# Homework 5: Model Predictions

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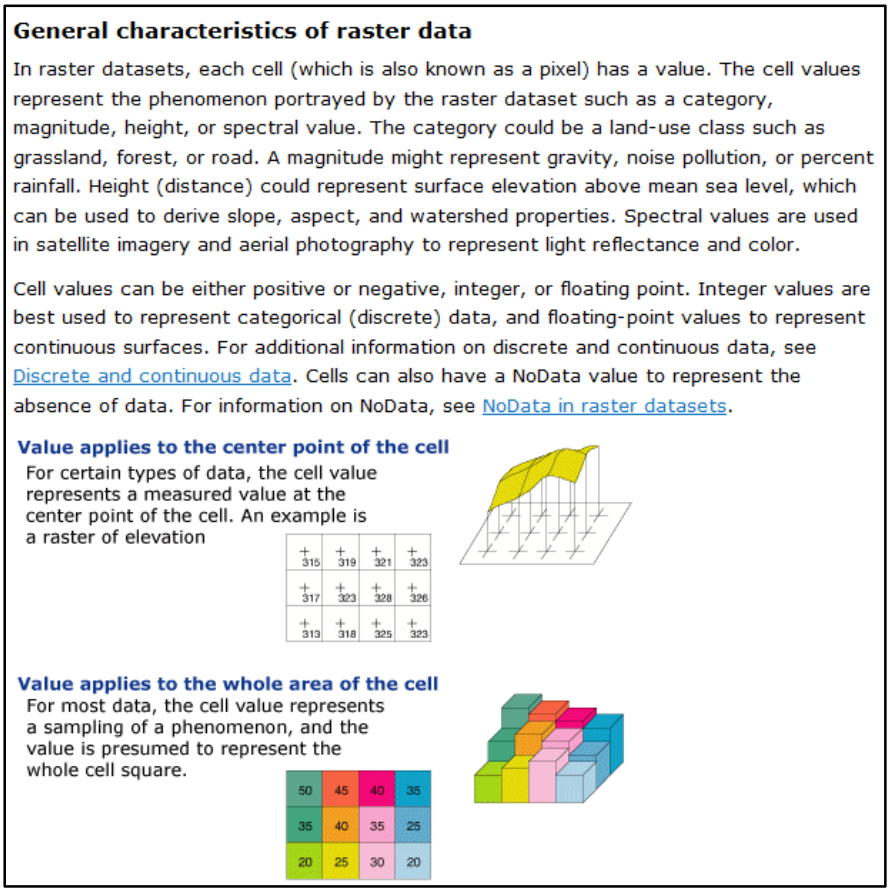
## Rasters

In its simplest form, a raster consists of a matrix of cells (or pixels) organized into rows and columns (or a grid) where each cell contains a value representing information, such as temperature, elevation or precipitation. Rasters are digital aerial photographs, imagery from satellites, digital pictures, or even scanned maps [1]. (Figure from ESRI.com)



## Homework Exercise (3 Points total)

These exercises rely on the cleaned lab data produced from your previous exercises (re-uploaded to CATCOURSES for comparison under `riparian_HW5.csv`. These are the same data from last week's homework.

Your document should have the following sections, and provide written explanations formatted in RMarkdown that explains your code, output and graphics in the following format:

**NAME**
**CLASS**
**DATE**

**Homework Assignment 5**

**Objective Statement**: [What are you trying to accomplish?]

**Methods**: [In general terms, what analyses are you doing?]
**Data**: [What are the data and where did they come from?]
**Code**: [In specific terms, what is the code that was used to conduct the analysis?]

**Results**: [What do the results show? Numerical evidence and graphic evidence are required.]

**Discussion**: [What do the results mean?]

**Limitations**: [What are the limitations, caveats, and assumptions of the analysis?]

### OBJECTIVE

You have been asked to finalize your analysis of riparian tree data by developing a predictive model to characterize the amount of biomass found in the riparian habitats of northern California. You have explored a dataset of field measurements and observations taken at various project sites throughout northern California that are intended to estimate aboveground carbon stocks in riparian areas. Based on your preliminary assessment, you realize that new data must be brought into the model to better allow for predictions in places not yet sampled, as your client has requested an assessment of standing carbon for a project site that has only tree diameters, not height. This will require prediction.

To finalize this investigation, you extend your analysis from last week (Homework 5) that developed a promising linear regression model. In order to make reasonable estimates of standing carbon in a new location, you decide to finalize a linear model that relates tree height as a function of its diameter (at breast height) or dbh and genus but with one additional covariate, such as temperature, precipitation, latitude, or elevation. In this exercise, you will

build a new report showing model results for the model of `ht ~ dbh * genus + parameter` where parameter is one of the covariates. In addition to defending the model -- based on performance and ecological justification -- use the model to predict the standing carbon (expressed as Mg of C per hectare) of a new project site.

### Step 1 - Adding Covariates to the Mix

Load the following raster data: `DEM.tif` (digital elevation model), `tmean_8.tif` (mean temperature in August) and `precip_8.tif` (precipitation in August) raster data using the `rgdal` and `raster` libraries. Use the following as a guide for loading rasters:

```
#read data from file (2 steps)
gdal_grid = readGDAL("rasterfile.tif")
r = raster(gdal_grid) #use data as a projected raster
```

Visualize your data by plotting the DEM raster and add the project locations (`ProjLoc` from homework 3 using aggregate) as points (use the plot and points functions).

Extract the values from the rasters at the locations of each points and add each of them as a new column in your riparian dataframe. Name your columns as follows:

| | |
|---|---|
| $Elevation | #extracted values from the DEM raster |
| $Temp_aug | #extracted values from the tmean8 raster |
| $Precp_aug | #extracted values from the precp8 raster |

Use the following as a guide for extracting values from rasters:

```
#Example lon and lat extraction
Longitude = c(-122,-121) #Just an example! Use the lon and lat
Latitude = c(36,38)      #from your data!

#x,y locations
xy = cbind(Longitude,Latitude)

#extract the values from raster r
vals = extract(r,xy)

#join columns to data frame using cbind() or similar method
#see melt() function in library(reshape) for more robust approach
```

Conduct exploratory data analysis on these new data. Are they normally distributed? Are they highly correlated?

### Step 2 - Final Model Selection

From the previous homework, it was concluded that the model using interaction with genus seemed to perform the best (`htcm~DBH*Genus`). But we would like to test whether the model could be improved using the covariates from Step 1. Along with these new parameters, latitude is also thought to have a relationship with tree heights. From these covariates, find the best parameter to add to the model (if any!).

Build models for each new predictor variable by adding it to the interaction model (`lm.pred1 <- lm( htcm~DBH*Genus + [predictor1])`, where [predictor] is the new parameter). Test all four models against each other and against the base interaction model to decide which is best. Considering p-values of parameters and $R^2$ of each model, plus AIC values (using the `AIC()` function) when comparing models, defend which model you would choose to predict new data.

Advanced users are encouraged to evaluate their models using `step()` and `stepAIC()`. Super advanced users are encouraged to develop a model that has a zero intercept.

### Step 3 - Predicting Carbon

A new dataset has been given to you (`new_data.csv`) that represents dbh measurements taken at a new project location. Use your chosen (final) model from Step 2 to predict (`predict.lm()`) the heights of the unmeasured trees in the 10 m x 10 m plot and then apply the following conversion to the volume of the tree (this equation, adapted from Pilsbury (1984) and Cornwell (2006), is specific to Valley oaks (*Quercus lobata*), but use if for all trees in the plot). Assume that C is 50% of biomass volume (it typically varies 45-55%). Report your results as Mg of C per hectare for the new site.

Above Ground Tree Volume = 705 * (0.0000334750*(dbh in cm $^{2.33631}$)*(ht in cm $^{0.74872}$))

Given the assumptions of density and the single allometric [2] equation, is your model likely to under or over-estimate your predicted C stocks? If you needed to estimate 95% confidence intervals around your fitted model, how might you do that? (See `help(predict.lm)` as a starting point.)

```
###NOTE###
#the way that predict works for new data requires that predictor
#variables have the same column names as in the model, for example:
```

```
lm1 = lm(slope~elev, data=dem) # create model
with(dem,plot(elev,slope)) # plot two variables
x = seq(0,2000) # create 'new' elevation values in sequence

### use predict() with new x values to get new y values ###
### newdata requires a data.frame or a list, not a vector ###
### column names need to match however, so check data first ###

lm1.pred.y <- predict(lm1,newdata=list(elev=x))

lines(x,lm1.pred.y,col="blue",lwd=3) # model predicted line on plot
```

## Resources

### Data

- `riparian_HW5.csv` on CATCOURSES (Resources→HOMEWORK→HOMEWORK 5)
- `DEM.tif` on CATCOURSES (Resources→HOMEWORK→HOMEWORK 6)
- `precip_8.tif` on CATCOURSES (Resources→HOMEWORK→HOMEWORK 6)
- `tmean_8.tif` on CATCOURSES (Resources→HOMEWORK→HOMEWORK 6)
- `new_data.csv` on CATCOURSES (Resources→HOMEWORK→HOMEWORK 6)

### References

- See Crawley sections on model selection and AIC.

### Citations

[1] http://webhelp.esri.com/arcgisdesktop/9.2/index.cfm?TopicName=What_is_raster_data%3F
[2] http://en.wikipedia.org/wiki/Allometry

## Keywords

`readGDAL(), raster(), cbind(), extract(), predict.lm()`