

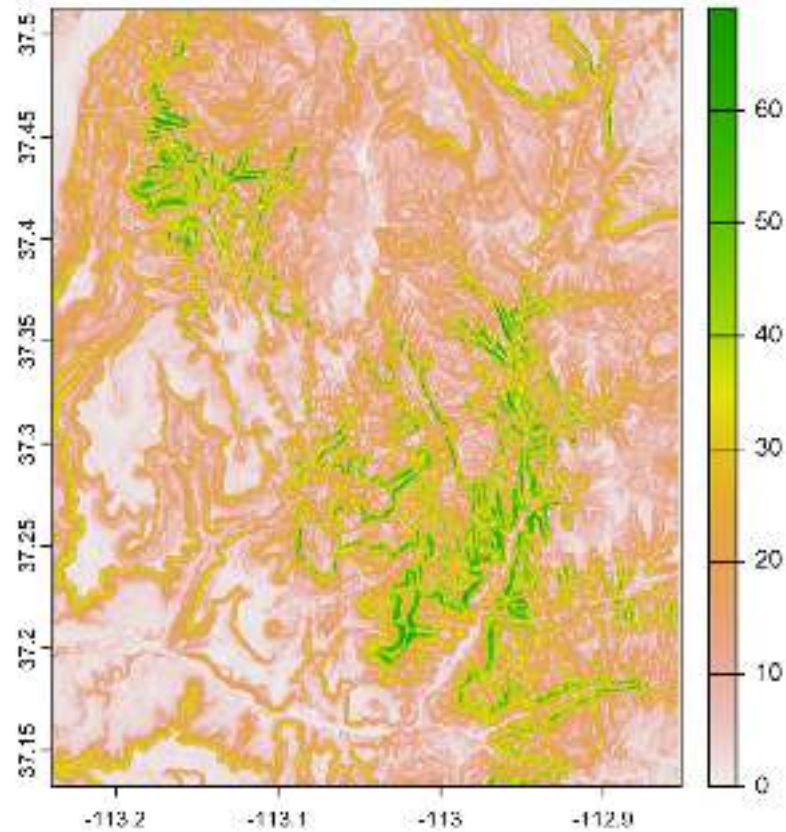
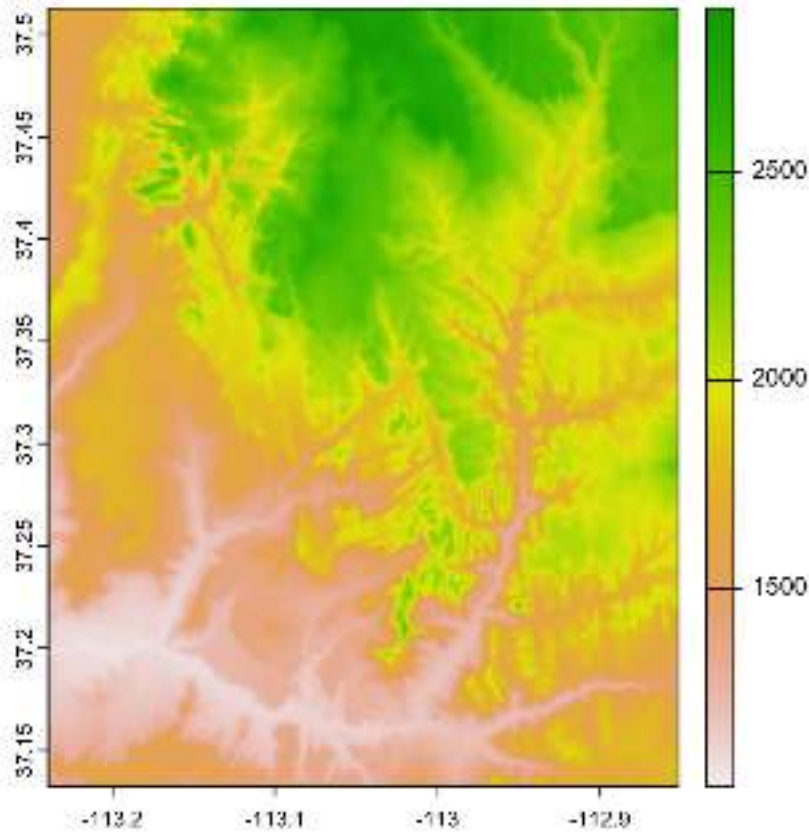
```
1 nlcd.segments <- segregate(nlcd)
2 names(nlcd.segments) <- levels(nlcd)[[1]][-1,2]
3 plot(nlcd.segments)
```





# Boolean Overlays

- Which types of land are appropriate?

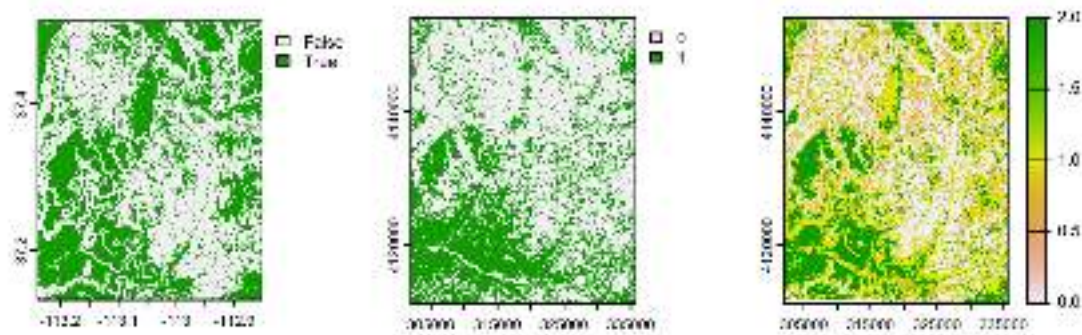


# Boolean Overlays

- Make sure data is aligned!

```
1 suit.slope <- slope < 10
2 suit.landcov <- nlcd.segments["Shrubland"]
3 suit.slope.match <- project(suit.slope, suit.landcov)
4 suit <- suit.slope.match + suit.landcov
```

# Boolean Overlays



# Challenges with Boolean Overlays

1. Assume relationships are really Boolean
2. No measurement error
3. Categorical measurements are known exactly
4. Boundaries are well-represented

# A more general approach

- Define a *favorability* metric

$$F(\mathbf{s}) = \prod_{M=1}^m X_m(\mathbf{s})$$

# Weighted Linear Combinations

$$F(\mathbf{s}) = \frac{\sum_{M=1}^m w_m X_m}{\sum_{M=1}^m w_i}$$

