Overlays

HES 505 Fall 2022: Session 18

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Objectives

By the end of today you should be able to:

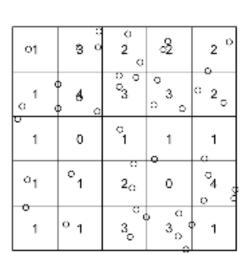
- integrate a covariate into KDE's
- Describe the utility and shortcomings of overlay analysis
- Describe and implement different overlay approaches

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



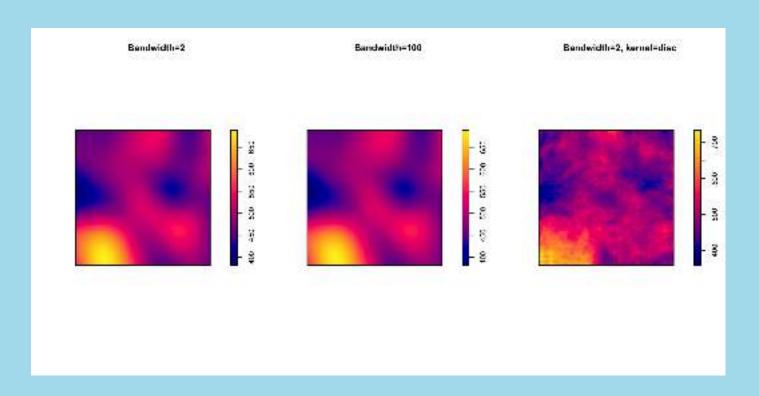
Kernel Density Estimates (KDE)

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

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

Kernel Density Estimates (KDE)

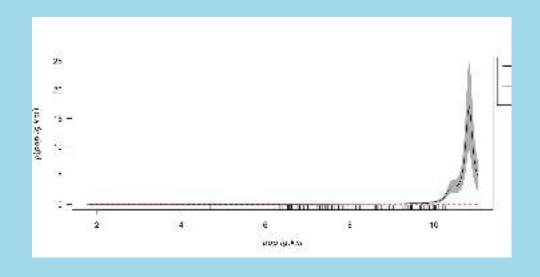
- h is the bandwidth and k is the kernel
- We can use stats::density to explore
- **kernel**: defines the shape, size, and weight assigned to observations in the window
- bandwidth often assigned based on distance from the window center



Kernel Density Estimates (KDE)

• **rhohat** computes nonparametric intensity ρ as a function of a covariate

$$\lambda(\mathbf{u}) = \rho(\mathbf{Z}(\mathbf{u}))$$





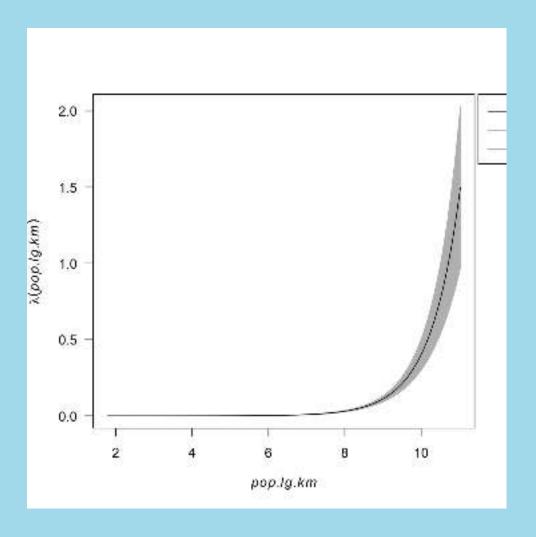
- We can also think more generatively
- Model explicitly as a Poisson Point Process using ppm

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

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

Nonstationary Poisson process

```
Log intensity: ~pop.lg.km
Fitted trend coefficients:
(Intercept) pop.lq.km
 -13.710551 1.279928
             Estimate
                            S.E.
CI95.10
          CI95.hi Ztest
                             Zval
(Intercept) -13.710551 0.46745489
-14.626746 -12.794356
                       *** -29.33021
pop.lg.km
              1.279928 0.05626785
1.169645
          1.390211
                          22.74705
Problem:
```



Overlays

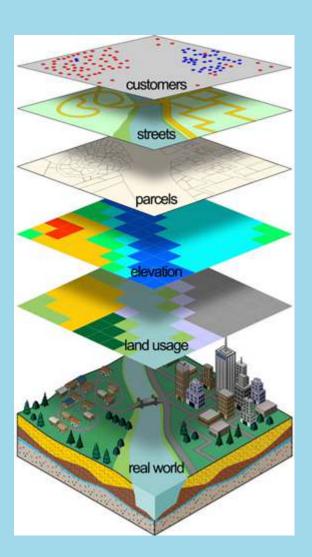
Overlays

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

Getting Started

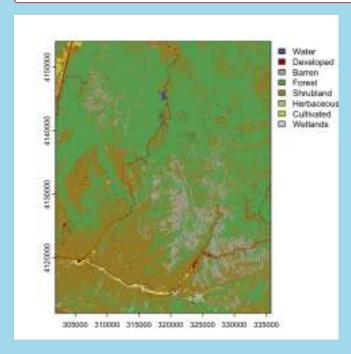
- 1. Define the problem.
- 2. Break the problem into submodels.
- 3. Determine significant layers.
- 4. Reclassify or transform the data within a layer.
- 5. Add or combine the layers.
- 6. Verify

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



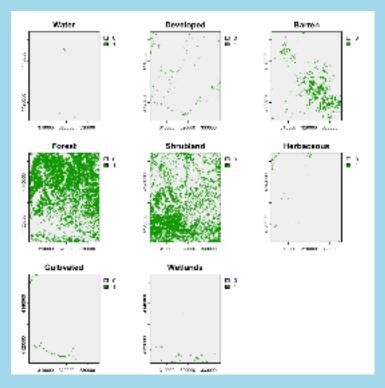
- Reclassifying
- Which types of land are appropriate

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

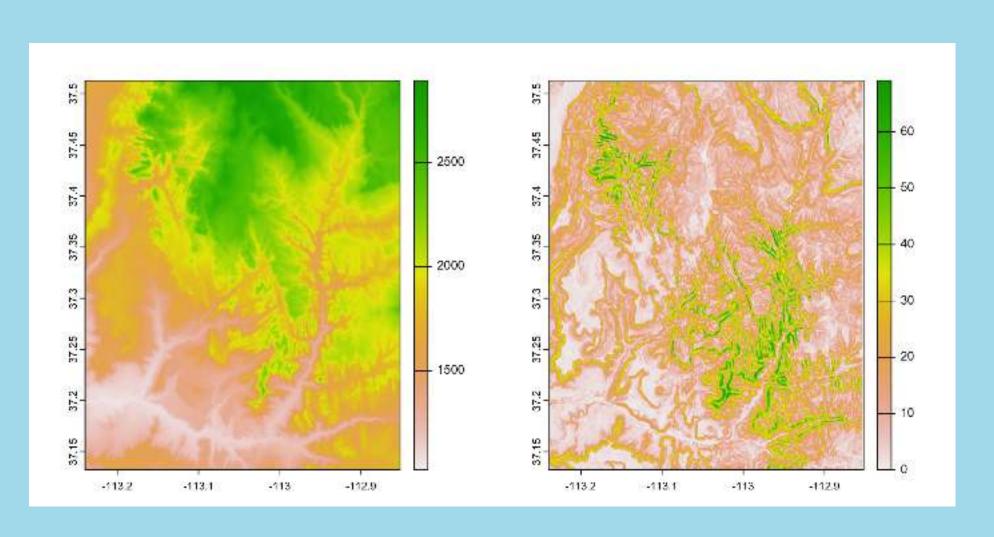


Which types of land are appropriate?

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

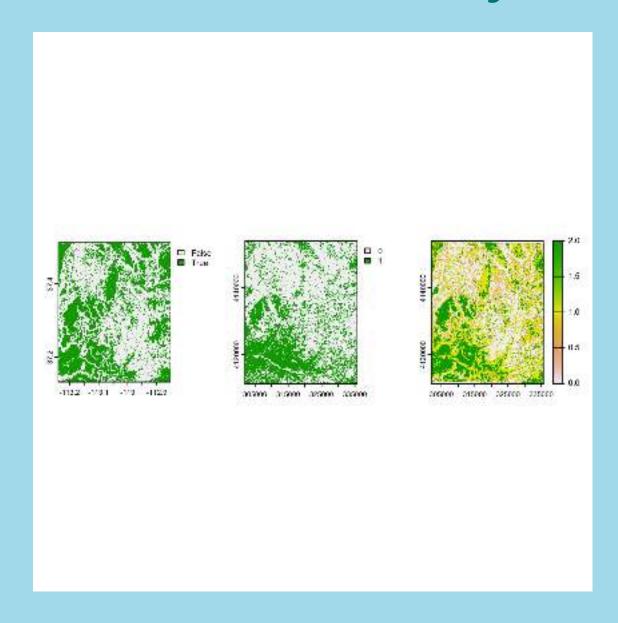


Which types of land are appropriate?



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</pre>
```



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

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

