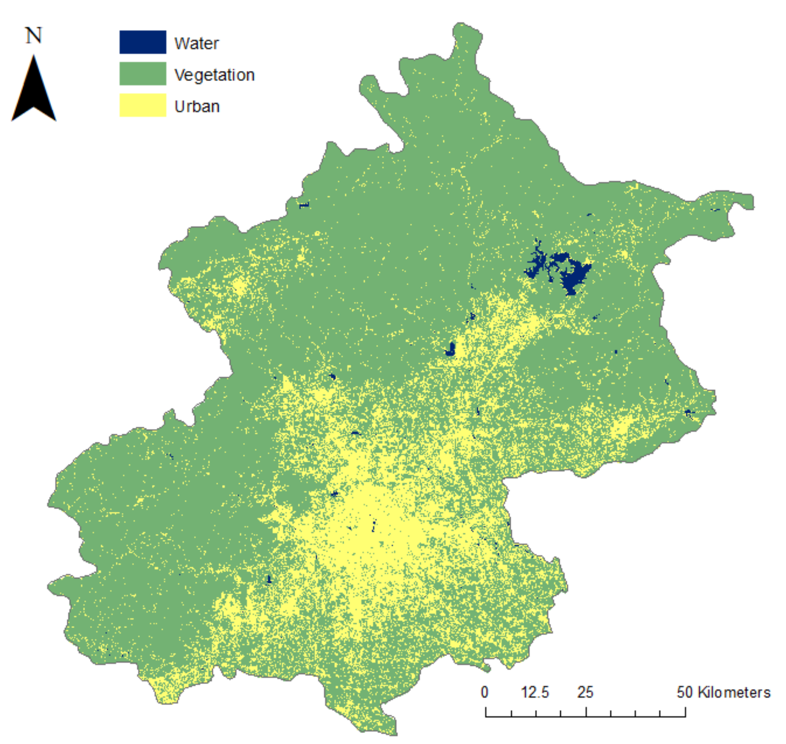
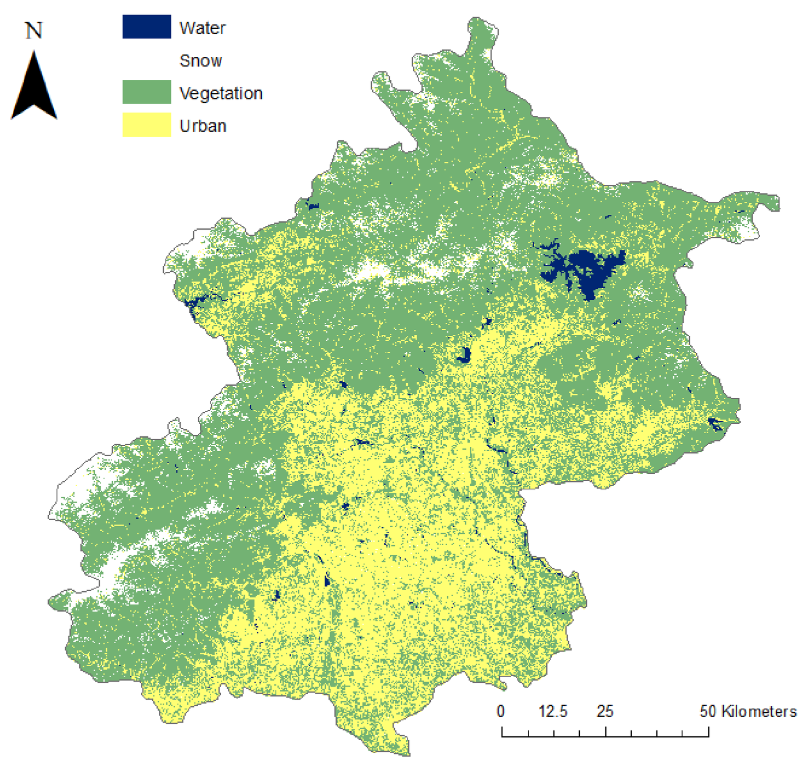
BEIJING Urban Development 2008-2018

A brief discussion on urban sprawl from the perspective of urban land change & land use efficiency using remote sensing



Major Land Cover Types of Beijing in 2008



Major Land Cover Types of Beijing in 2018

Method applied to identify urban land in Beijing

Data

- For 2008: 2 imageries from Landsat 7 ETM (from April 2008, row/path being 123/32 and 123/33), downloaded form USGS explorer;
- For 2018: 3 imageries from Landsat 8 OLI/TIRS (from September 2018, row/path being 123/32, 123/33, and 124/32)

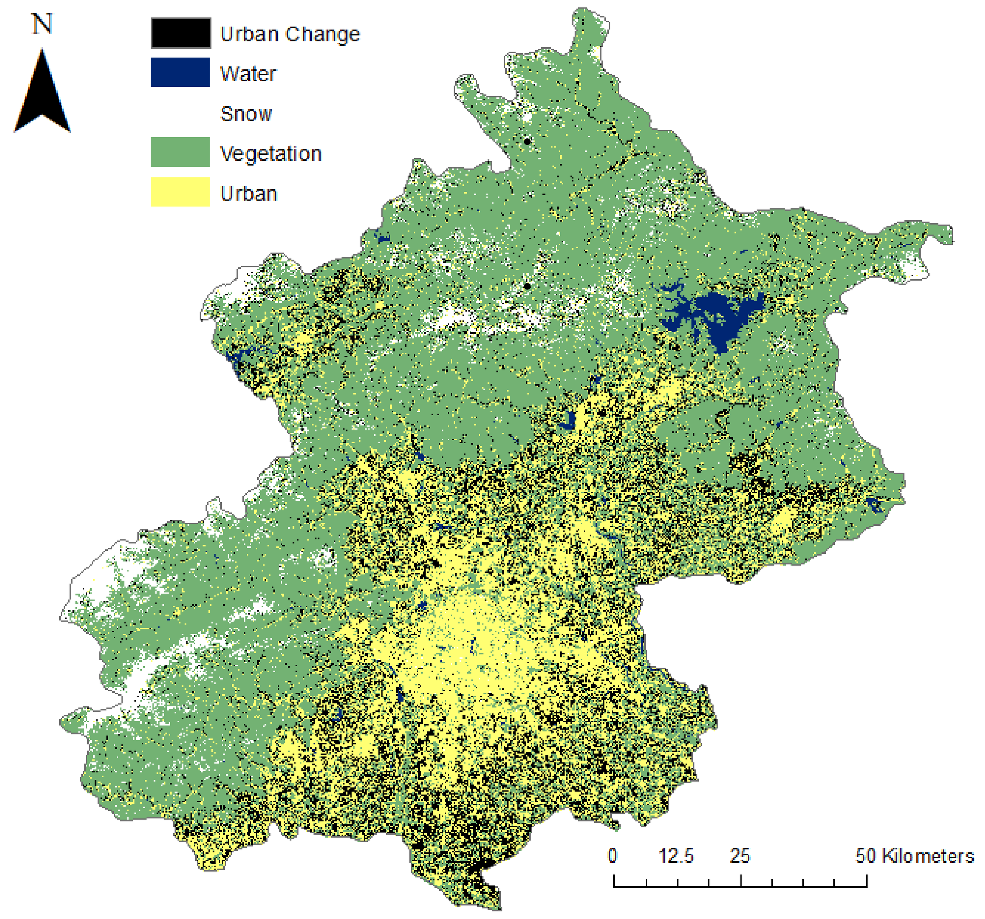
Step 1: preprocessing

- Mosaiced the imageries, and extracted by mask into the shape of Beijing in ArcGIS Desktop;
- Filled gap using the Landsat Gapfill plugin in ENVI Classic.

Step 2: applying supervised classification

- Calculated NDVI to assist finding training points, and created a training set of different land use types;
- Applied supervised classification of Maximum Likelihood to get the maps of land use types.

What the changes tell us: Beijing is sprawling, but...



Highlighting new urban land of major land use in 2018

	2008	2018	Net change	Change rate
Urban Land	3636 km²	5366 km²	1730 km²	48%
Population	18 million	22 million	4 million	22%

Data source: Beijing Municipal Bureau of Statistics

Land Use Efficiency: 2.2

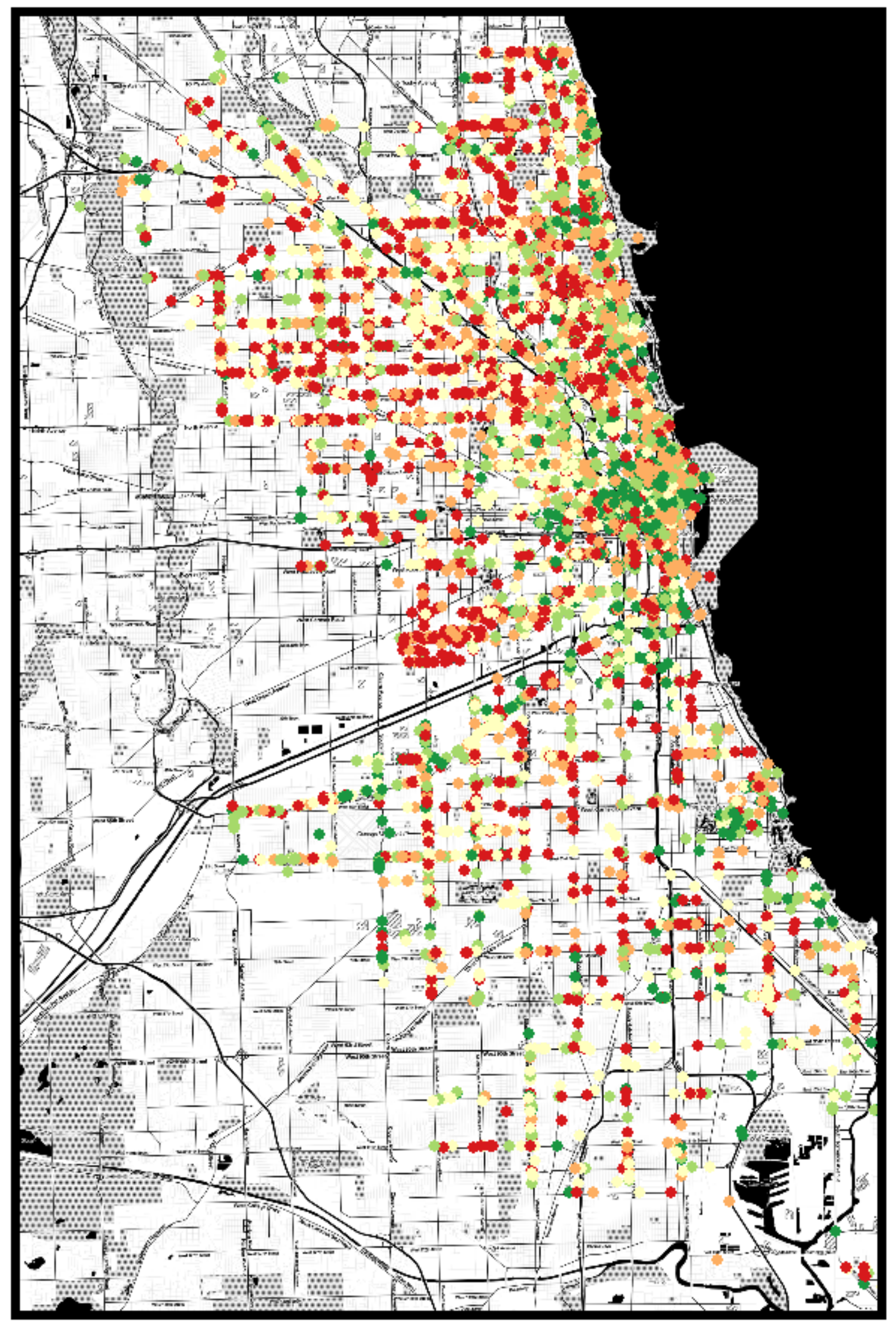
According to calculation, the land use efficiency of Beijing from 2008 to 2018 is 2.2. It's bigger than 1, which means that the expansion rate of land exceeded the expansion rate of population. This is a sign of sprawl.

However, it doesn't mean that residents in Beijing will have to live with worse environment in the years to come. According to the maps, the area of water bodies has increased. Besides, more and more attention are being paid to building green spaces and shifting industrial factories. With more efforts into creating a more livable Beijing, trends shown in the past decade might be bent in the future.

Food Inspection Efficiency Booster CHICAGO

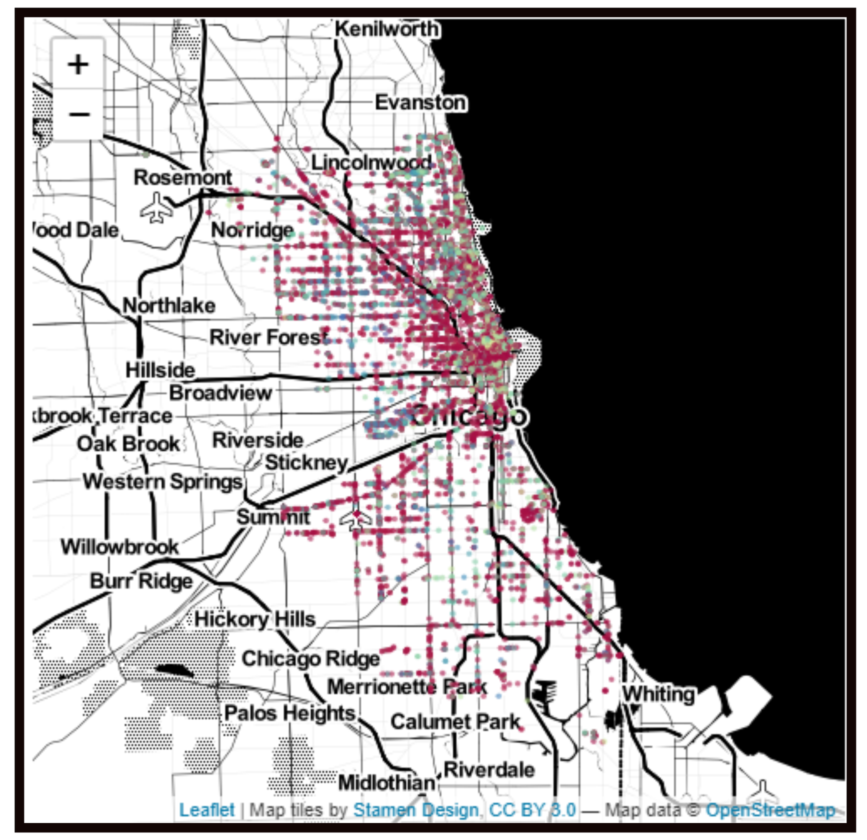
A user-friendly online toolkit that use prediction to help make food inspectors' work faster and more accurate

Chicago Food Inspection Risk Score



Risk Score (Quintile Breaks)

- 0.0180448289153252
- 0.0205185914655991
- 0.0250391723588962
- 0.0345925492885281
- 0.634042155856225



Introduction

This analysis applies logistic regression to predict whether a certain food establishment will fail in a food inspection or not. It is intended to help make the process of food inspection more efficient by both identifying the food establishments that are more likely to fail and providing additional information to make the selection and routing process faster. By using prediction to assist in prioritizing resource allocation, the application proposed is designed as a supplemental tool to help battle foodborne illnesses.

Based on previous work done by the Department of Public Health in Chicago, we propose a method that integrate 311 complaints, socioeconomic data with previous inspection result to forecast food establishments that are most likely to fail to suggest higher priority of their inspection. Specifically, the expected users of this application are food inspectors.

Methods

Data Inventory

1. **Food inspection result**: the binary dependent variable of whether the food establishment will fail in the food inspection or not (1:failed; 0:not failed).
2. **Density of Sanitation Code Complaints**: a continuous predicter gathered from 311 Service Requests data.
3. **Density of Garbage Cart Removal**: a continuous predicter gathered from 311 Service Requests data.
4. **Critical violations found in last visit**: the number of critical violations found in the last visit.
5. **Serious violations found in last visit**: the number of serious violations found in the last visit.
6. **Elapse time since last visit**: time since last inspection.
7. **Age of business license**: age of business license at the inspection time.
8. **Facility type**: a categorical predictor that describes the type of the inspected food establishment.
9. **Density of crime**: a continuous predictor that describes the density of burglary near the food establishment.
10. **Tobacco license**: a binary predictor of whether the food establishment has a tobacco license (1:yes; 0:no).
11. **License for consumption activity**: a binary predictor of whether the food establishment has a license for consumption activity (1:yes;0:no).
12. **Season of inspection**: a categorical predictor derived from the date of inspection.

- How we evaluate the model performance
    - Accuracy: Prediction error; Misclassification rate; AUC
    - Generalizability: cross validation
- How we determine the best cut-off value: ROC curves

Mapping Future Inundation in Chesapeake Bay, MD

A case study of an approach that aims to assist making climate mitigation and adaptation plan

Introduction

Background

One of the major climate-induced problems that a large amount of population will have to face in the near future all over the world is water level rise caused by both sea level rise and storm surge.

As a measure against future climate change, it is usual and becoming more and more necessary for municipalities in the U.S. to make climate mitigation and adaptation plans.

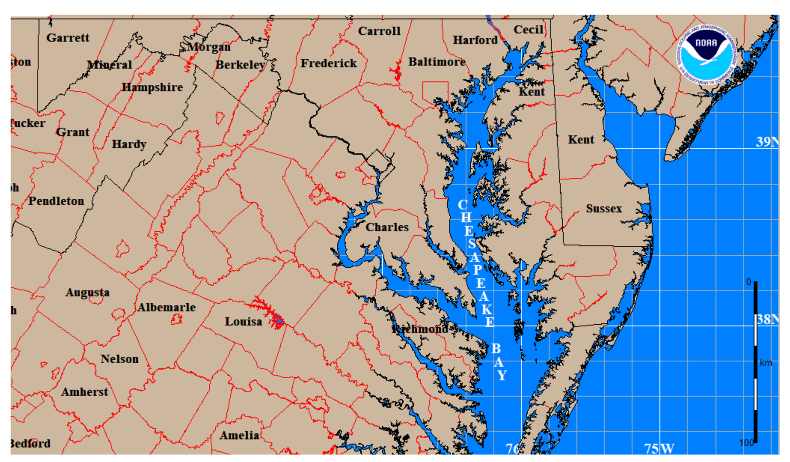
Purpose and Goal

When making climate mitigation and adaptation plans, a clear understanding of what influence future climate change might cast is fundamental. It usually starts with creating an inventory for specific features or topics to be studied, and then perform a set of analysis (sometimes scenario analysis, which will be applied in this report) to specify and visualize future change. For areas with high risks of future inundation, analyses as such are very important yet sometimes inadequate, especially for small towns where technical support might be insufficient.

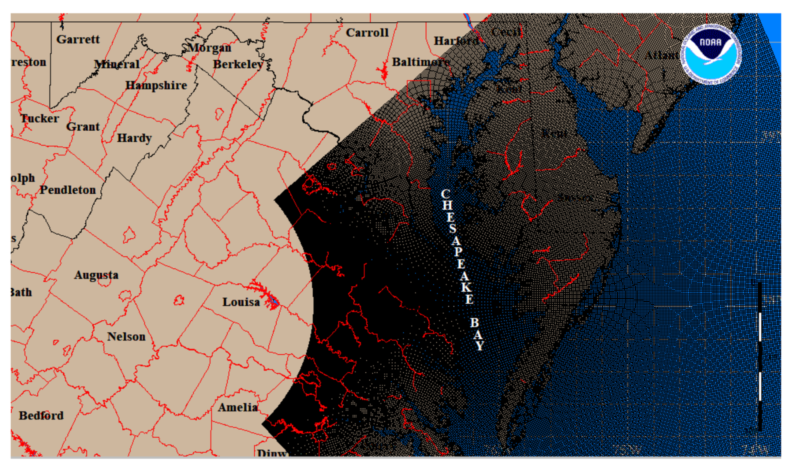
Intended for assisting these plan making processes, the modules designed in this study are mainly for practical uses and are aimed to be easy to use.

Study Area

→ A map of Maryland and Chesapeake Bay, generated from the SLOSH Display Program , which is used for generating storm surge prediction when hit by different categories of storms with different wind direction at different speed



The Chesapeake Bay Basin grid in the SLOSH Display Program.



Methods

1 *Data Gathering*

- Storm surge data for Chesapeake Bay Basin
- DEM data
- Data of features to be analyzed

2 *Data Preparation*

- Define **projection** information for the data
- Calculate **water rise** under different levels of sea level rise and storm surge
- Transform water rise data into **raster** type so as to calculate **inundation**
- Transform inundation data into **polygon** so as to perform function with data of features to be analyzed

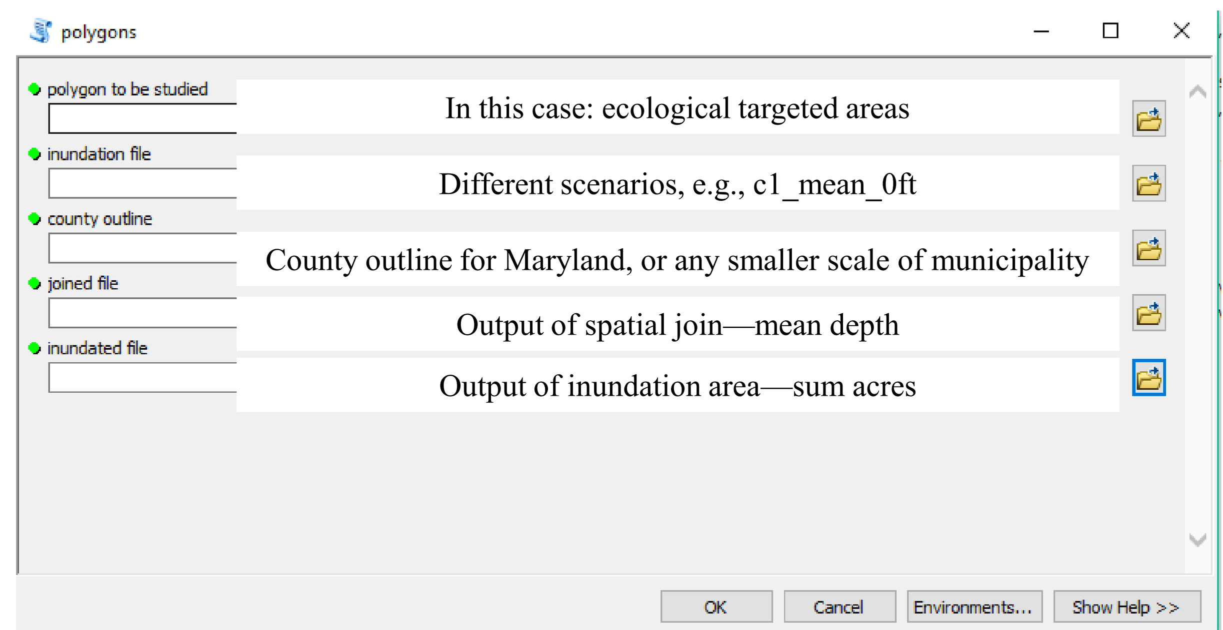
3 *Analysis (Module Design)*

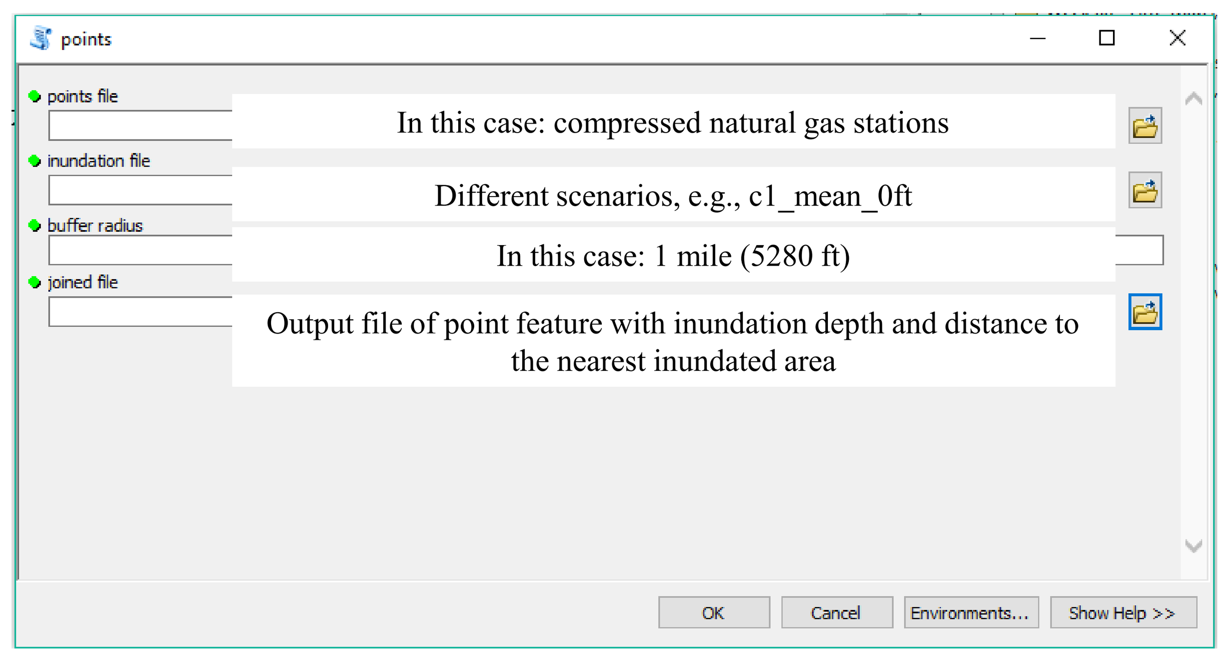
Different scenarios of inundation data

Polygon Data	Point Data
• **Spatial join** feature data with inundation data • **Select by attribute** to save only those that will be inundated • **Spatial join** county data with inundated data to get area of inundation by counties	• **Spatial join** feature data with inundation data • Use **near function** to add distance from the closest inundation point • **Create buffer** to simplify the area from which it might be affected • **Spatial join** buffer with inundation data • **Tabular join** points with each buffer's inundation data

4 *Final Outcome*

- Comparison of different scenarios
- Maps & Graphs that can be used for assisting the planning process





Access this link for more detail