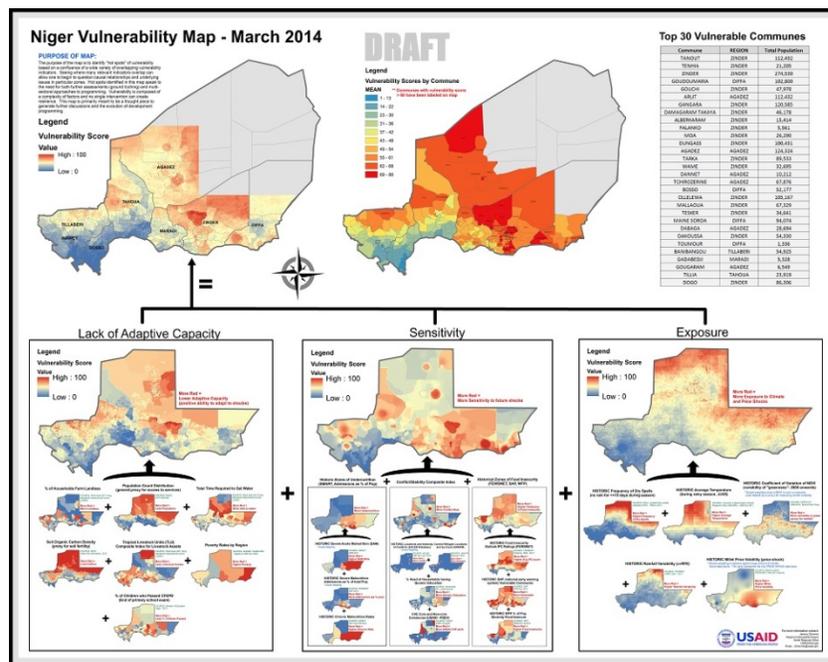


Step-by-Step Guide to Vulnerability Hotspots Mapping: Implementing the Spatial Index Approach



Developed by the
Center for International Earth Science Information Network (CIESIN),
The Earth Institute, Columbia University

Under contract with TetraTech/ARD for the US Agency for International Development (USAID)
Planning for Resilience in East Africa through Policy, Adaptation, Research, and Economic Development
(PREPARED) Project

November 2015

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Acknowledgements

This work was performed under contract with TetraTech/ARD for the US Agency for International Development (USAID) Planning for Resilience in East Africa through Policy, Adaptation, Research, and Economic Development (PREPARED) project. The work also benefited greatly from vulnerability mapping efforts under the USAID-funded African and Latin American Resilience to Climate Change (ARCC) project.

Slides on Installing and configuring R adapted from R-Cran available at:
<http://cran.r-project.org/bin/windows/base/rw-FAQ.html>

We wish to acknowledge the contributions of Dr. idris Bexi Wasama, University of Djibouti, who reviewed the draft manual while visiting CIESIN as a Hubert H. Humphrey Fellow through the University of California, Davis.

Cover image by Jeremy Chevrier, USAID Sahel Regional Office.

Citing this Guide

CIESIN (Center for International Earth Science Information Network), Columbia University. (2015). *A Step-by-Step Guide to Vulnerability Hotspots Mapping: Implementing the Spatial Index Approach*. Palisades NY: CIESIN. Available at http://ciesin.columbia.edu/documents/vmapping_guide_final.pdf

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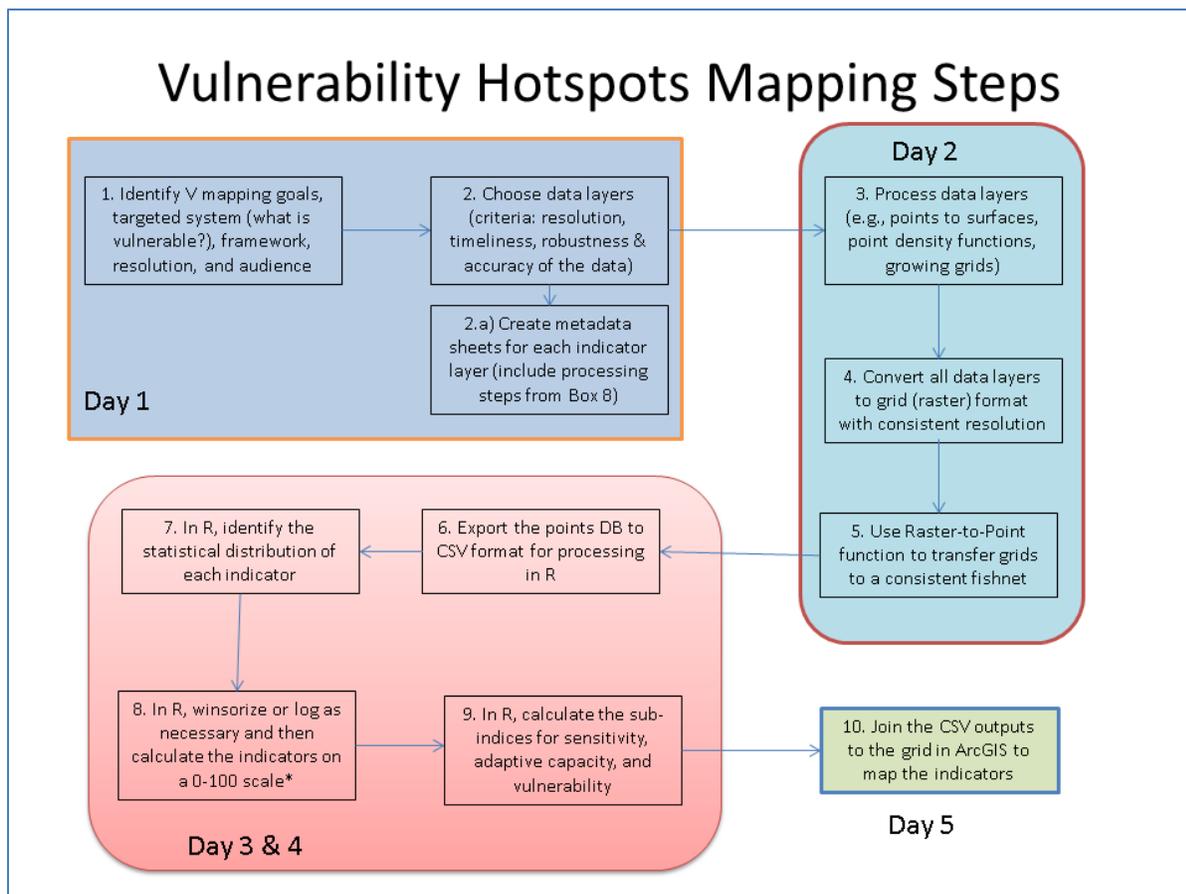
Description

This manual was designed for a five-day training program in Entebbe, Uganda, in August 2015. CIESIN provided a comprehensive training in the framework, data and methods utilized to develop a spatial vulnerability assessment for Kenya using the spatial index approach. Data sets and potential indicators to be derived from them were assembled and evaluated in advance of the workshop. The workshop's primary focus was on the methods needed to process and transform the spatial data in order to develop a spatial vulnerability index (and constituent indices for exposure, sensitivity, and adaptive capacity).

The workshop was intended for GIS analysts who regularly use ArcGIS 9.x or later versions, who are broadly familiar with a variety of geospatial data formats, and who have the ability to do advanced geospatial processing (e.g., editing data sets, creating buffers, conducting overlay analyses, running zonal statistics, etc.).

While vulnerability index maps can be produced entirely in ArcGIS environment, we use R statistical computing and graphics software for the component of part in this training. R is a free software with a wide variety of statistical and graphical techniques that have proven to be very efficient in handling large data sets as the one we encounter in spatial vulnerability index mapping.

The workshop was divided into the following modules, which are addressed in greater detail in the lectures and exercises that follow.



Lecture 1. Introduction to Vulnerability Hotspots Mapping

A large body of evidence going back more than two decades shows that exposure alone is not sufficient for understanding trends in disaster losses, and that social and economic vulnerability are critical ingredients (Mechler and Bouwer 2014, Cutter et al. 2003). Africa has been identified as one of the regions that is most vulnerable to climate change both in terms of exposure to climate hazards (Turco et al. 2015, Muller et al. 2014) and social vulnerability (Busby et al. 2014, Lopez-Carr et al. 2014). Tools such as spatial vulnerability assessment are useful for understanding patterns of vulnerability and risk to climate change at multiple scales, and have been applied in Africa perhaps more than any other region (e.g. Busby et al. 2014, Lopez-Carr et al. 2014, and Midgely et al. 2011). The demand for vulnerability maps among development agencies and governments is increasing as greater emphasis is placed on scientifically sound methods for targeting adaptation assistance (de Sherbinin 2014a).

Mapping is useful because climate variability and extremes, the sensitivity of populations and systems to climatic stressors, and adaptive capacities are all spatially differentiated. The interplay of these factors produces different patterns of vulnerability. Typically spatial vulnerability assessment involves data integration in which geo-referenced socio-economic and biophysical data, including those derived from remote sensing, are combined with climate data to understand patterns of vulnerability and, in turn, inform where adaptation may be required. Maps have proven to be useful boundary objects in multi-stakeholder discussions, providing a common basis for discussion and for deliberations over adaptation planning (Preston et al. 2011). Maps can help to ground discussions on a solid evidence base, especially in developing country contexts where geographic information may not be easily accessible for all stakeholders.

Spatial data integration and spatial analysis have become standard tools in the toolkit of climate change vulnerability assessments. The United Nations Environment Programme (UNEP) Programme of Research on Climate Change Vulnerability, Impacts and Adaptation (PROVIA) Research Priorities on Vulnerability, Impacts and Adaptation (PROVIA 2013) highlights “measuring and mapping vulnerability” as a first priority for supporting adaptation decision-making. In many cases vulnerability assessment (VA) is synonymous with spatial vulnerability assessment, owing in part to an understanding that vulnerability and its constituent components exhibit high degrees of spatial and temporal heterogeneity

(Preston et al., 2011). The purposes vary according to the specific study, but spatial VAs are generally intended to identify areas at potentially high risk of climate impacts — so-called climate change “hotspots” (de Sherbinin 2013) — and to better understand the determinants of vulnerability in order to identify planning and capacity building needs.

Any vulnerability mapping effort needs to be guided by a theoretical framework. de Sherbinin (2014b) provides a review of a number of different frameworks. In addition, the selection of indicators should be guided by theoretical linkages to the concept of interest – whether vulnerability, or its constituent elements such as exposure, sensitivity, and adaptive capacity. In a mapping effort for Mali (de Sherbinin et al. 2015), which served as a model for the Kenya mapping described in this guide, indicator selection was guided by the literature on factors known to contribute to each component of vulnerability, as well as by data availability and quality. Each data layer was justified based on its conceptual proximity to the three vulnerability components (Hinkel 2011), and choices were consistent with the variables that have been found to be associated with harm from climate variability and change, including education levels (Lutz et al. 2014), climate variability (Hall et al. 2014), and marginal (semi-arid and arid) environments and geographically remote areas in poor developing regions (de Sherbinin et al. 2013, Gray and Moseley 2005). The guiding approach should be to identify a limited number of high-quality spatial data sets that best represent the component of interest while avoiding the temptation to add low-quality data (data of high uncertainty or coarse spatial resolution), thereby “contaminating” the results. We had reasonably high confidence in the validity and reliability of each of the data sets included; data limitations are explored in Annex IV of the overall report.

Vulnerability mapping and the quantification of vulnerability is not without shortcomings, and more critical perspectives are provided in a number of other publications (de Sherbinin 2014a, de Sherbinin 2013, Preston et al. 2011, Hinkel 2011). Users of this guide who desire a more in depth look at the challenges of vulnerability mapping, including issues around uncertainty, are advised to read these publications. Despite these caveats, the spatial vulnerability index construction methods described here are widely used in the literature and have been found to be useful to policy audiences seeking to better understand the factors contributing to vulnerability (e.g., Busby et al. 2014, Midgley et al. 2011, Preston et al. 2011, BMZ 2014). Those wishing an overview of different vulnerability mapping methods may wish to refer to de Sherbinin et al. (2014b).

The following slide show provides an overview of vulnerability mapping.

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Outline

- What is Vulnerability?
 - As a function of susceptibility and lack of resilience
- Dimensions of vulnerability
 - Social, economic, ecological, Institutional, cultural and Physical
- Hotspot Mapping
 - What is a hotspot?
 - Why map hotspots and what are common methods?
- Issues with current vulnerability mapping efforts
 - Vulnerabilities in East Africa (EA)
 - Data Issues

Definitions of vulnerability

- IPCC defines as “the extent to which climate change may damage or harm a system”
- Watson et al 1993 – vulnerability depends not only a system’s sensitivity, but also on its ability to adapt to new climatic conditions

What is a vulnerability map?

- A vulnerability map gives the location of sites where people, the natural environment or property are at risk due to a potentially catastrophic event
 - E.g. a map showing the housing areas that are vulnerable to a flooding along a river.
- Vulnerability maps are most often created with the assistance of geographic information systems (GIS) but can also be created manually using background maps such as satellite imagery, property boundaries, road maps, or topographic maps.

What is a hotspot?

- Term derived from early work by Norman Myers to identify areas at risk of biodiversity loss
 - Wikipedia: *The original hotspots map*

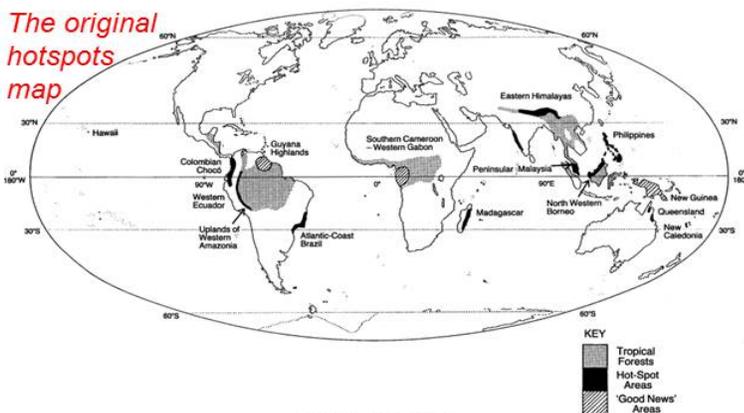
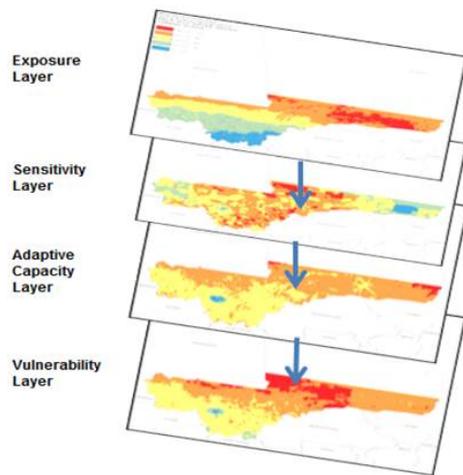


Fig.1. Tropical Forests: Hotspot Areas.

Source: Myers, N. 1988. Threatened biotas: "Hot spots" in tropical forests. *The Environmentalist* 8 187-208.

What is a climate change hotspot?

- Integrates *spatial variability* in:
 - Climate / biophysical changes
 - Human / system vulnerabilities



- Climate change exposure is **spatially** differentiated
- Vulnerabilities are **spatially** differentiated
- Adaptive/coping capacities are **spatially** differentiated

Mapping can illuminate key vulnerabilities in the coupled human-environment system and, in turn, inform where adaptation may be required

Why map vulnerability hotspots?

- Climate change vulnerability and hotspots maps convey the degree to which a system is likely to be negatively affected by climate change impacts
- By describing the nature of stressors in the most vulnerable areas, the maps help to inform the design of responses
- They are utilized by governments and a number of donors to target development, adaptation, and disaster risk reduction funding
- There is a proliferation of mapping efforts in academia and more refined methodologies are being developed

Mapping methods

1. Modeling efforts
2. GIS data integration
 - a) Creation of spatial indicators and indices
 - b) Use of spatial data to tell a story
3. Expert judgment (free hand mapping)

Mapping themes

1. Exposure hotspots based on climate variables
2. Focus on vulnerable populations and migration
3. Humanitarian crises and conflict
4. Agriculture and food security
5. Water resources

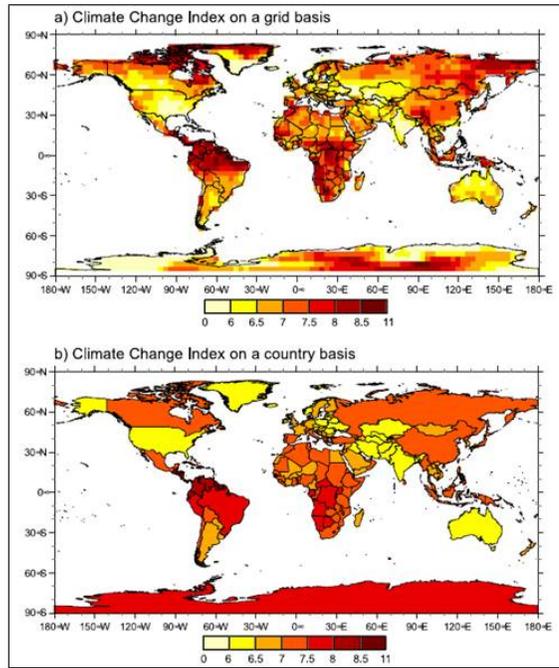
*Common caveat: "Given the extreme complexity of climate change and human vulnerability, this study should be considered as **indicative only**. We have taken a pragmatic approach in order to produce useful results and analysis within the scope and resources of this project."*

– Thow & de Blois 2008

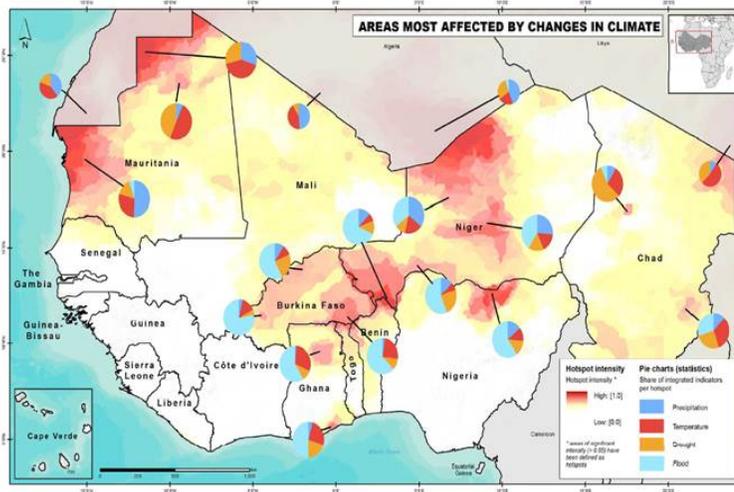
Climate Change Index

- Tracks increases in the probabilities of extreme events relative to a 1 in 20 year return cycle for the same events under current climatology
- Based on SRES A2 and B2 scenarios
- Indicators: additional hottest years, driest years, and extremely warm/wet/dry seasons

Source: Baettig, M.B., M. Wild, and D.M. Imboden. 2007. A climate change index. *Geophysical Research Letters*, 34, L01705



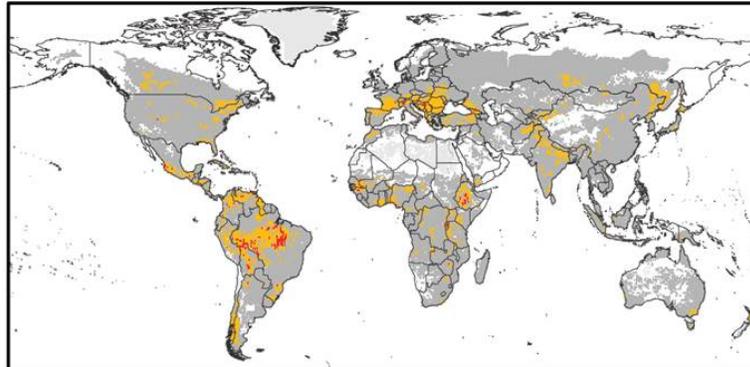
Cumulative Climate Change Index of the Sahel



Hotspots are identified as areas where temperature and precipitation trends are pronounced and drought and flood events over the past 24-36 years have been severe, with a focus on the rainy season from May to October.

Source: Hagenlocher, M., et al. 2013. Modeling Hotspots of Climate Change in the Sahel Using Object-Based Regionalization of Multidimensional Gridded Datasets. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. doi: 10.1109/JSTARS.2013.2259579

Multisectoral Hotspots of Impacts

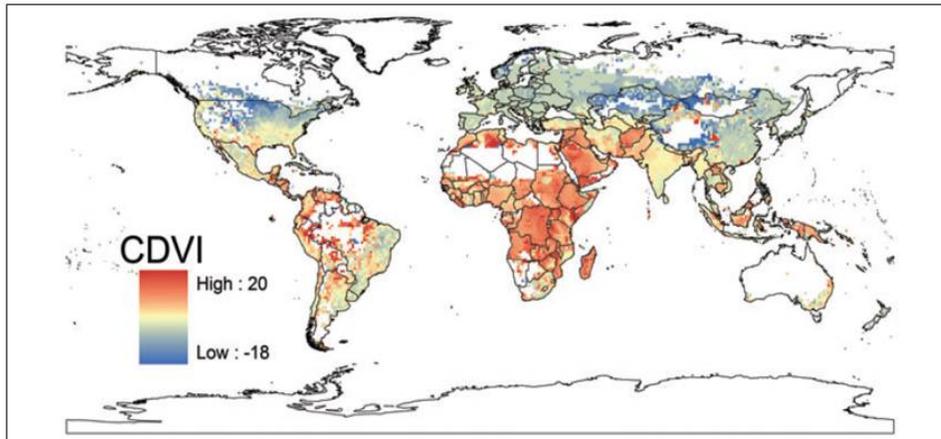


■ 2 overlapping sectors ■ 3 overlapping sectors

Based on sector specific thresholds for climate change impacts in water, agriculture, ecosystems and health. The above map shows where 50% of GIM-GCM combinations agree on the threshold crossing in each sector, for a GMT change of up to 4.5 °C. Regions in light gray are regions where no multisectoral overlap is possible.

Source: Piontek F, Müller C, Pugh TAM et al (2013) Multisectoral climate impacts in a warming world. *Proceedings of the National Academy of Sciences*. doi:10.1073/pnas.1222471110.

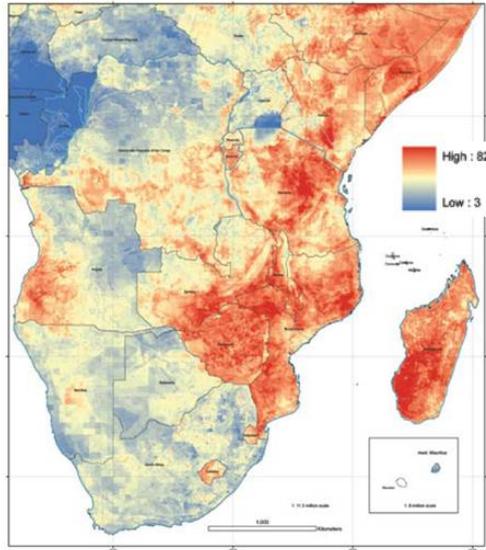
Climate-demography vulnerability index



Red areas = high vulnerability, where current demographic growth vastly exceeds “climate consistent” population growth
Blue areas = low vulnerability, where population growth is lower than “climate consistent” population growth

Source: Samson, J., D. Berteaux, B.J. McGill and M.M. Humphries. 2011. Geographic disparities and moral hazards in the predicted impacts of climate change on human populations. *Global Ecology and Biogeography* doi:10.1111/j.1466-8238.2010.00632.x

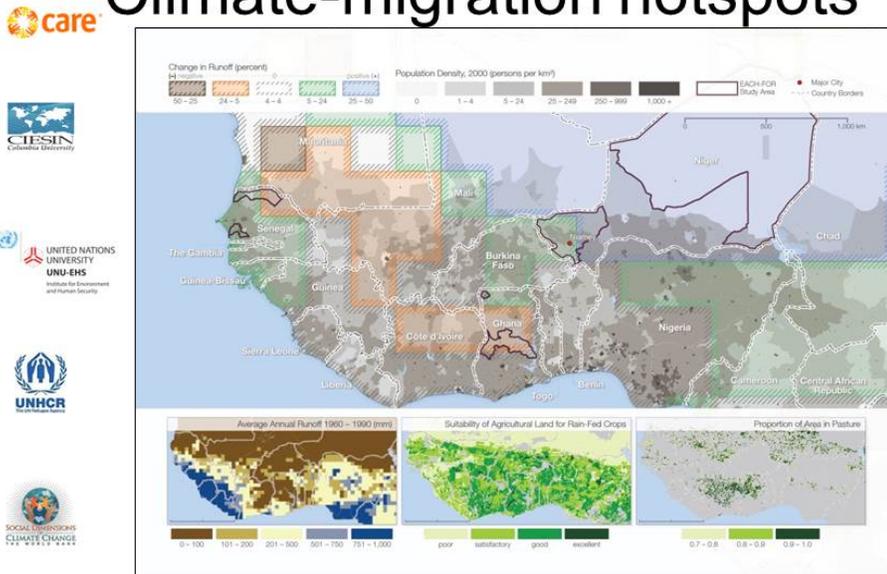
Risk and vulnerability mapping in Southern Africa



- Combines *exposure* (climate hazards such as droughts, floods, rainfall variability), *future exposure* (ensemble climate model precip, temp change and SLR), *sensitivity* (irrigated lands, crowding on agricultural lands, length of growing period, soil degradation, etc.), and *adaptive capacity* (night-time lights, education, malaria index, HIV prevalence, accessibility, etc.)
- Climate impacts

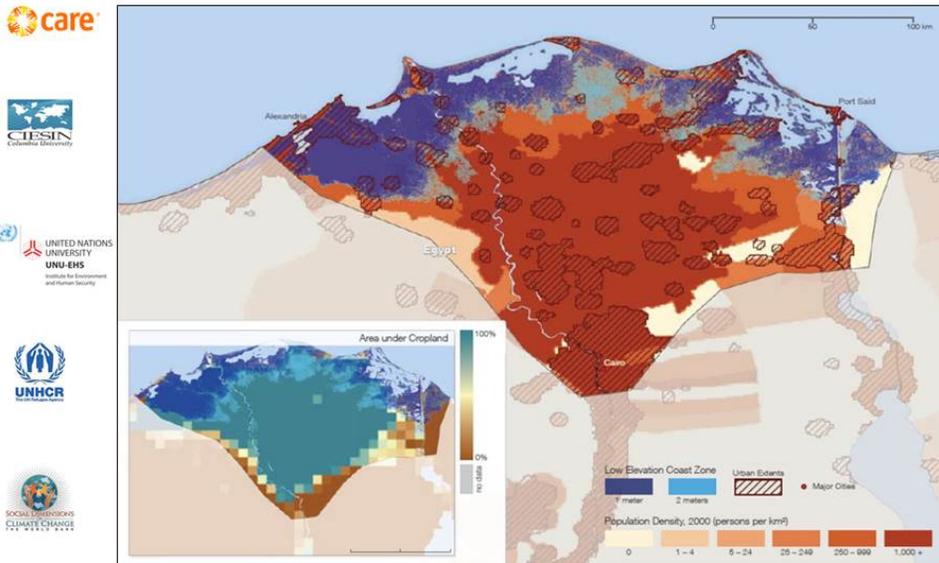
Source: Davies, R.A.G., and S.J.E. Midgley. 2010. Risk and Vulnerability Mapping in Southern Africa: A Hotspots Analysis. Cape Town, South Africa: OneWorld Sustainable Investments (Pty) Ltd.

Climate-migration hotspots



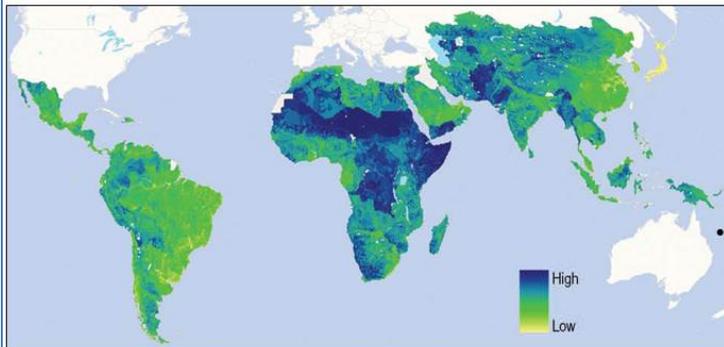
Source: Warner, K., C. Erhart, A. de Sherbinin, S.B. Adamo, T.Chai-Onn. 2009. *In search of Shelter: Mapping the effects of climate change on human migration and displacement*. Bonn, Germany: United Nations University, CARE, and CIRESIN-Columbia University.

Sea level rise displacement



Source: Warner, Ehrhardt, de Sherbinin, Adamo, and Chai-Onn. 2009 *In Search of Shelter*. UNU, CARE, CIESIN. Available at http://www.ciesin.columbia.edu/documents/clim-migr-report-june09_final.pdf

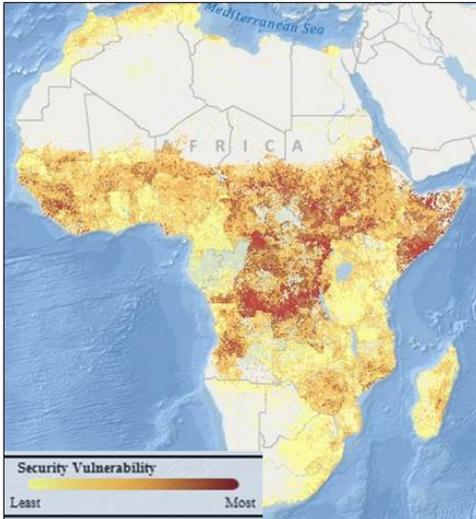
Humanitarian implications of climate change



Source: CARE and Maplecroft. 2008. *Humanitarian implications of climate change: Mapping emerging trends and risk hotspots*. Geneva, Switzerland: CARE International.

- Uses combination of historical country-level data (refugees/displacement, conflict) and CIESIN's gridded data for population, poverty and climate hazard exposure
- Climate scenario data (A1B) for: % change in extreme precip, % change in maximum dry periods, and future dynamics of drought risk

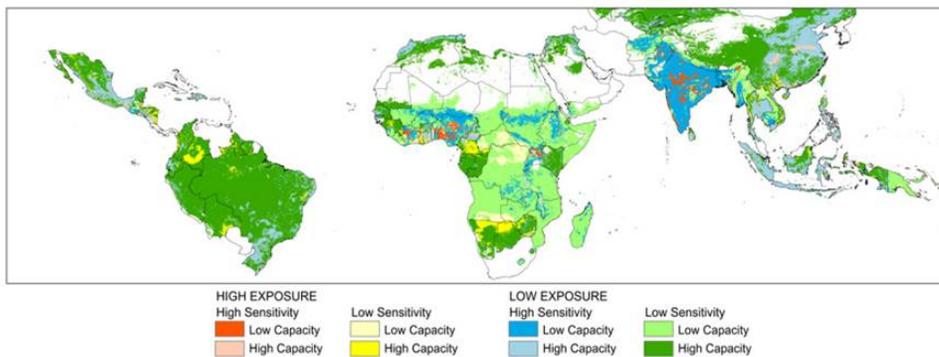
Climate change and African political stability



Four baskets of vulnerability are identified: *exposure* to climate hazards, *population density*, household and community *resilience* (health, education, access to health care), and *governance and political violence* (country level indicators of government responsiveness, effectiveness, polity, and violence against civilians)

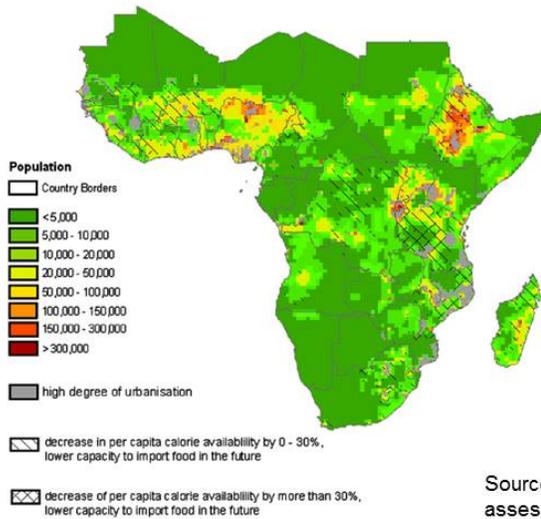
Source: Busby, J.W., T.G. Smith, and K.L. White. 2011. *Locating Climate Insecurity: Where are the most vulnerable places in Africa?* Climate Change and African Political Stability Program Policy Brief No. 3.

Vulnerability to maximum daily growing season temperature exceeding 30°C



Source: Ericksen, P., P. Thornton, A. Notenbaert, L. Cramer, P. Jones, M. Herrero. 2011. *Mapping hotspots of climate change and food insecurity in the global tropics*. CCAFS Report no. 5. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). Copenhagen, Denmark

Current and future hotspots of hunger in Sub-Saharan Africa in the context of global change



- Areas experiencing under-nutrition were assessed
- Impact of climate change on the production of six major crops was analyzed
- Areas that are projected to experience hunger in the context of anticipated climate, social, economic, and biophysical changes were mapped

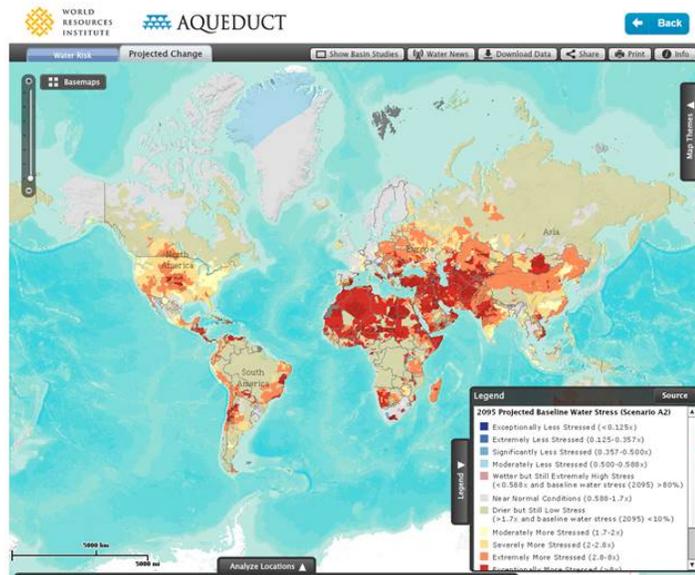
Source: Liu, J., et al. 2008. A spatially explicit assessment of current and future hotspots of hunger in Sub-Saharan Africa in the context of global change. *Global and Planetary Change*, 64 (2008): 222–235

5. Water resources

Aqueduct Water Risk Management

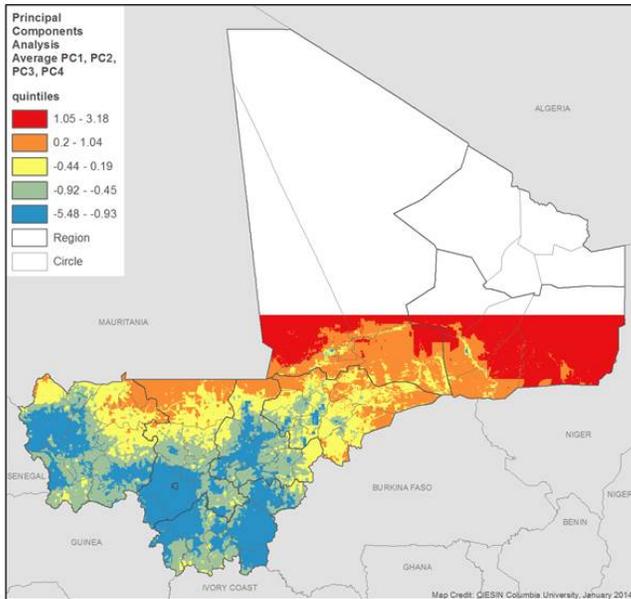
Creates a water risk score based on multiple climate scenarios and a hydrological model for use by “companies, investors, and governments”.

Here baseline conditions and projections to 2050 (SRES A2 scenario) are provided.



Source: <http://aqueduct.wri.org/atlas>.

Mali Climate Vulnerability Mapping



- Created separate maps for:
 - Exposure
 - Sensitivity
 - Lack of Adaptive Capacity
 - Vulnerability
- Explores PCA as an alternative aggregation tool

Mali Climate Vulnerability Mapping

Component	Indicator Code	Data Layer
Exposure	PRCP	Average annual precipitation (1950-2009)
	IACV	Inter-annual coefficient of variation in precipitation (1950-2009)
	DCVAR	% of precipitation variance explained by decadal component (1950-2009)
	NDVICV	Coefficient of variation of NDVI (1981-2006)
	TTREND	Long-term trend in temperature in July-August-Sept. (1950-2009)
Sensitivity	FLOOD	Flood frequency (1999-2007)
	HHWL	Household wealth (2006)
	STNT	Child stunting (2006)
	IMR	Infant mortality rate (IMR) (2006)
	POVI	Poverty index by commune (2008)
	CONF	Conflict events/political violence (1997-2012)
	CARB	Soil organic carbon/soil quality (1950-2005)
Adaptive Capacity	MALA	Malaria stability index
	EDMO	Education level of mother (2006)
	MARK	Market accessibility (travel time to major cities)
	HEALTH	Health infrastructure index (2012)
	ANTH	Anthropogenic biomes (2000)
	IRRI	Irrigated areas (area equipped for irrigation) (1990-2000)

Baseline assessment using the IPCC definition of vulnerability and an additive approach

Climate Change Issues in East Africa

- Increase number of hot days and nights (mean temperature): High exposure
- Less frequent and more intense rainfall: High exposure
- More frequent and intense drought periods: Mid resilience and Adaptive Capacity
- Increases in infectious diseases to both human and livestock: Sensitivity and Adaptive Capacity

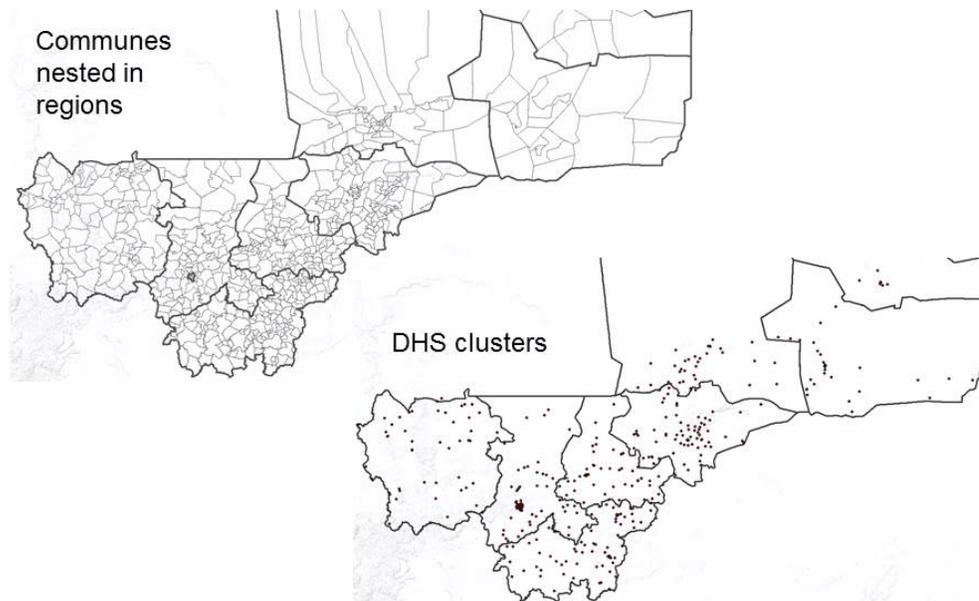
Why East Africa is particularly Vulnerable

- Over-dependence on natural resources; primary production
- Over-reliance on rain-fed agriculture for livelihood support
- Low level of development
- Inadequate institutional and economic capabilities

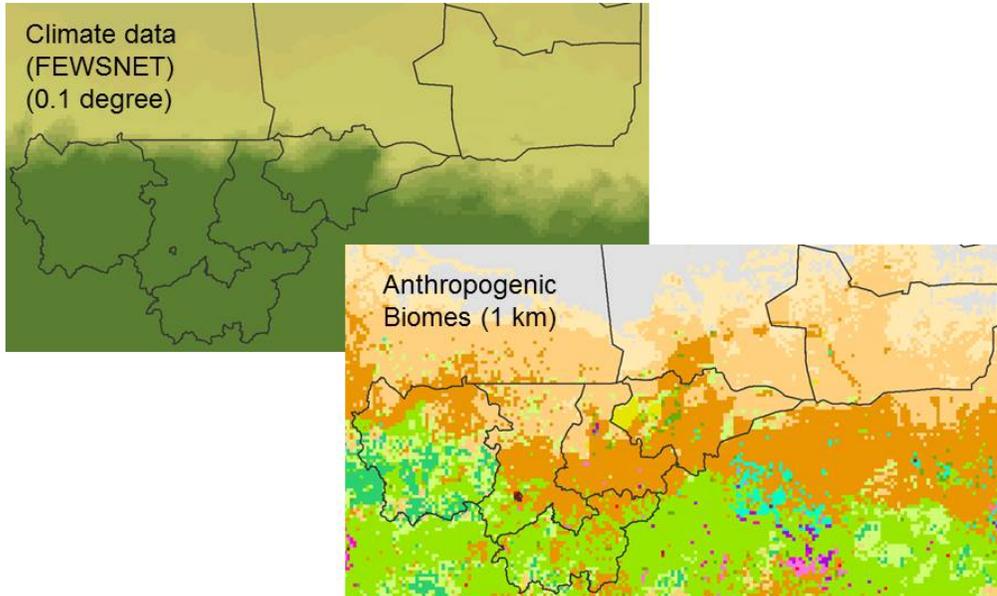
Hotspots mapping: Data issues

- Artifacts of spatial data integration:
 - Combinations of country-level, subnational and continuously varying variables such as precipitation leads to discontinuities across admin units
 - Speckling effect from higher resolution data reduces ability to interpret results

Mali VA Mapping: Sample Resolutions

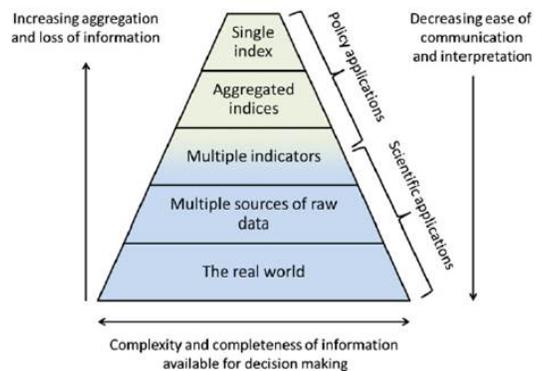


Mali VA Mapping: Sample Resolutions



Hotspots mapping: Policy communication issues

- If results do not conform to the policy maker's own mental models, they may not be widely accepted
- Tradeoff: commun complex



Source: Abson DJ et al. (2012). *Appl Geogr* 35:515–524

Hotspots mapping: Vulnerability Assessment

- Don't understand the functional form of the relationship between indicators and components and between components and vulnerability
 - Assume that the observed minimum and maximum values have the same meaning across input layers
 - Some indicators have long tail extreme values that may overly influence results
 - Assume fungability, i.e., high scores in one indicator/component can offset low scores in another
- Assume a linear relationship between the input layers and the conceptual category being measured
 - It might be a step function, or sigmoid, or asymptotic if there are critical thresholds involved, or it might be exponential if high values trigger cascading problems
- Assume equal weights across components, but the relationship to overall vulnerability may be very different
 - It could be that one unit of exposure has the same effect on vulnerability as ten units in sensitivity

*Exercise 1. Developing Vulnerability
Mapping Framework and Selecting
Variables*

1.0 Variable Listing

In this exercise we will examine the variables under each of the components, Exposure, Adaptive Capacity and Sensitivity to climate change and vulnerability

Exposure

- Seasonal temperature
- Average Annual Precipitation
- Long-term trend in temperature in July-August-Sept. (1950-2009)
- Flood frequency (1999-2007)

Adaptive Capacity

- Education level of mother (2006) point/polygon
- Market accessibility (travel time to major cities)
- Anthropogenic biomes (2000)
- Irrigated areas (area equipped for irrigation) (1990-2000)

Sensitivity

- Household wealth (2006)
- Child stunting (2006)
- Infant mortality rate (IMR) (2008)
- Soil organic carbon/soil quality (1950-2005)

1.1 Variable definition

Variable name:.....

Briefly explain three ways in which this variable may contribute to social vulnerability to climate change.

1.....
.....
.....

2.....
.....
.....

3.....
.....
.....

List and briefly explain two alternative variables you know that can be used to substitute for this variable

1.....
.....

2.....
.....

3.....
.....

List in order of importance which component of vulnerability (exposure, adaptive capacity and sensitivity) does this belong.

1.....

2.....

3.....

1.2 Final variable listing

Sensitivity:

- 1.
- 2.
- 3.
- 4.
- 5.

Exposure

- 1.
- 2.
- 3.
- 4.
- 5.

Adaptive Capacity

- 1.
- 2.
- 3.
- 4.
- 5.

Lecture 2. Writing metadata for spatial data

Metadata is data that describes other data. Metadata summarizes basic information about data such as the author, date created and date modified and file size. The main purpose of metadata is to facilitate in the discovery of relevant information. Metadata also helps organize electronic resources, provide digital identification, and helps support archiving and preservation of the resource. Having the ability to filter through that metadata makes it much easier for someone to locate a specific document.

Metadata in GIS describe geographic objects (such as shapefiles, satellite imagery, maps, features, or simply documents with a geospatial component). Metadata can be created manually, or by automated information processing. Manual creation tends to be more accurate, allowing the user to input any information they feel is relevant or needed to help describe the file. Automated metadata creation can be much more elementary, usually only displaying information such as file size, file extension, when the file was created and who

created the file.

What is Metadata?

• Data 'reporting'

- **WHO** created the data?
- **WHAT** is the content of the data?
- **WHEN** was it created?
- **WHERE** is it geographically?
- **HOW** was the data developed?
- **WHY** was the data developed?



Definition

• Metadata:

- Refers to data about the meaning, content, organization, or purpose of data.
- Metadata may be as simple as a relational schema or as complicated as information describing the source, derivation, units, accuracy, and history of individual data items.
- set
- explain the role of metadata in the National Spatial Data Infrastructure

What is Metadata ?



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What is Metadata?



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•entity

•attributes

Nutrition Facts	
Serving Size ½ cup (114g)	
Servings Per Container 4	
Amount Per Serving	
Calories 90	Calories from Fat 30
% Daily Value*	
Total Fat 3g	5%
Saturated Fat 0g	0%
Cholesterol 0mg	0%
Sodium 300mg	13%
Total Carbohydrate 13g	4%
Dietary Fiber 3g	12%
Sugars 3g	
Protein 3g	
Vitamin A 80%	Vitamin C 60%
Calcium 4%	Iron 4%
* Percent Daily Values are based on a 2,000 calorie diet. Your daily values may be higher or lower depending on your calorie needs:	
Calories: 2,000 2,500	
Total Fat	Less than 65g 80g
Sat Fat	Less than 20g 25g
Cholesterol	Less than 300mg 300mg
Sodium	Less than 2,400mg 2,400mg
Total Carbohydrate	300g 375g
Dietary Fiber	25g 30g
Calories per gram:	
Fat 9 • Carbohydrate 4 • Protein 4	

Types of Metadata

- System catalogs metadata
 - e.g. catalogs maintained by relational databases
- Relationship metadata
 - Information about relationship between data entities
- Content metadata
 - descriptions of the contents of stored data at an arbitrary granule.
- Data lineage metadata
 - it includes information about the creation of data
- Technical metadata
 - is technical information about stored data. It includes such information as the format
- Data usage metadata

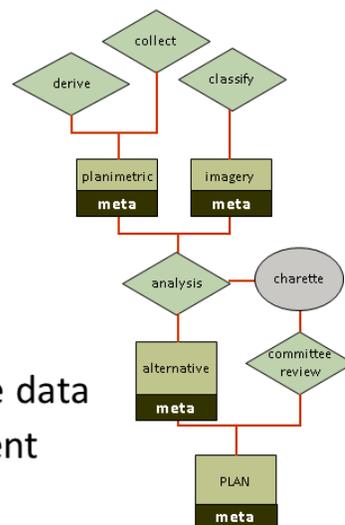
Utility of Metadata

- Metadata can support:

- data distribution
- data management
- project management

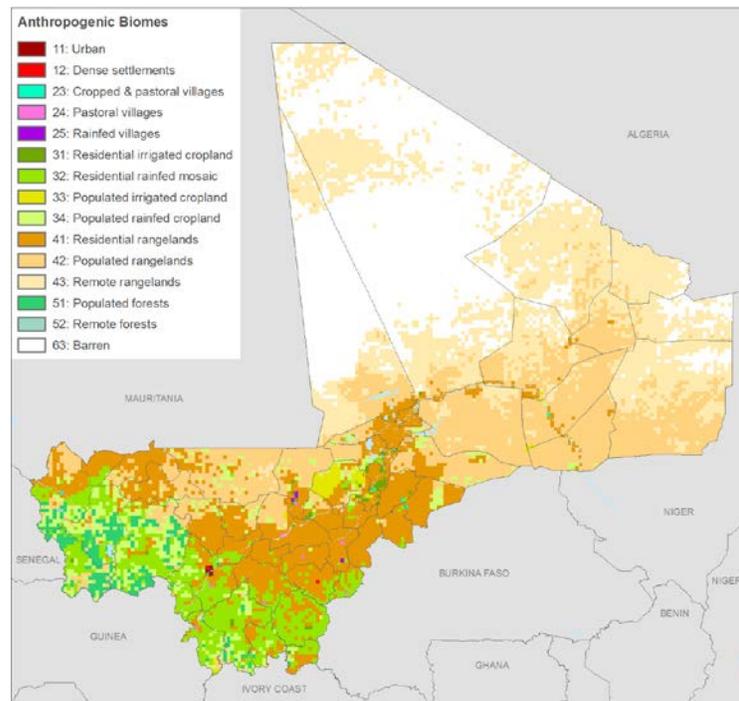
- If it is:

- considered a component of the data
- created during data development
- populated with rich content



*Exercise 2. Writing metadata for spatial
data*

Anthropogenic Biomes Metadata Sheet



Title:	Anthropogenic Biomes of the World, v1 (2001-2006)
Indicator Code:	ANTH
Component:	<i>Adaptive Capacity</i>
Rationale:	<p><i>Corresponds to the field 'Rationale' in Indicator sheets in methodology. Include brief description of the indicator in the context of:</i></p> <ul style="list-style-type: none"> ▪ <i>why the issue is important globally;</i> ▪ <i>what are some of the impacts of the issue (these two may overlap);</i> ▪ <i>what the results of the indicator show; and how they can be interpreted.</i>
Source Data Set:	<p>Anthropogenic Biomes of the World, v1 (2001-2006)</p> <p>The Anthropogenic Biomes of the World, Version 1 data set describes globally-significant ecological patterns within the terrestrial biosphere caused by sustained direct human interaction with ecosystems, including agriculture, urbanization, forestry and other land uses.</p> <p>Anthropogenic biomes were identified and mapped using a multi-stage procedure based on population (urban, non-urban), land use (percent area of pasture, crops, irrigation, rice and urban land) and land cover (percent area of trees and bare earth). Input datasets include population data (Landsat 2005), land use data (percent area under cropland, pasture, irrigation and rice) and land cover (vegetation, continuous fields, tree cover, and bare earth proportion layers).</p> <p>Dataset released in 2009.</p> <p>Citation: Ellis, E. C. and N. Ramankutty. 2008. Putting people in the map: anthropogenic biomes of the world. Data distributed by the Socioeconomic Data and Applications Center (SEDAC): http://sedac.ciesin.columbia.edu/es/anthropogenicbiomes.html. Accessed 9/6/2013.</p>

Units:	Biome analysis was conducted at 5 arc minute resolution (5' grid cells cover ~ 86 km ² at the equator), a spatial resolution selected as the finest allowing direct use of high-quality land-use area estimates.
Computation:	The data were subset to the Mali national boundary extent using ArcGIS Extract by Mask tool and a 30 arc-second raster mask generated from a 30 arc second fishnet. Raster values were extracted using ArcGIS Extract Values to Points tool and the 30 arc-second fishnet centroids. The output was exported to a .csv table for re-coding and statistical analysis.
Statistics for raw data:	<i>Min = 11, Max=63, Median=43, Mean=47.15, Standard Deviation=10.62</i>
Scoring system:	<p><i>Raster values were re-coded as follows:</i></p> <ul style="list-style-type: none"> 11 (urban) = 10 12 (dense settlements) = 15 22 (irrigated villages) = 15 [not present in Mali] 23 (cropped pastoral villages) = 20 24 (pastoral villages) = 30 25 (rainfed villages) = 30 26 (rainfed mosaic villages) = 30 [not present in Mali] 31 (residential irrigated cropland) = 20 32 (residential rainfed mosaic) = 30 33 (populated irrigated cropland) = 20 34 (populated rainfed cropland) = 30 35 (remote croplands) = 50 [not present in Mali] 41 (residential rangelands) = 50 42 (populated rangelands) = 60 43 (remote rangelands) = 80 51 (populated forests) = 30 52 (remote forests) = 50 61 (wild forests) = 20 [not present in Mali] 62 (sparse trees) = 30 [not present in Mali] 63 (barren) = 100
Statistics for transformed data:	<i>After recode: Min=10, Max=100, Median=80, Mean=70.26, Standard Deviation=24.24</i>
Limitations:	The data set is a conceptual model and not intended to replace existing biome systems based on climate, terrain, and geology. Rather it is intended that wide availability of an anthropogenic biome system will encourage a richer view of human–ecosystem interactions across the terrestrial biosphere, and that this will, in turn, guide our investigation, understanding, and management of ecosystem processes and their changes at global and regional scales.
Spatial Extent:	Global
Spatial Resolution:	Raster cell sizes are 5 arc-minute or 0.08333 degree decimal (about 10 kilometers at the equator)
Year of Publication:	2009
Time Period:	2001–2006

Additional Notes:	
Date:	Obtained: 9/6/2013
Format:	Raster data available in GeoTiff and Esri Grid formats. The Africa Esri Grid was downloaded for this analysis.
File Name:	\\Dataserver0\arcc\VAs\Mali\VulnerabilityMapping\data\AnthropogenicBiomes\af_anthrome_ESRI grid\af_anthrome
Contact person:	N/A, downloaded from http://sedac.ciesin.columbia.edu/es/anthropogenicbiomes.html
Contact details:	N/A.

Exercise Task: Given the metadata template provided, add as much information for each of the variables as possible following the sample metadata provided above.

List of indicators for Vulnerability Mapping

Indicator Code	Data Layer
PRCP	Average annual precipitation (1950-2009)
TTREND	Long-term trend in temperature in July-August-Sept. (1950-2009)
FLOOD	Flood frequency (1999-2007)
HHWL	Household wealth (2006)
STNT	Child stunting (2006)
IMR	Infant mortality rate (IMR) (2006)
CARB	Soil organic carbon/soil quality (1950-2005)
EDMO	Education level of mother (2006)
MARK	Market accessibility (travel time to major cities)
ANTH	Anthropogenic biomes (2000)
IRRI	Irrigated areas (area equipped for irrigation) (1990-2000)

Lecture 3. Introducing ArcGIS Tools

Introduction

This lecture is a refresher for those who may not have been regular users of the ArcGIS software. It will introduce the Graphic User Interface (GUI) and basic navigation to access the different tools that we may be using in the vulnerability assessment. Lecture will be followed by exercises to process the data sets in each category.

Outline

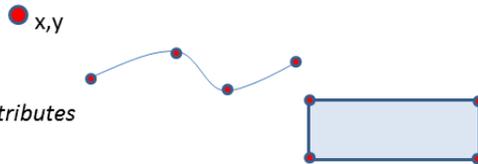
- GIS data types
- ArcGIS Software (ArcCatalog, ArcMap, ArcToolbox)
- Symbolize data
- Working with tables

GIS data types

- Digital representation of geography

➤ Vector data:

- Points
- Lines
- Polygons
- Create feature with *attributes*



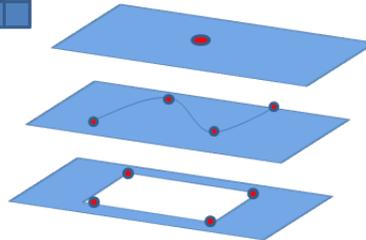
➤ Raster data:

- Cells/pixels with values
- Resolution (cell size)
- Create Image



- Layers

- From Bottom to Top
- Order matters



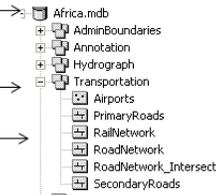
Vector Files

- Shapefile



- Geodatabase

- Feature dataset
- Feature class



Raster Files

- Esri grid
- DEM (Digital Elevation Model)
- ERDAS IMAGINE
- MrSID
- TIFF
- JPEG
- GIF
- PNG



Pros and Cons of Vector vs Raster

- Vector

- better for Cartography
- can have more than one attribute per Feature (columns of joined data)

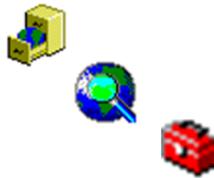
- Raster

- more powerful and better for spatial analysis calculations
- can only have only one value/ feature
- uses more memory

ArcGIS for Desktop

- Mostly use:

- ArcCatalog (Manage)
- ArcMap (Visualize)
- ArcToolbox (Process)



- Can explore (3D):

- ArcScene
- ArcGlobe





ArcCatalog

- Manage your data



ArcCatalog

- 'Windows' for ArcGIS
- **Use ArcCatalog** to copy, delete, move, rename etc.
- In ArcCatalog GIS files are represented as one icon
- Windows shows you the multiple files that create a single GIS file

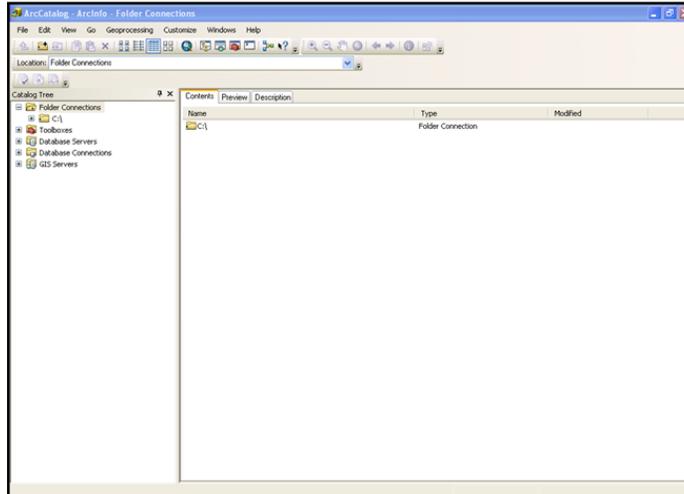
 CSI_settlements.shp Shapefile

	CSI_settlements	190 KB	DBF File
	CSI_settlements.prj	1 KB	PRJ File
	CSI_settlements.sbn	8 KB	SBN File
	CSI_settlements.sbx	1 KB	SBX File
	CSI_settlements.shp	22 KB	SHP File
	CSI_settlements.shp	8 KB	XML Document
	CSI_settlements.shx	7 KB	SHX File



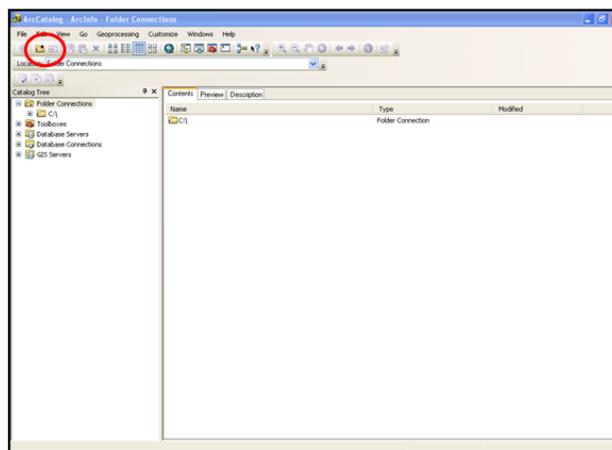
ArcCatalog

- Start>All Programs>ArcGIS>ArcCatalog 10



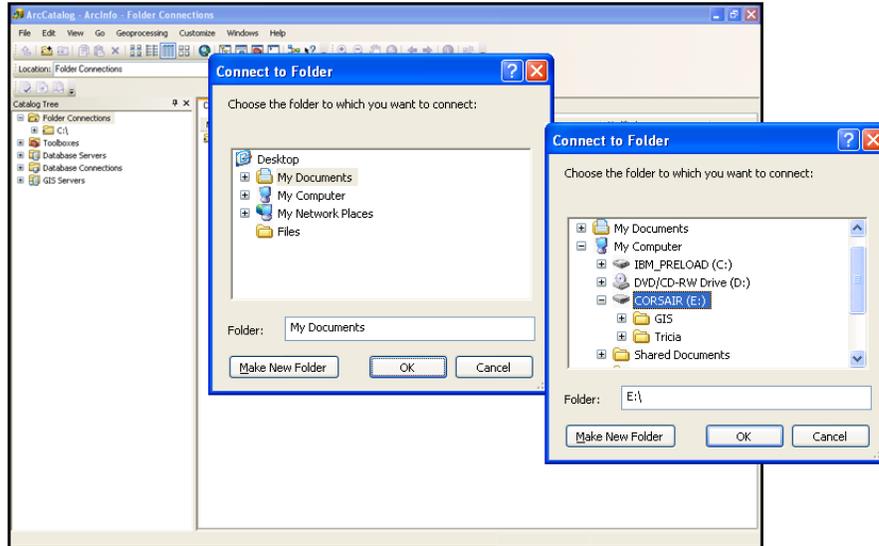
Connect To Folder

- Use Connect to folder if cannot find the drive where your data is stored (eg. E:\)

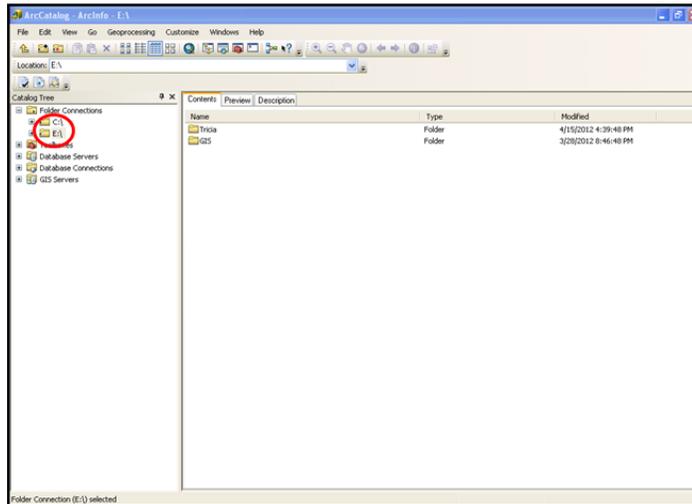




Connect To Folder



Connect To Folder





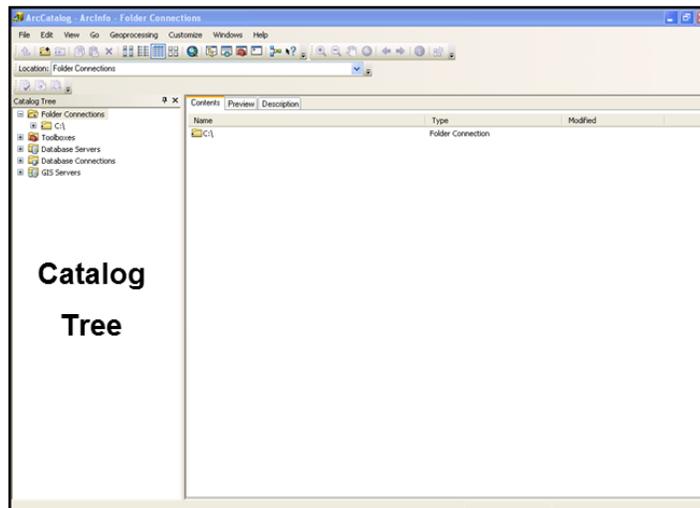
Connect To Folder Exercise

- Use Connect To Folder to find the **Sample** folder where you downloaded the sample data



ArcCatalog- Catalog Tree

- shows folders and layers

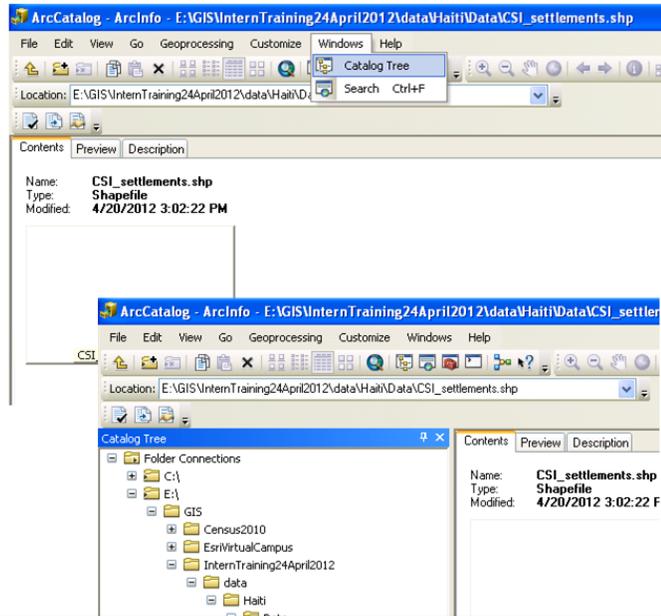


**Catalog
Tree**



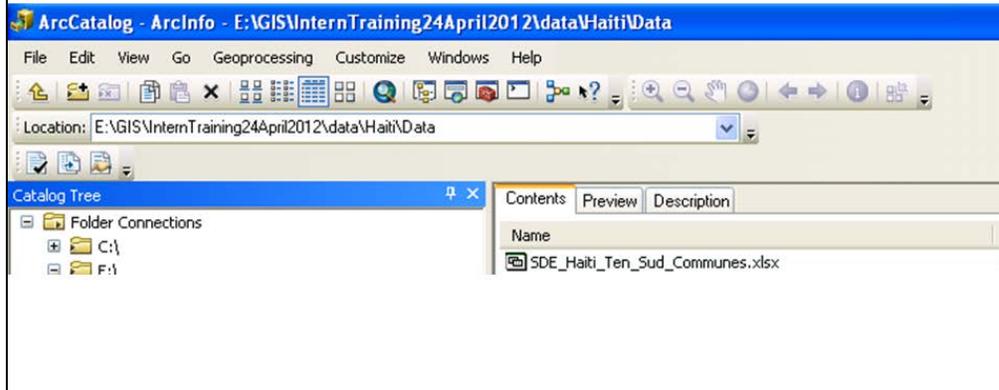
ArcCatalog- Catalog Tree

- If you close Catalog Tree by accident
- Go to Windows> Catalog Tree to bring it back



ArcCatalog

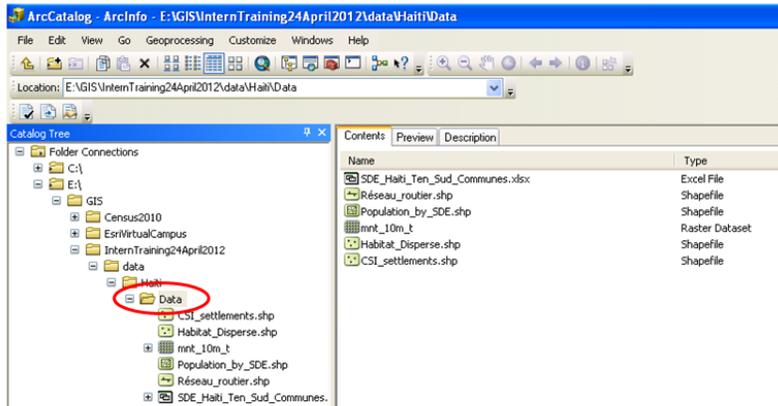
- Quick exploration of your data
- 3 Tabs: Contents, Preview, Description





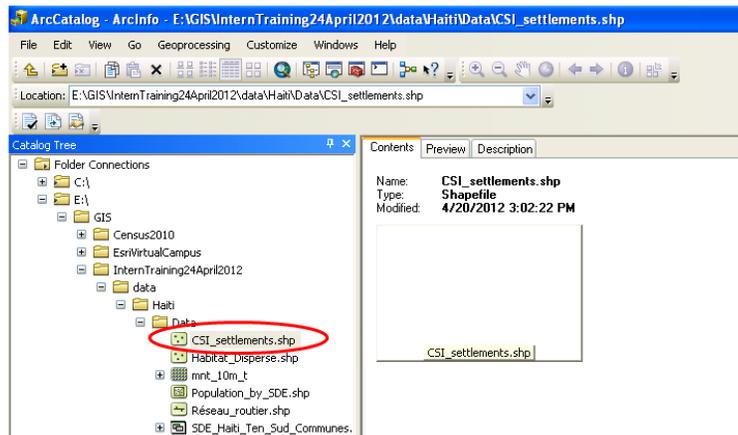
ArcCatalog- Contents Tab

- View Contents of folder



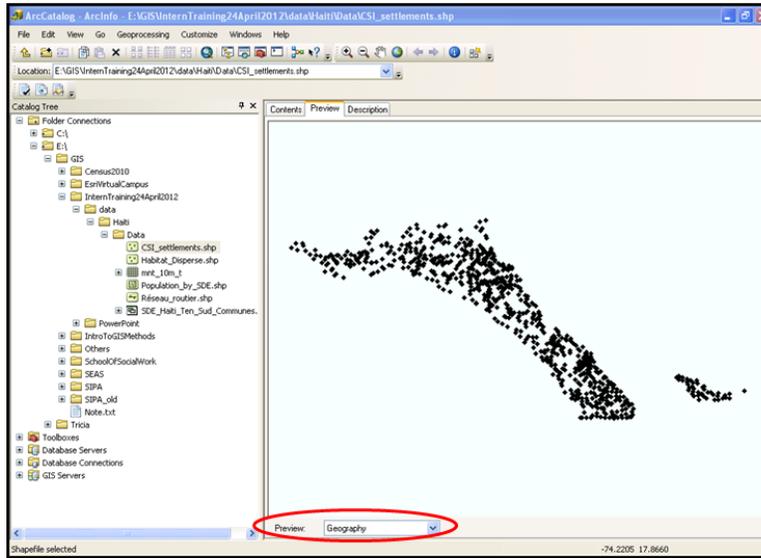
ArcCatalog – Contents Tab

- View data set details - Name, Type, Modified date



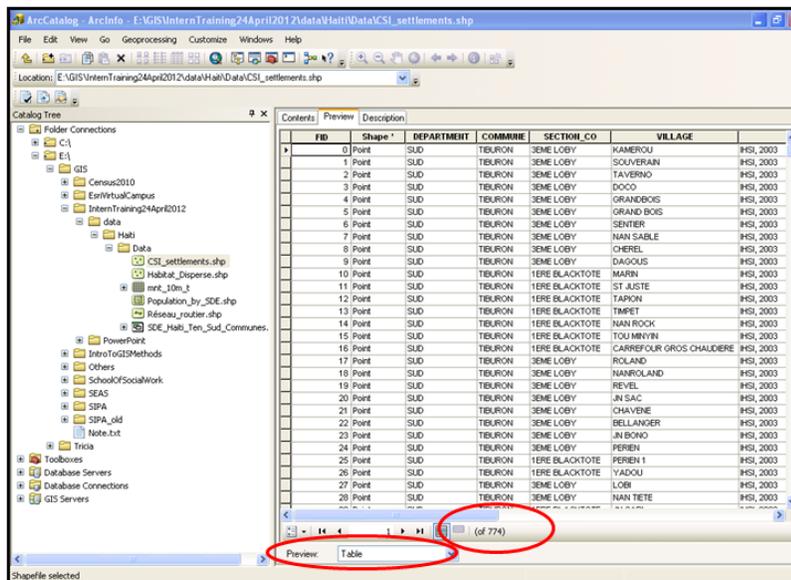


ArcCatalog – Preview Tab - Geography



ArcCatalog – Preview Tab - Table

- shows # of records (rows)





ArcCatalog Questions

- How many records are in the “kenya_Admin5.shp” attribute table?
- Are there more records in the COAST Admin2 or CENTRAL?

FID	Shape	SHAPE_Length	SHAPE_Area	
0	Polygon	0.0057019007723	0.00015002001002	See a Vi
1	Polygon	0.152330601263	0.000361187194019	See a Vi
2	Polygon	0.108450818263	0.00042503166625	See a Vi
3	Polygon	0.0447705618966	9.01132834829E-05	See a Vi
4	Polygon	0.0530701996732	0.000108554525484	See a Vi
5	Polygon	0.0839929200213	0.00026188425772	See a Vi
6	Polygon	0.0704333038434	0.000185045461794	See a Vi
7	Polygon	0.0756200000697	0.000164894534576	See a Vi
8	Polygon	0.159673972614	0.000386119309292	See a Vi
9	Polygon	0.319280541289	0.00131987330747	See a Vi

Answers:

- 1152
- CENTRAL

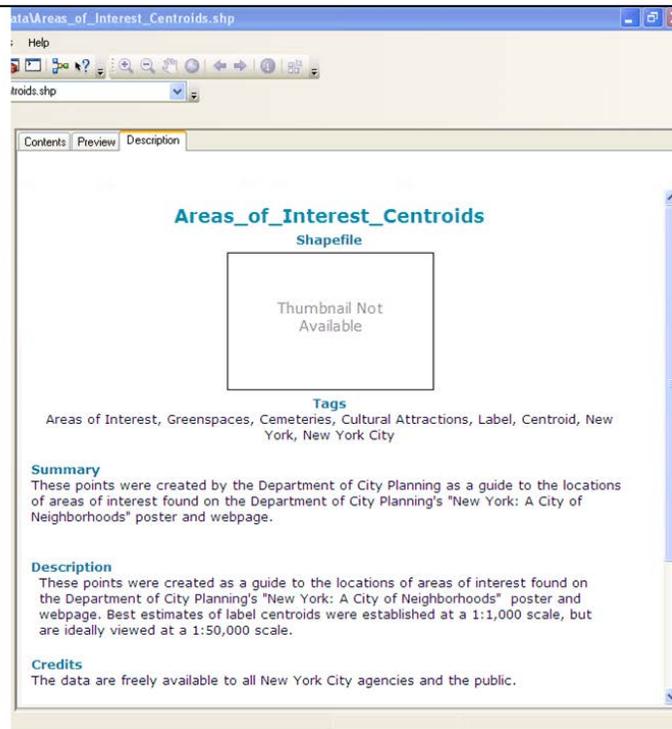


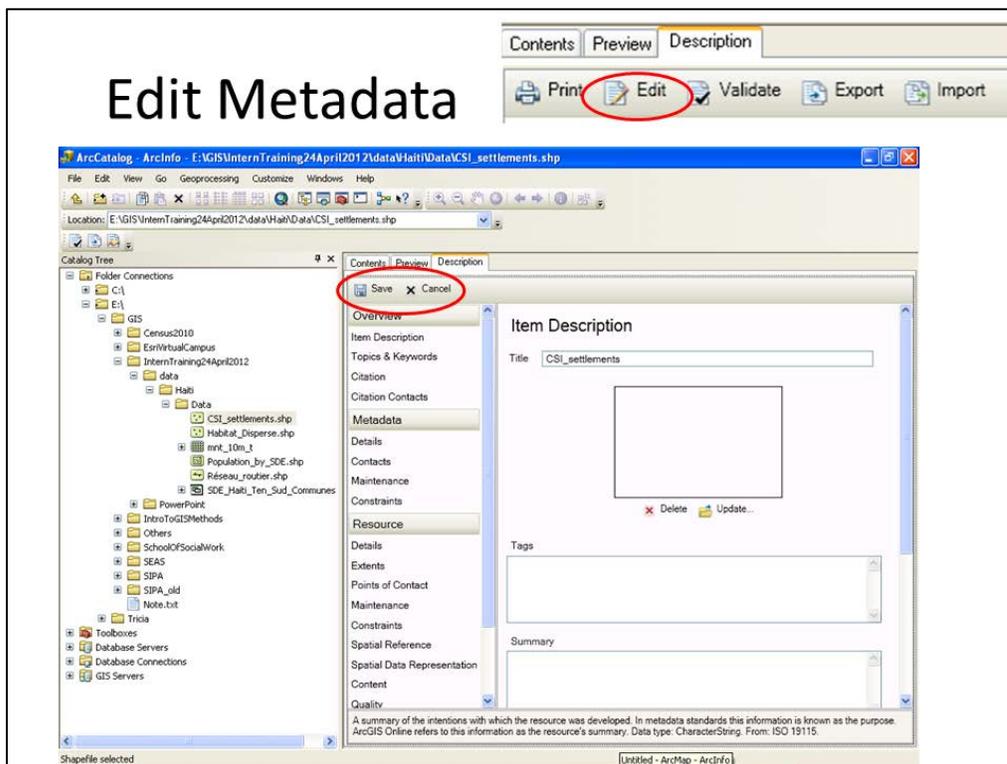
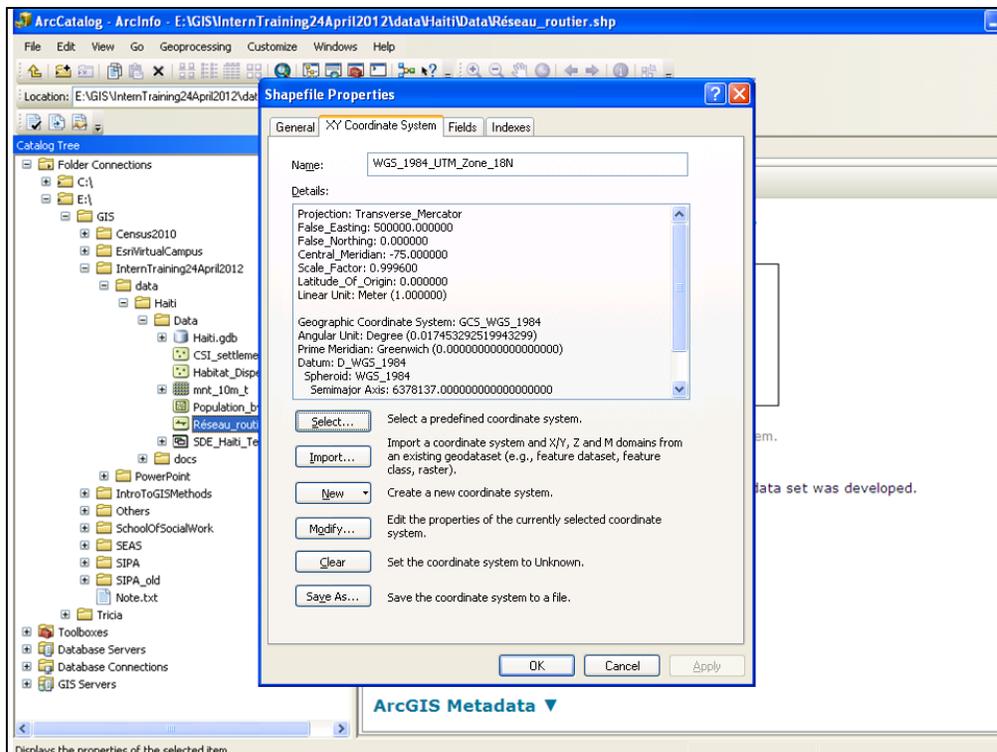
ArcCatalog – Description Tab



- Has Metadata – Data about data
- Contains: Summary, Spatial Information (Coordinate Reference), field and subtypes etc.
- It is important to document the data especially if you plan on sharing data with others
- Creates a “Data Dictionary”

- Metadata Example





Types of Attribute Data

- String – text
- Date
- Precision – Maximum length
- Scale – Max. Decimal places

Data type	Storable range	Size (Bytes)	Applications
Short integer	-32,768 to 32,767	2	Numeric values without fractional values within specific range; coded values
Long integer	-2,147,483,648 to 2,147,483,647	4	Numeric values without fractional values within specific range
Single-precision floating-point number (float)	approximately -3.4E38 to 1.2E38	4	Numeric values with fractional values within specific range
Double-precision floating-point number (double)	approximately -2.2E308 to 1.8E308	8	Numeric values with fractional values within specific range



ArcMap

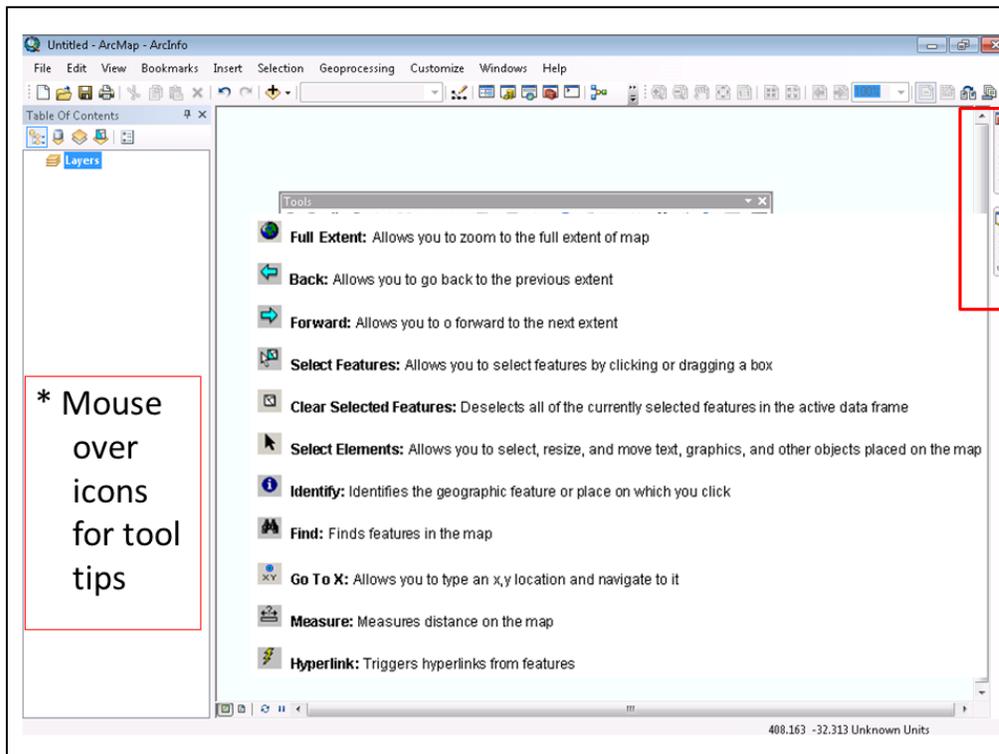
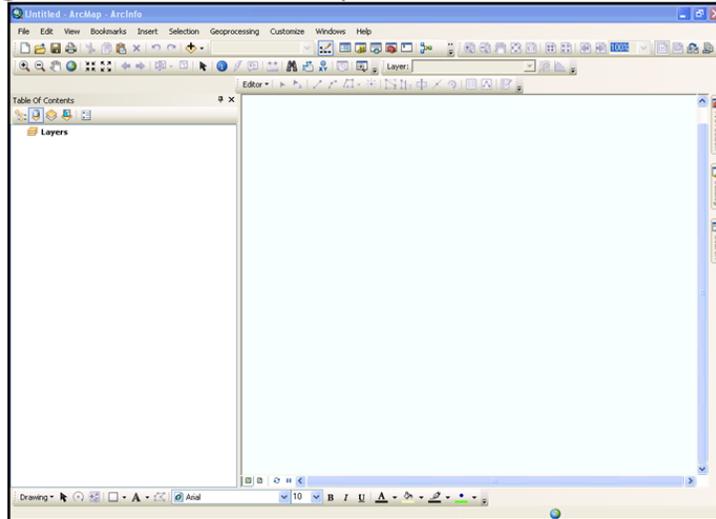
- Explore & Analyze data
- Create maps in a Map Document
- Save Map documents as _____.mxd



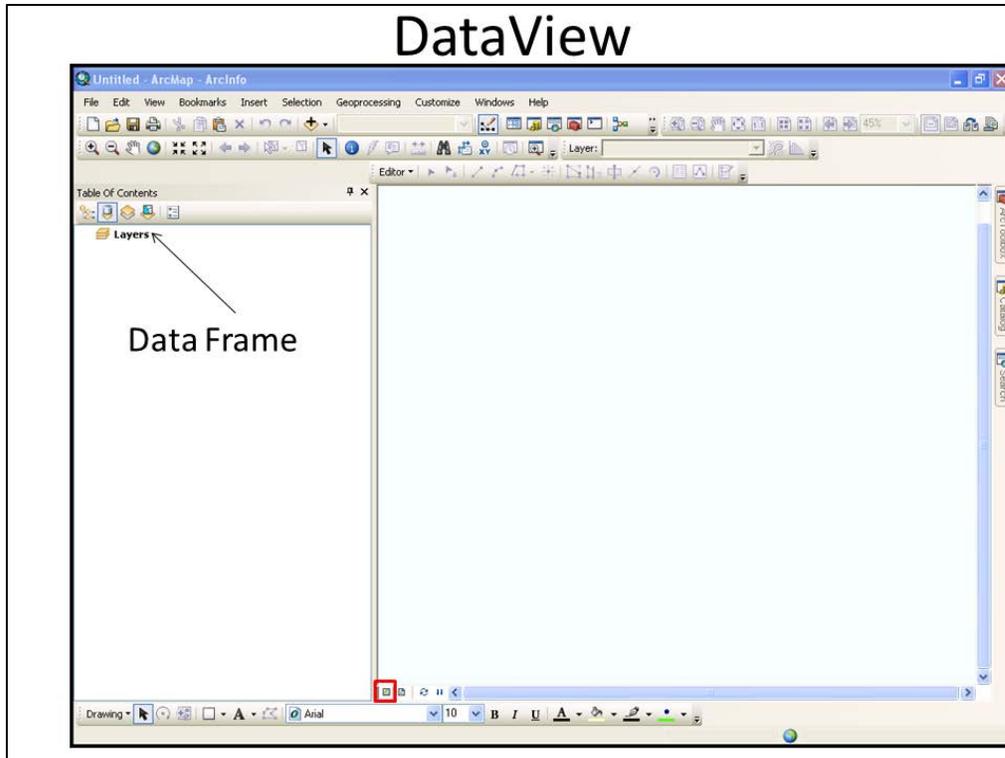


ArcMap

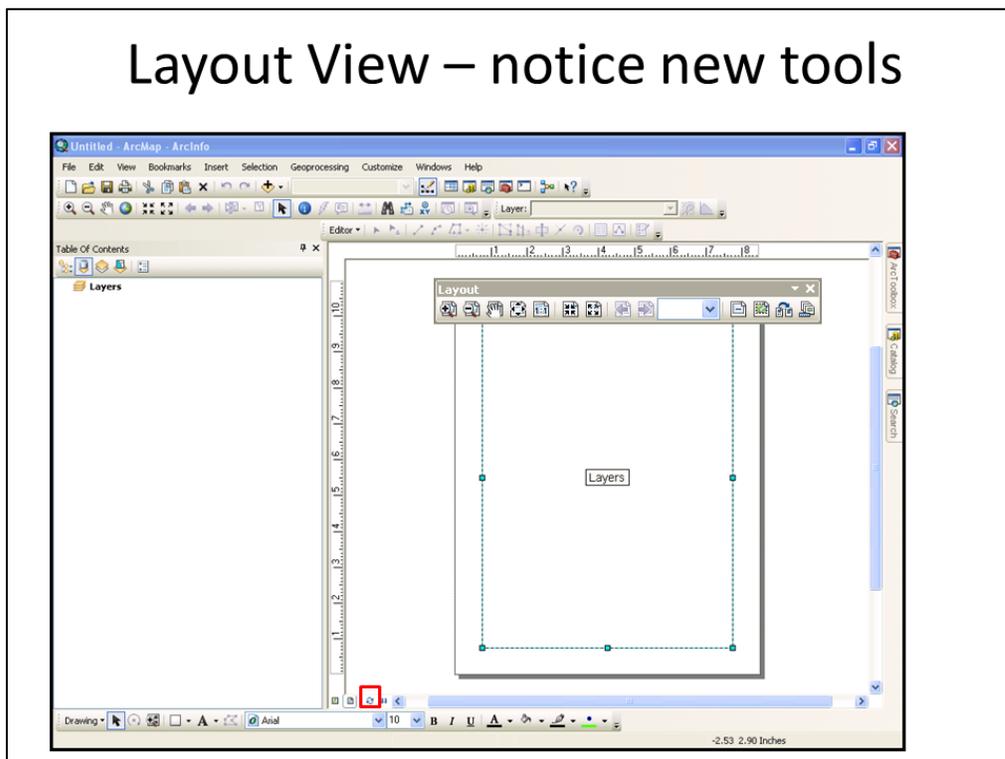
- Programs>ArcGIS>ArcMap



DataView



Layout View – notice new tools





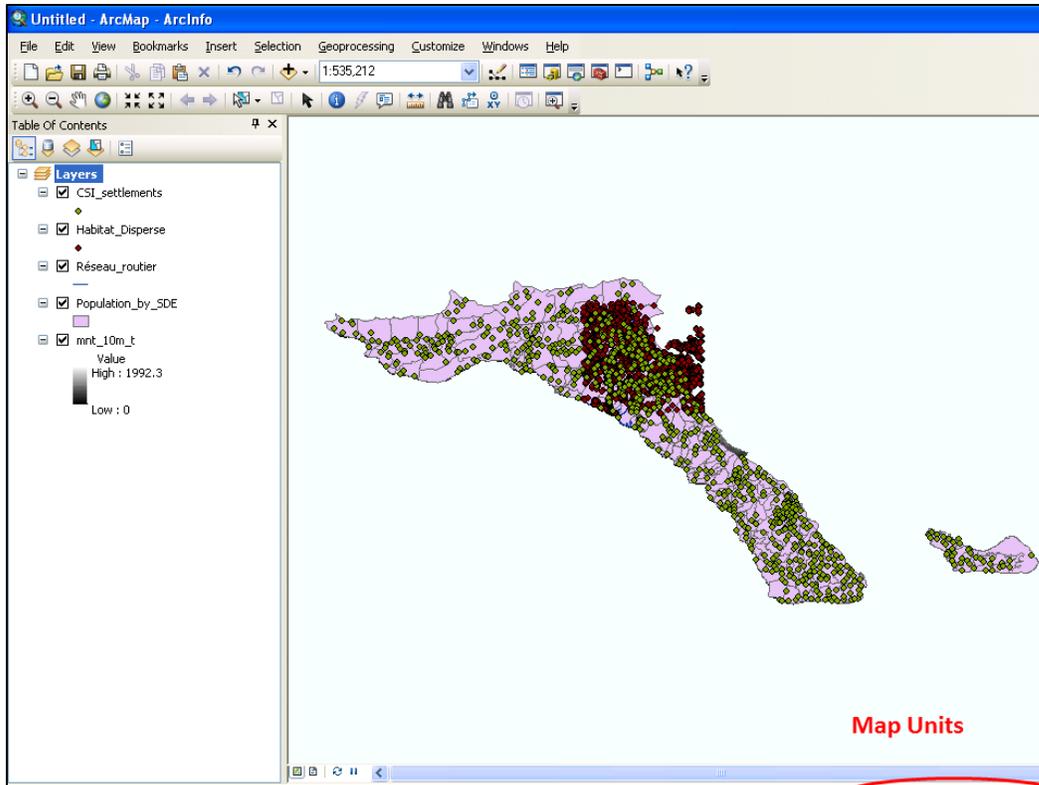
Adding Data

- Add data layers in ArcMap using the... 
 'Add Data' button or
 Drag and drop from ArcCatalog 
- Remember if you cannot find the folder where
 your data is use the Connect To Folder button

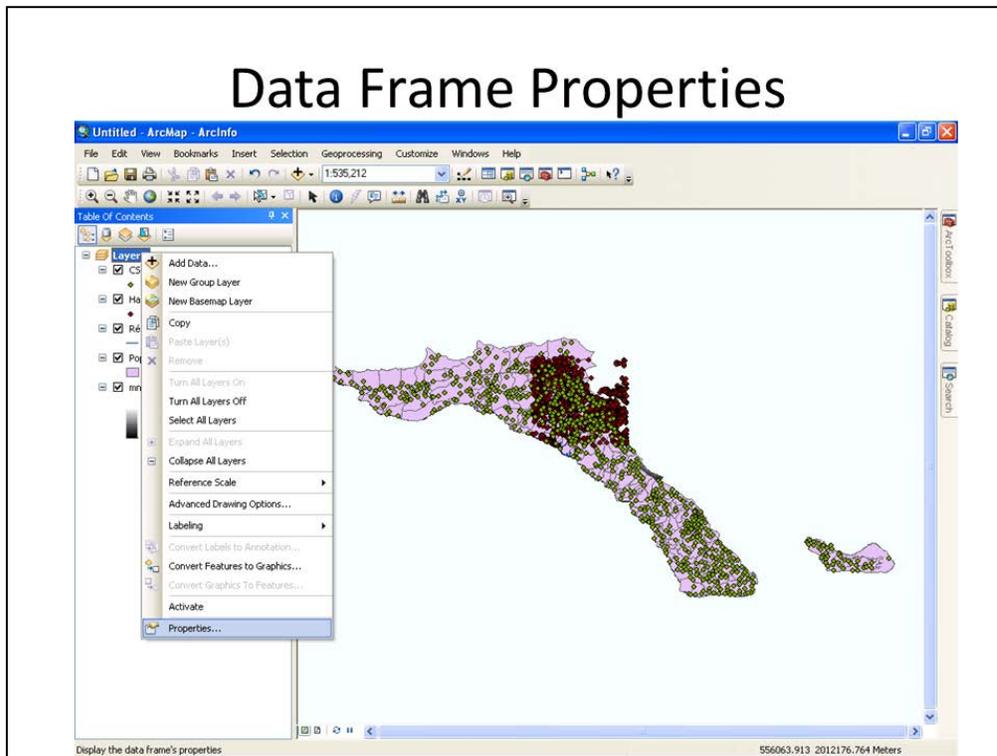


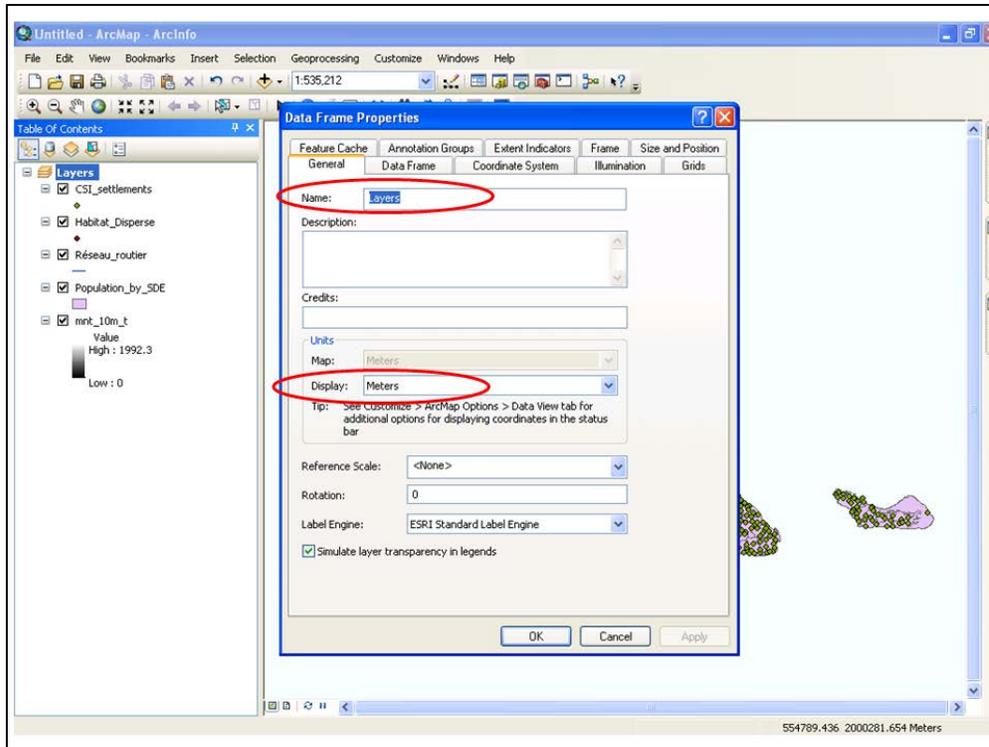
Adding Data Exercise

- Add the "kenp10g" raster data set to ArcMap



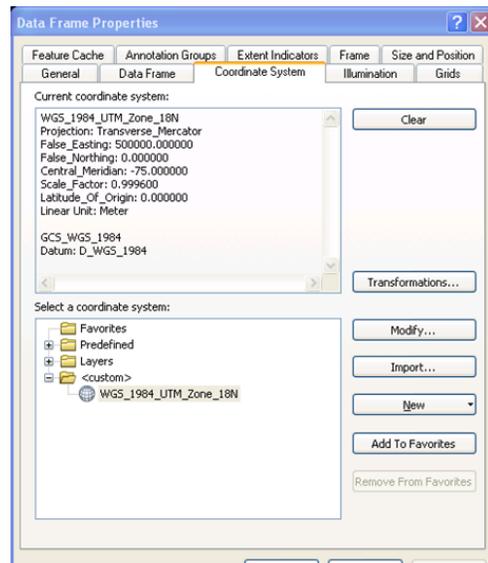
Data Frame Properties





Data Frame Coordinate System

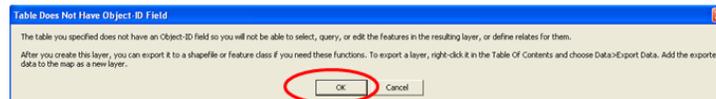
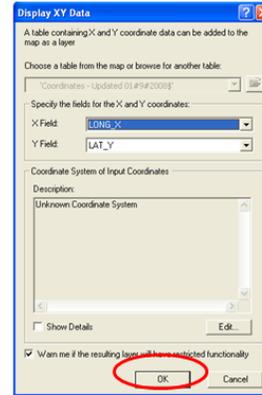
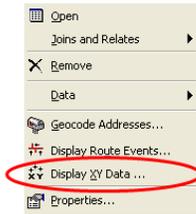
- The first layer that is added to the data frame sets the projection



Adding XY Coordinates



- Use  and double click on the Excel Spreadsheet (select worksheet\$)
- Right click on spreadsheet
- Display XY Data...>



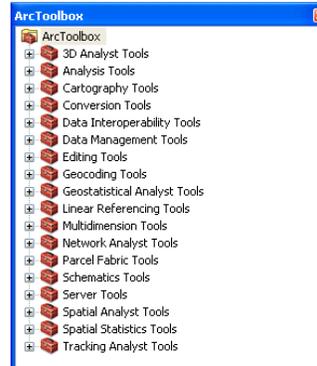
Adding x,y data Exercise

- Add ken_admin5 centroids Excel Spreadsheet called "ken_admin5.xls" to ArcMap
- Display x,y data to see the centroids using lon for x and lat for y



ArcToolbox

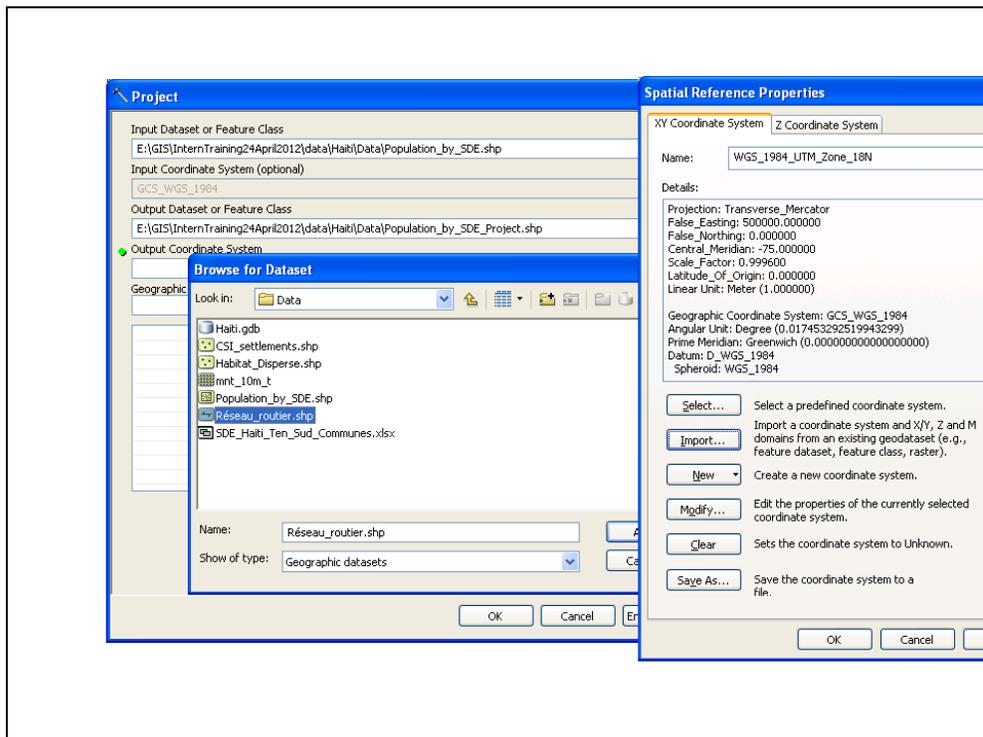
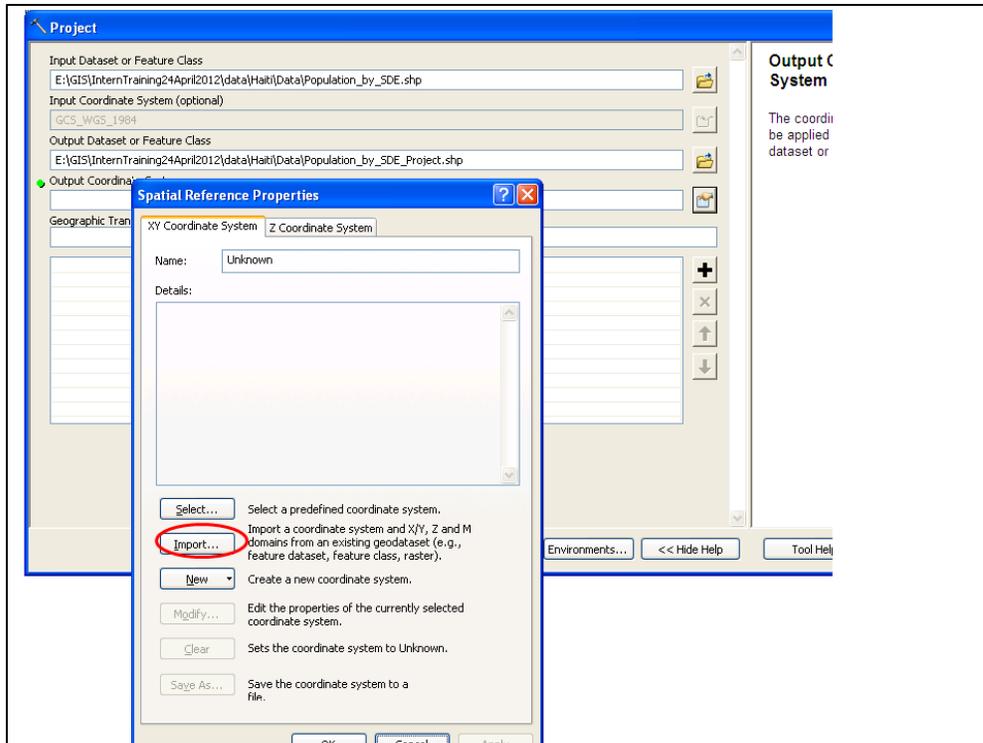
- Contains tools for processing/analyzing data
- Click on the icon to open ArcToolbox within ArcCatalog or ArcMap

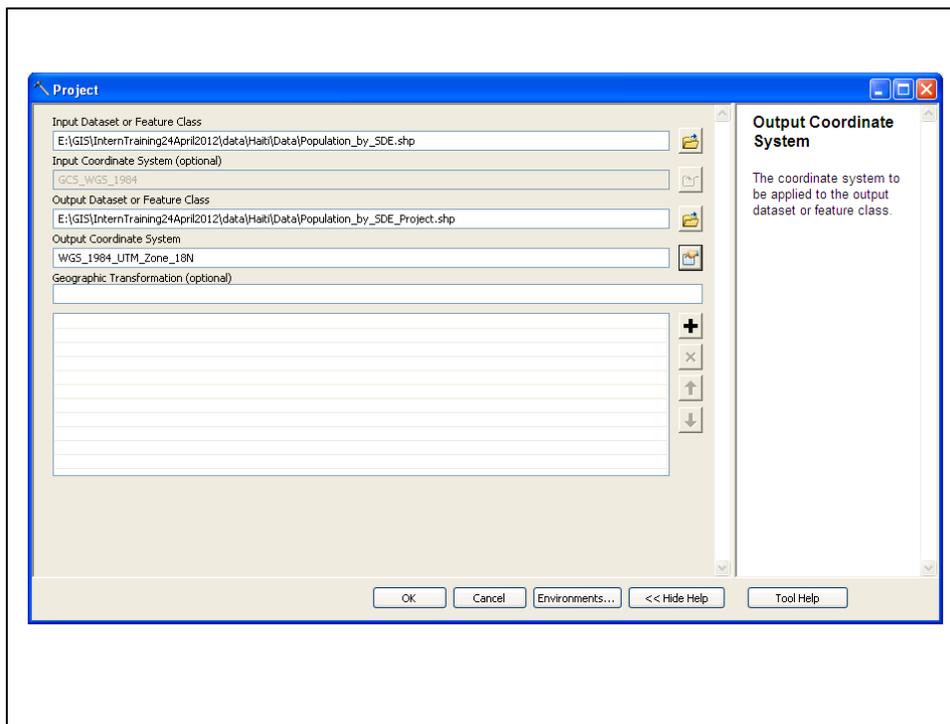
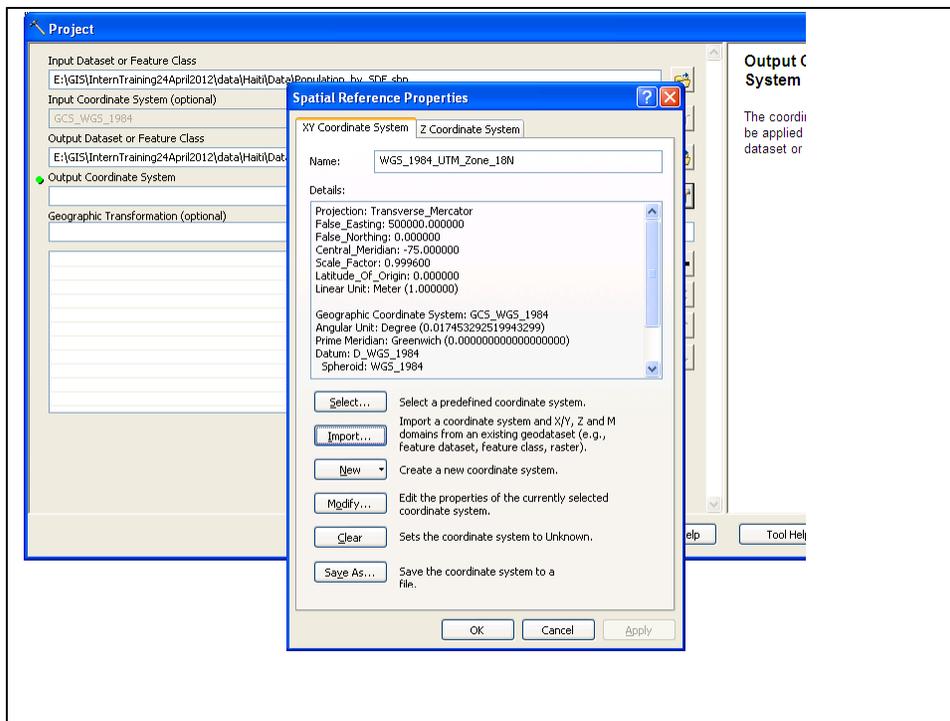


Projections

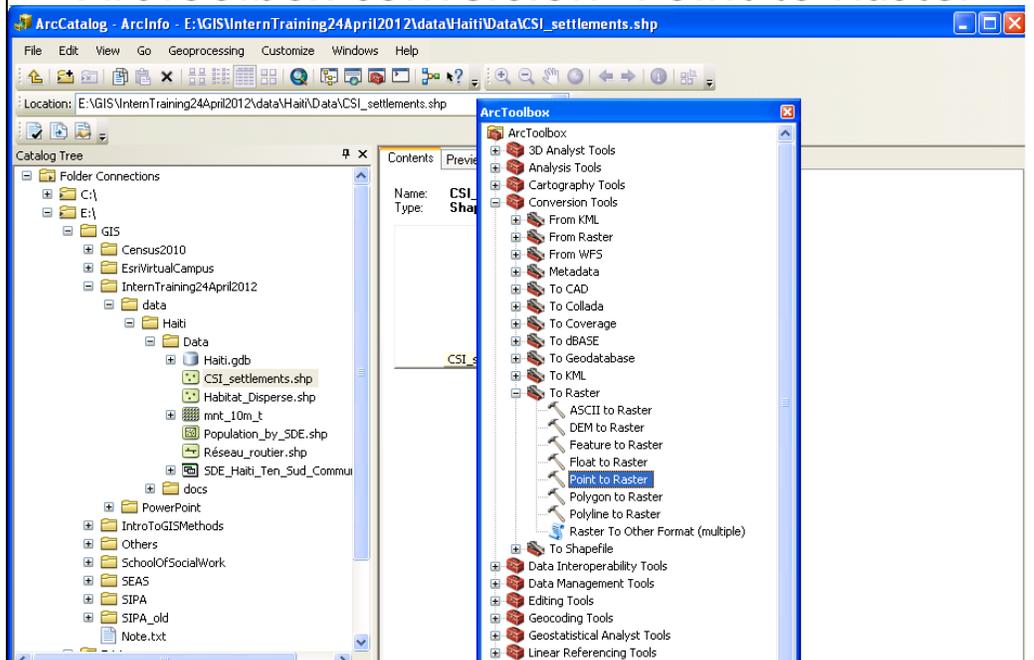
- Create a new data set with an Imported projection



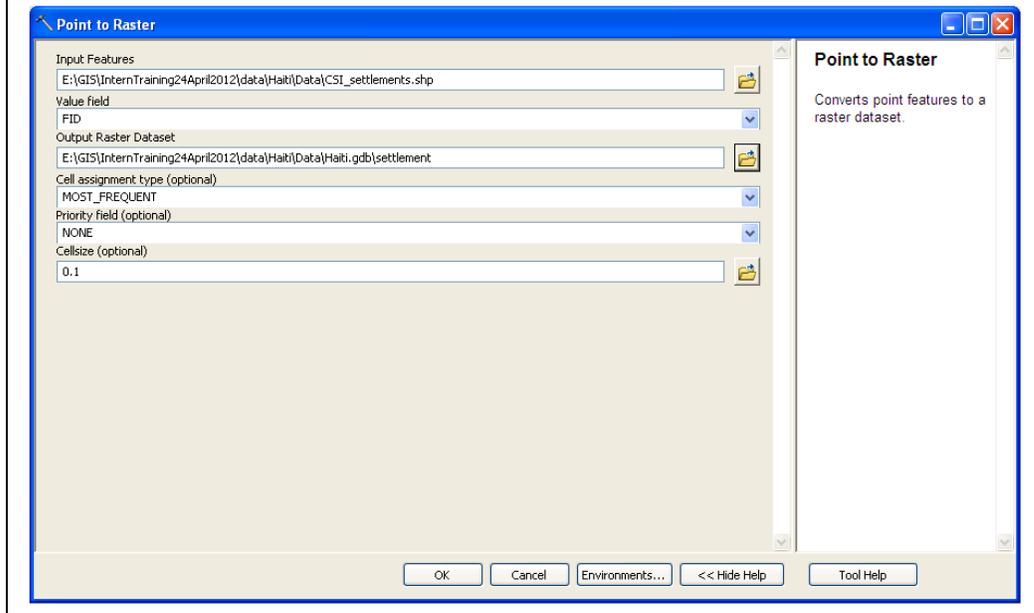




ArcToolbox conversion- Point to Raster

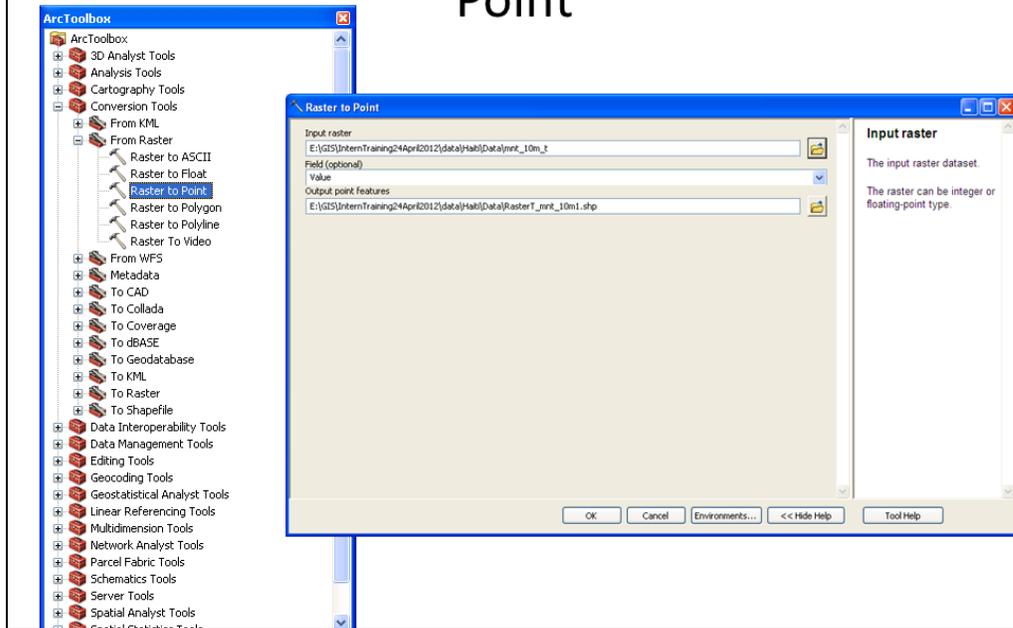


ArcToolbox conversion- Point to Raster





ArcToolbox Conversion – Raster to Point



Exercise 3. Data Processing in ArcGIS

In this exercise we will process the various input GIS datasets and convert export them to comma separated variable (.CSV) tables. First we will create a common reference system for our area of interest, then process vector files (points, lines and polygons) and finally process raster data.

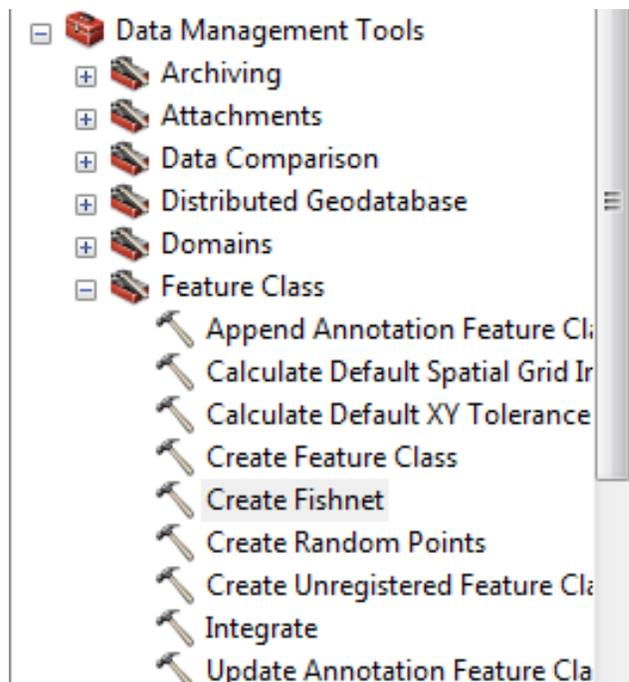
3.1 Preparing a Common Reference System

A common reference system consists of a fishnet covering the entire area of interest and a point file representing the centroids of each polygon in the fishnet. Each polygon and centroid representing a pixel location has a pixel identification number, **pixel_id**. The **pixel_id** is the attribute used to join other variables to create the tabular files.

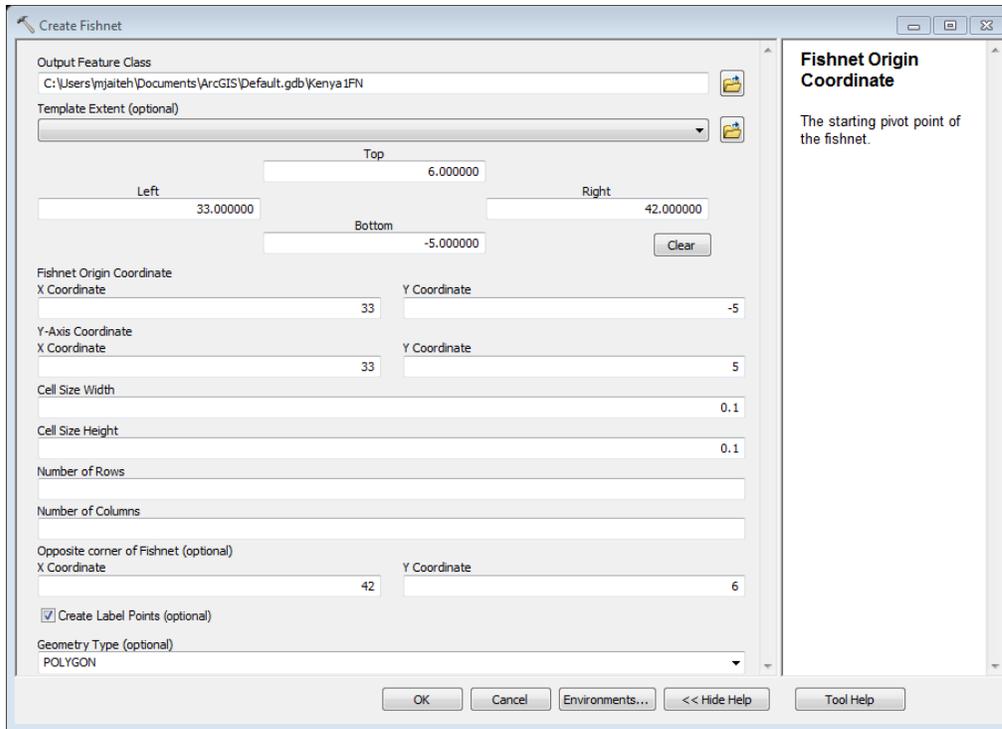
Preparing the Common Reference System involves the following steps:

3.1.1 Create Fishnet

1. Start a new ArcMap session and navigate to Create Fishnet tool under the Data management/Feature Class tool box.

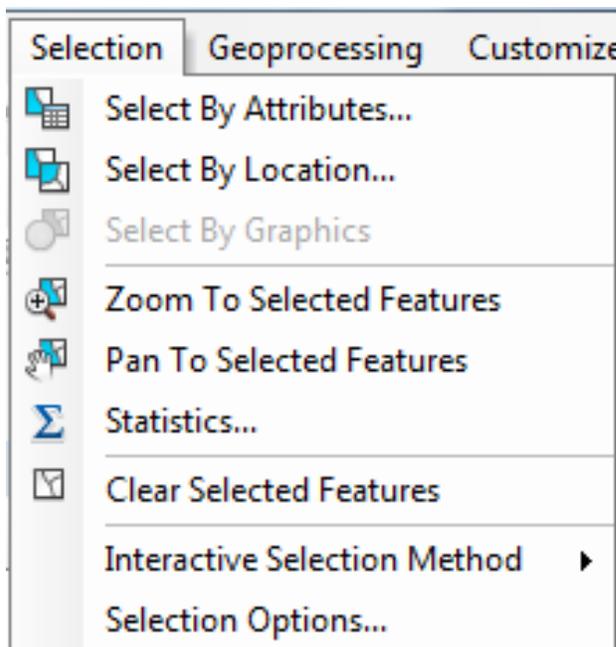


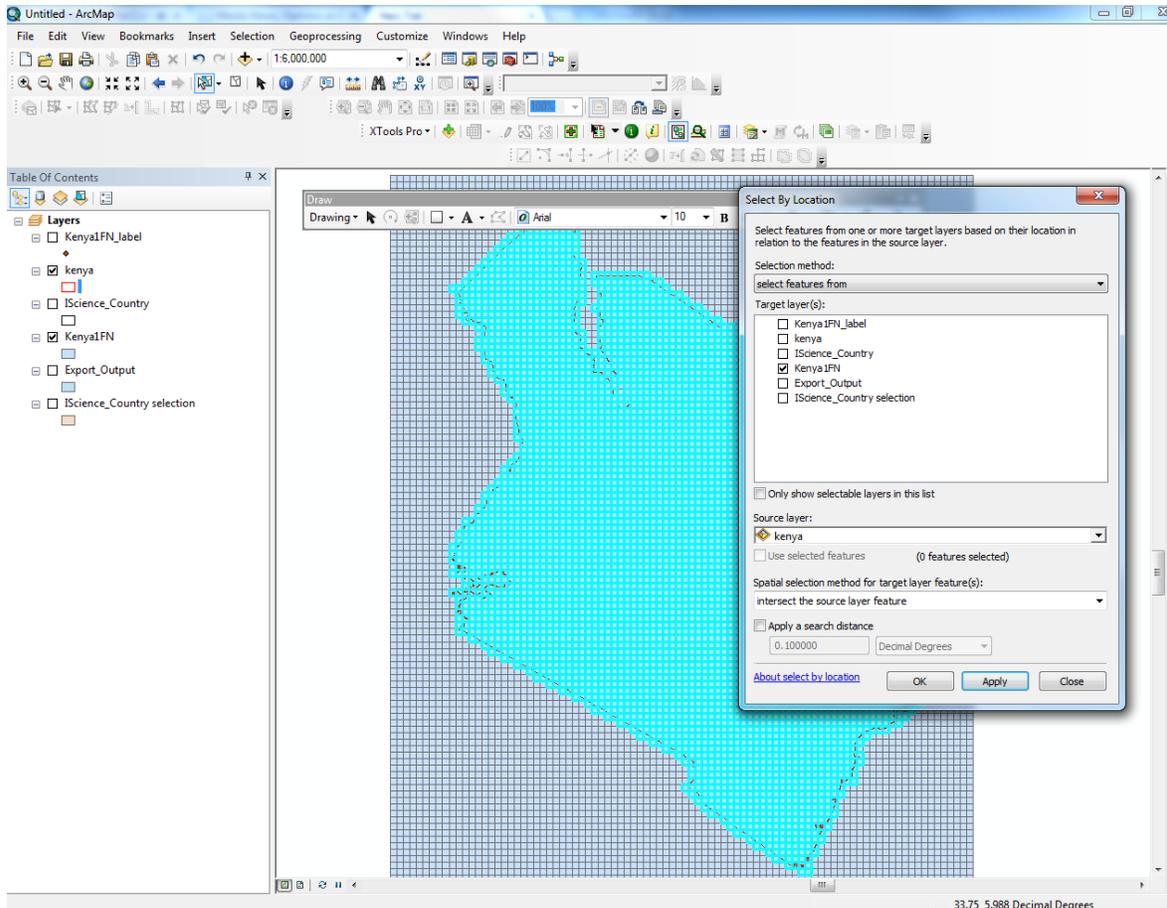
2. Start the Create Fishnet tool, name *Output Feature Class* as KenyaFN, spatial extent information as shown below. Make sure to check box next to *Create Label Points* and select POLYGON as *Geometry Type*.



The fishnet created extends beyond Kenya's boundary, Longitude 33E to 42E and Latitude 5S to 6N. Next we will extract only those polygons in the fishnet that intersects with the Kenya's country, using the **Select by Location** tool.

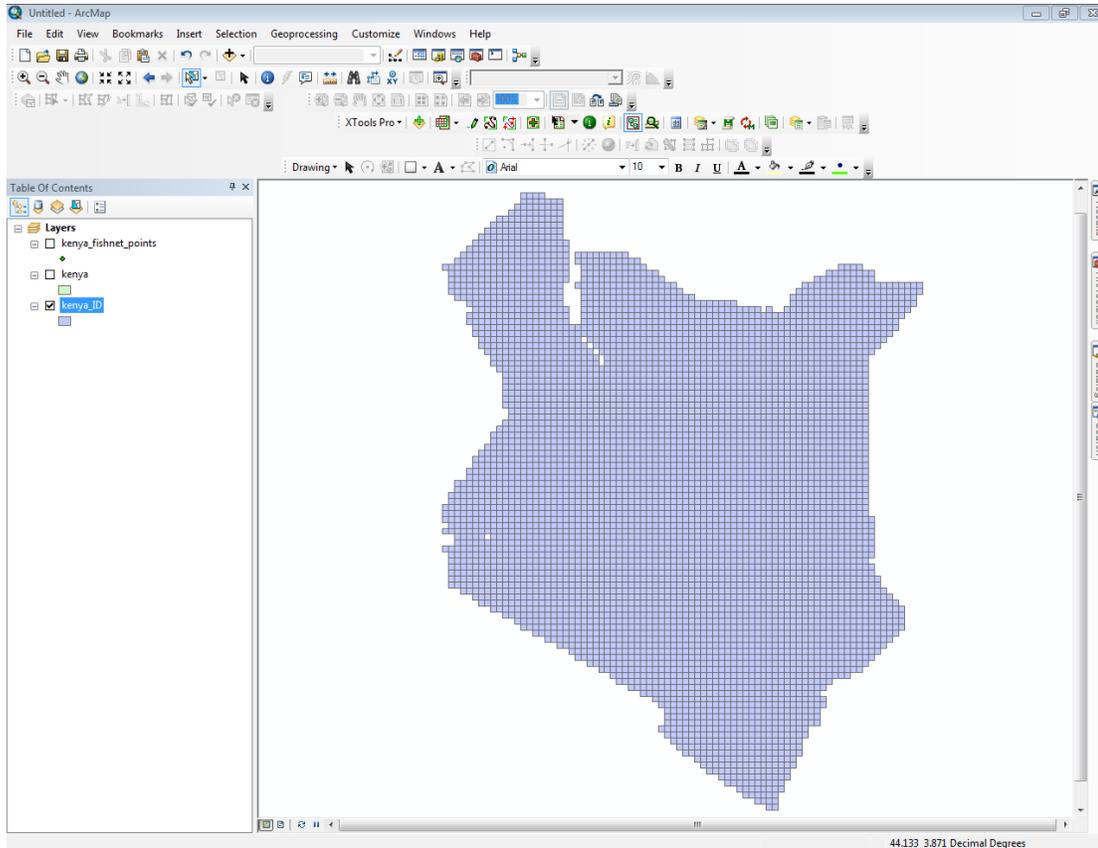
3. Under the selection menu, use the **Select by Location** option to select polygons in the fishnet that intersect with the Kenya country boundary. (Click **Selection** on the menu bar and)





4. Export the features selected above to a new feature class, name it **yourCountyNameID**:
 - a. Use the **Select By Location** to :
 - b. Selection Method: **Select Features From**
 - c. Target: **"YourCountryNameFN"**
 - d. Source Layer: **yourCountry** admin. For those from Uganda this is Uganda admin layer
 - e. Spatial Selection: **intersect the source layer feature**

5. Export Selected cells "yourCountryNameID" fishnet polygon feature class
 - Right click on YourCountryName feature >selected features> This layer is the source data

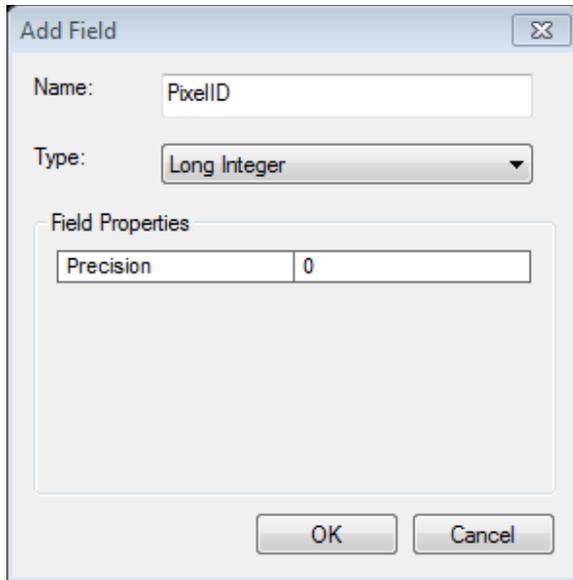


3.1.2 Create Fishnet Centroids

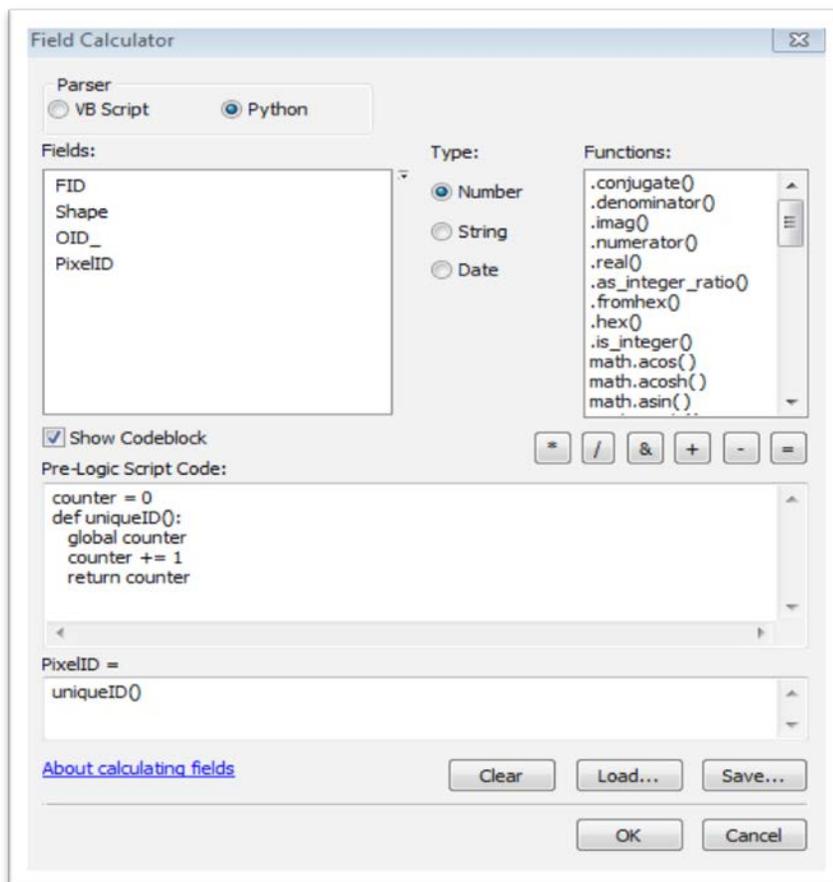
Select only the fishnet centroids that intersect the country boundary. Use the yourCountryNameID feature class created above to select by location the fishnet centroids that intersect with the yourCountryNameID .

1. Use the following steps to run the **Select by Location** tool to create fishnet centroids layer :
 - a. Selection Method: **Select Features From**
 - b. Target: “yourCountryNameFN_label” points
 - c. Source Layer: “Kenya boundary” polygon fishnet
 - d. Spatial Selection: **intersect the source layer feature**
 - e. Export selected points>Data>”**yourCountryName_centroids**” point feature class

2. Add a new field to the Kenya_Centroids attribute table. Call it PixelID. Make this field Long Integer.



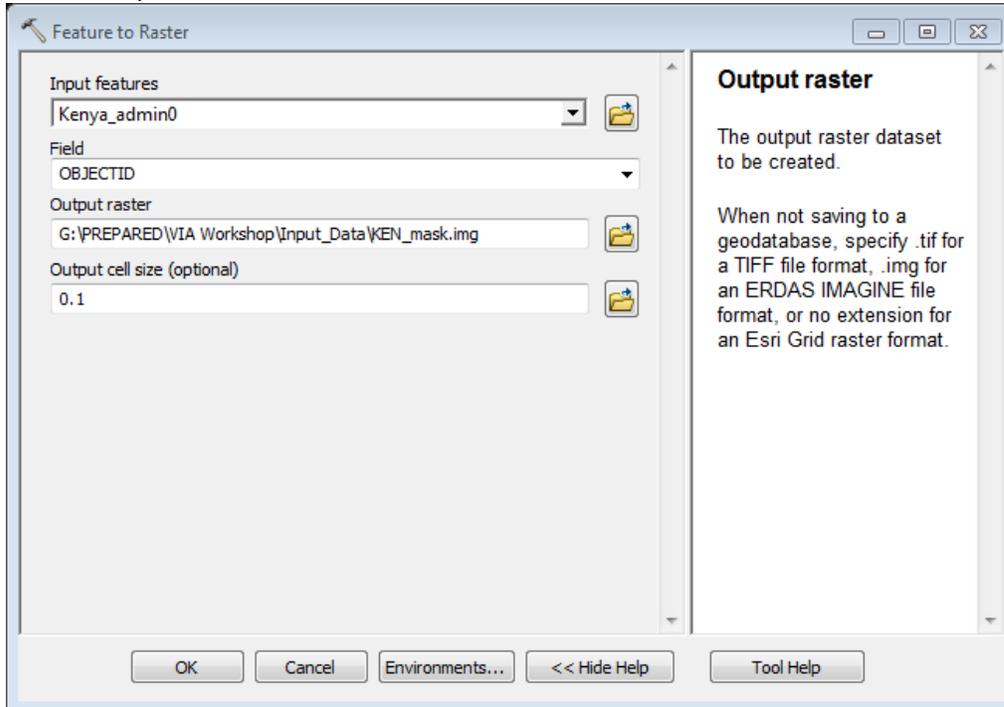
3. Calculate PixelID values using the following code. This gives a unique identification number for each of the centroid points. Warning: Python is case sensitive. Make sure you type in the code as is with line 3-5 starting 2 spaces after line begins.



3.1.3 Create Mask

A raster mask is dataset that defines **area of interest** in the input rasters. It is often a 1 and NoData raster, with 1 defining areas included. Cells that are NoData in a raster mask will be NoData in the output. We use a raster mask to create country raster of raster of small spatial extent from a global or regional raster.

1. To create a Kenya country raster mask, Use **Feature To Raster** tool to create raster of **YourCountryName** admin0 shapefile. (ArcToolbox\Conversion Tools\To Raster\Feature To Raster.)



Input features: “Kenya_admin0.shp” polygon feature class

Field: ObjectID

Output raster: **ken_mask.img**

Output Cell Size: 0.01 dd (~10km)

*Set Environment: Extent to Kenya_admin0.shp.

2. Use the Extract by Mask tool in Spatial Analyst to extract all raster datasets to “Ken_Mask.img” extent.

3.2 Processing Vector Data

The goal in this exercise is to convert all input vector layers, tables, points, lines and polygons to text files that can be joined to the Fishnet Centroids created above. The processing steps needed are to convert all vector data to raster, then extract the values of the raster to the centroids and export the values to a file text.

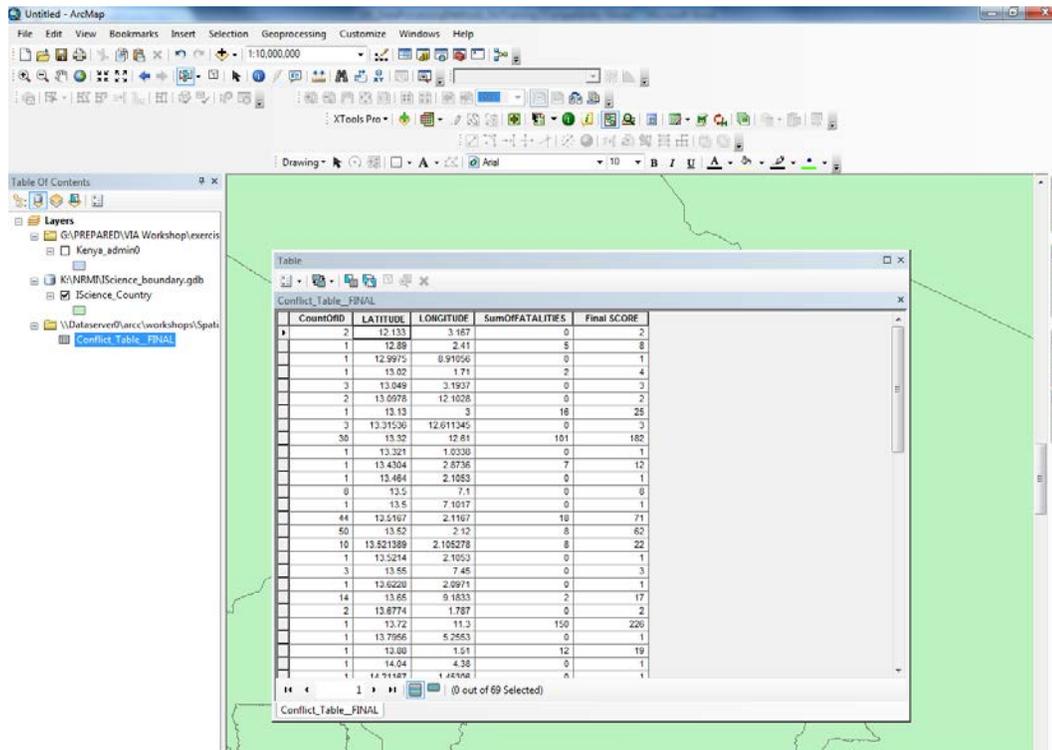
3.2.1 Point/Tabular Data

Some vector data such as survey analysis results from Microsoft Excel and other statistical packages are available as tables. These tables often contain fields representing coordinate information. The following steps are needed to process tabular vector files

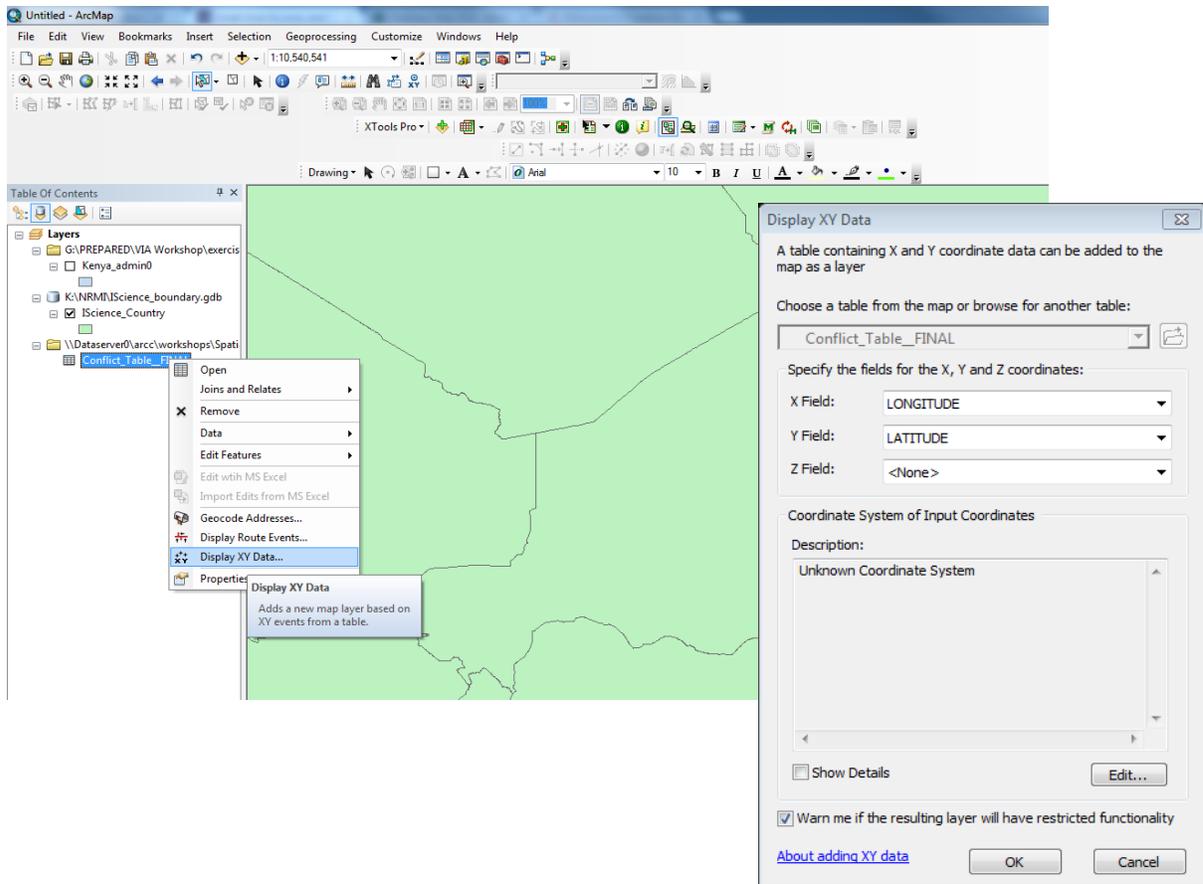
- 1) Plot XY events layer in ArcMap
- 2) Export the events layer to shapefile or geodatabase Feature Class
- 3) Create a raster surface using one of several Interpolation methods
- 4) Close all ArcMap sessions before the next section

Plot XY Events layer in ArcMap

1. Start a new ArcMap session
2. Add the conflict_Table_FINAL.xlsx file in the exercise folder to your map. This is the file containing the data we are converting.
3. Open the attribute table to confirm that there is latitude and longitude field.



4. Right-click on the Table of Contents and select Display XY Data.... This opens the Display XY Data dialog box. Make sure you chose field for longitude for X Field and latitude for Y Field (see below).



5. Right-click on the newly created feature class and export to a shapefile.

Create an Interpolation Surface raster

ArcGIS Spatial Analyst and Geostatistics extensions have Interpolation toolsets containing numerous tools for creating continuous surface from point data. Surface interpolation tools make predictions from point measurements for all locations in an output raster dataset, whether or not a measurement has been taken at the location.

The interpolation tools are generally divided into deterministic and geostatistical methods:

The deterministic interpolation methods assign values to locations based on the surrounding measured values and on specified mathematical formulas that determine the smoothness of the resulting surface. The deterministic methods include the Inverse Distance Weighting (IDW) Natural Neighbor, Trend, and Spline.

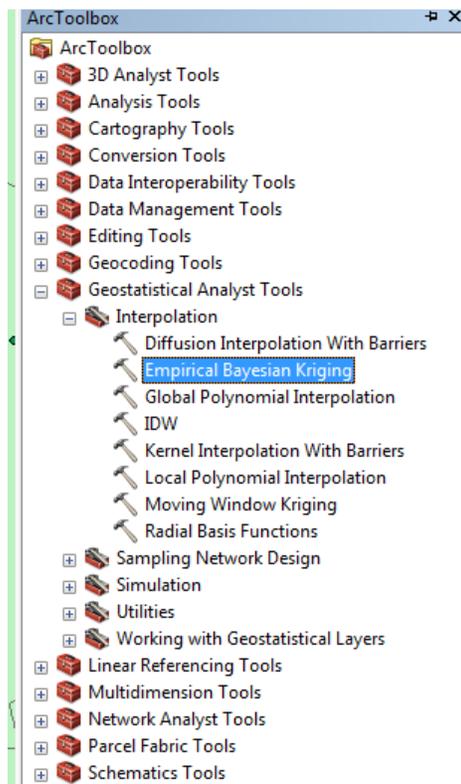
- The geostatistical methods are based on statistical models that include autocorrelation (the statistical relationship among the measured points). Because of this, geostatistical techniques not only have the capability of producing a prediction surface but also provide some measure of the certainty or accuracy of the predictions. Empirical Bayesian Kriging (EBK) is a geostatistical method of interpolation.

Interpolating Cluster Data

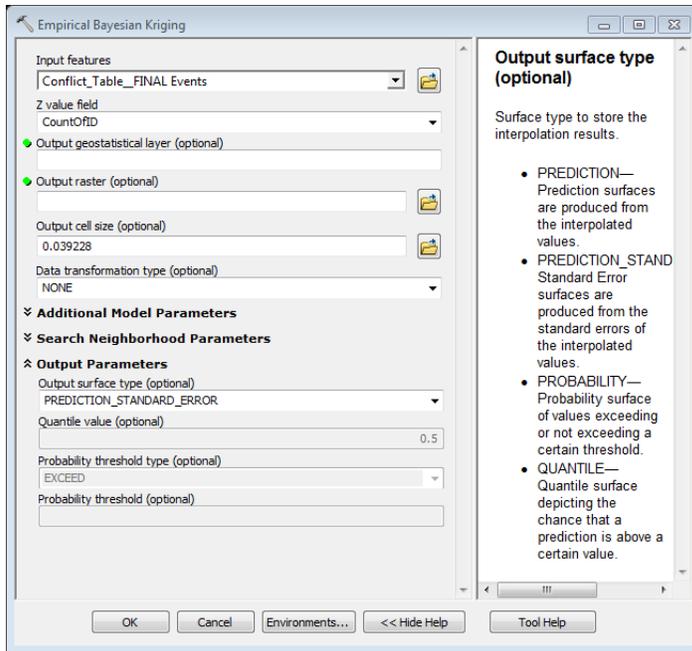
Empirical Bayesian Kriging (EBK) is a geostatistical interpolation method that automates the task of building a valid kriging model. EBK automatically calculates model parameters through a process of subsetting and simulations. In addition to creating a prediction surface, EBK also allows you to create a prediction standard error surface. For further details, please connect on ESRI website (<http://www.esri.com/news/arcuser/0704/files/interpolating.pdf>).

You will need to activate the Geostatistical Analyst and Spatial Analyst extensions to use interpolation tools. (Customize>Extensions).

1. Under ArcToolbox/Geostatistical Analyst Toolbox, start the Empirical Bayesian Kriging tool.



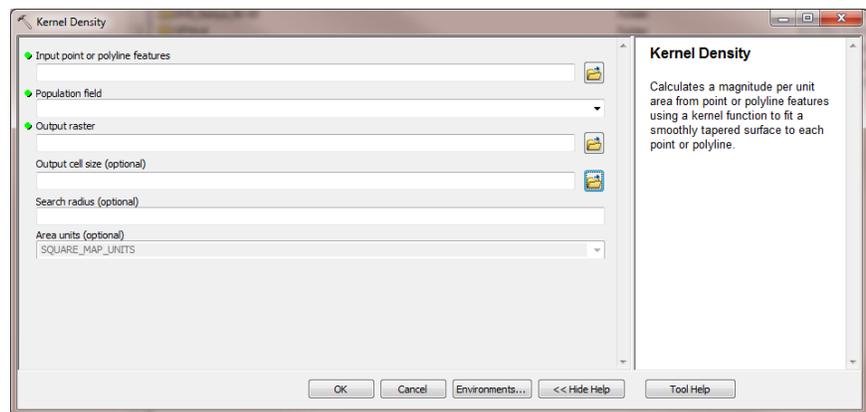
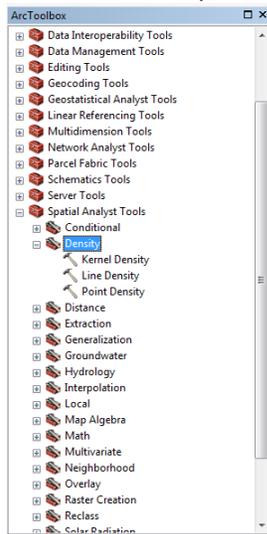
2. Set Environments: Set Mask and Raster Analysis Cell Size. This should be equal to the fishnet resolution.
3. Output Parameters: Output surface type choose PREDICTION
4. Run the EBK Tool again but this time choose for Output surface type choose PREDICTION STANDARD ERROR.



Kernel Density/Point Density

Create a surface to calculate the density of points or number of points per unit area is another way of interpolating points. The search radius of the kernel function will vary the results. Only the points that fall within the search radius will be included in the density calculation. A large radius will create a more generalized or smoother output raster. A small radius will create a more detailed raster. The input layer should be in projected coordinate system to use the kernel density tool.

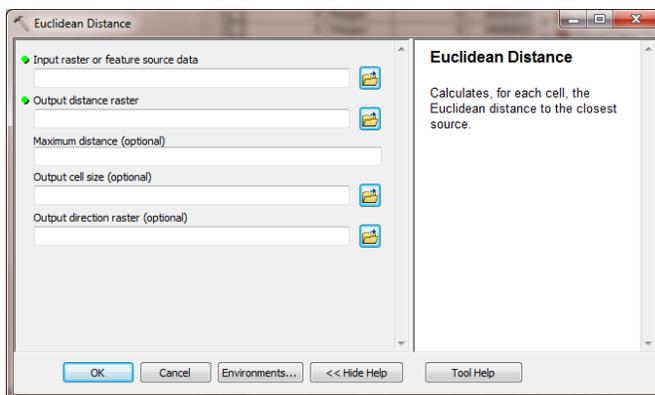
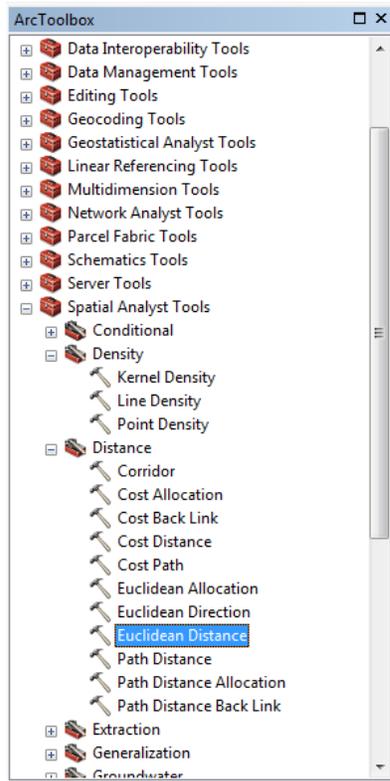
Under ArcToolbox/Spatial Analyst Tools/Density/Kernel Density



3.2.2 Line

For line data create a surface of the distance from the lines.

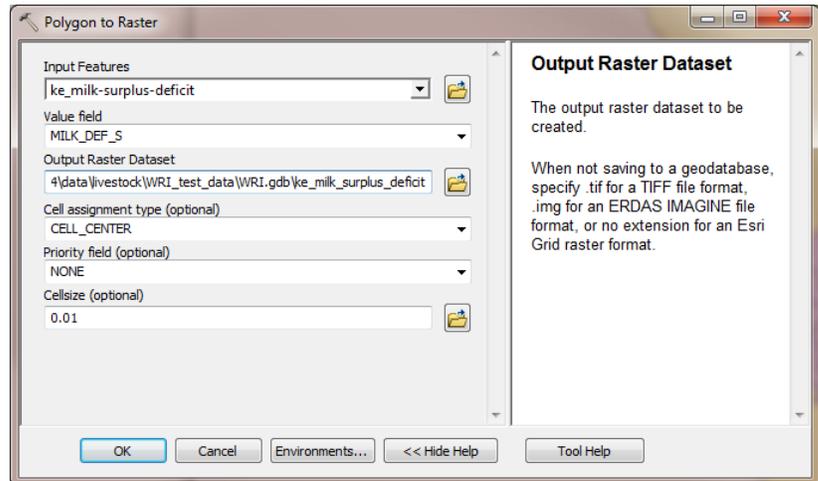
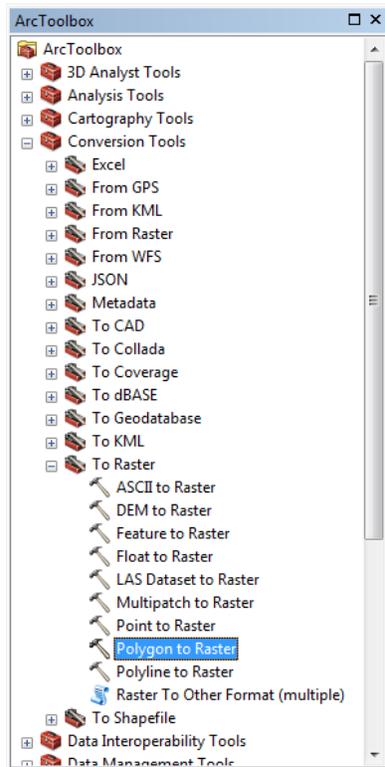
ArcToolbox\Spatial Analyst Tools\Distance\Euclidean Distance



3.2.3 Polygons

For polygons that have integer values create a surface of the polygon data using the conversion, **Polygon to Raster** tool.

ArcToolbox\Conversion Tools\To Raster\Polygon To Raster



Example:

Input: ke_milk-surplus-deficit

Value: MILK_DEF_S

Output Raster: WRI.gdb\ke_milk_surplus_deficit

Cell assignment type: CELL CENTER

Priority field: NONE

Cellsize: Set to Kenya_Mask

Set Environments: Set Processing Extent: Kenya_Mask,

Raster Analysis: Kenya_Mask

Categorical polygon data

For polygon data that have text values, say land cover types, we will need to assign the categories a numeric equivalence before converting to raster using **Feature to Raster** tool.

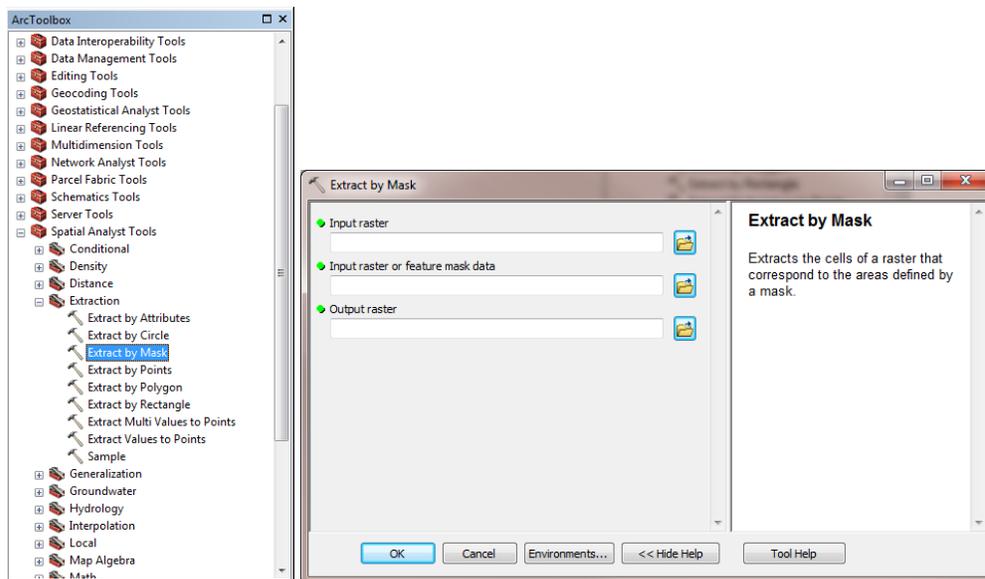
Alternatively we can execute *Spatial Join* (ArcToolbox\Analysis\Overlay\Spatial Join) in which the attributes of the polygon features are joined to the point features, i.e., the “target feature”=points and the “join feature”=polygon

3.3 Processing Raster Data

Processing Raster Data requires the use of a number of tools including, **Extract by Mask**, **Aggregate**, **Resample**, **Reclassify**, **Nibble** and **Extract Values to Points**

3.3.1 Subset Raster Data

Subset the data set to the country national boundary extent using ArcGIS *Extract by Mask* tool (ArcToolbox\SpatialAnalyst\Extraction\Extract By Mask).



Input raster:Kenya _Mask

-(Set Environment: Processing Extent to "mask"; Cell Size to the "mask".) All cells outside the mask are assigned No Data value -9999. Check that output has same number of columns, rows and cell size for all data sets.

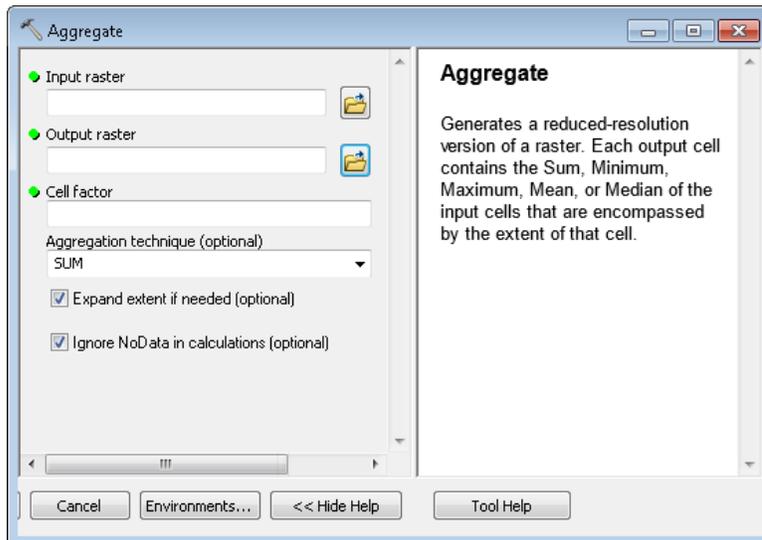
3.3.2 Matching Rasters

Ensure that all your raster files have the same resolution and extent. If not then either *aggregate* higher resolution to lower resolution, *nibble* to grow a raster to your extent or *resample* lower resolution to higher resolution.

Toolboxes\System Toolboxes\Spatial Analyst Tools.tbx\Generalization\Aggregate

Aggregate

- Aggregate tool is used to merge fine resolution raster cells into coarse resolution cell size.
- Eg. If you have a data set with a resolution of 100m then you use aggregate tool to create a raster with 1,000m cell size.
- Make sure tif's are converted to rasters before aggregating (Export>Data>Geodatabase Raster)



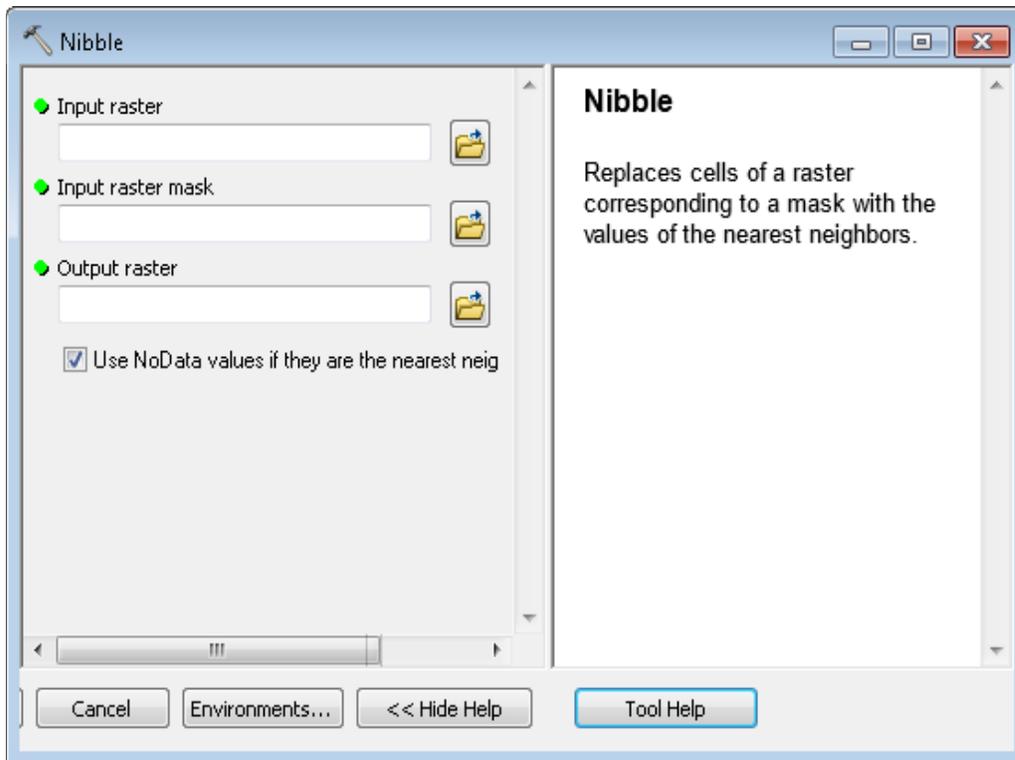
Input raster: Raster (100m)
Output raster: Aggregate_Raster
Cell Factor: **10**
Aggregate: SUM
***Keep checked: Expand extent if needed and Ignore NoData in calculations**
***Set Environments: Set Processing Extent: Kenya_Mask (1,000m), Raster Analysis: Raster (1000m ~0.008333dd)**

*****Remember to Divide Values by Factor using Raster Calculator*****

Nibble Rasters

Sometimes we have raster files that are smaller than our Mask. In such case we use **Nibble** tool to grow raster to match the Mask raster. Nibble works only with integer raster. If you have a float or continuous raster, you will need to convert it to an integer first. Also nibbling will occur where there are no NoData values in the mask.

Toolboxes\System Toolboxes\Spatial Analyst Tools.tbx\Generalization\Nibble



The following steps are needed to run Nibble Tools:

- 1) Convert input raster to integer using Raster Calculator by multiplying raster by a factor of 10
- 2) Create nibbling mask
- 3) Run Nibble
- 4) Export to Raster

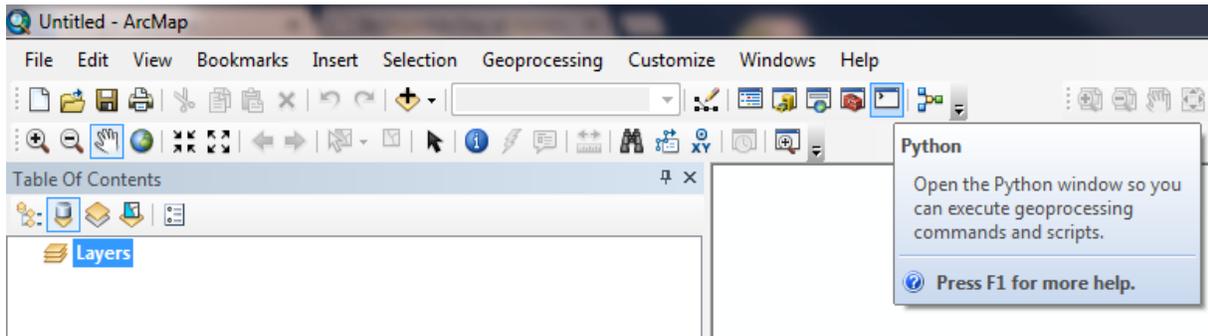
Using Python to Nibble

In Python console:

#: indicates Python comments or notes that are not part of the script,

>: indicates what is typed in the Python window one line at a time.

1. Start Python window to execute commands. Type commands one line at a time.



2. Enter the following code in the console:

```
#import arcpy library from arcpy library
>import arcpy
>from arcpy import env
#import all (*) arcpy spatial analyst libraries
>from arcpy.sa import *
```

```
#create a new raster called test. Give 'test' the values of your raster file for nibbling that is an
#integer, if not then give it a value of 1
>test = Con(IsNull("<your raster file for nibbling that is an integer>"), 1, "<your raster file for
nibbling that is an integer>")
```

```
#Nibble test to the original mask as integer and write values that have data. Don't let no data
#values influence decision.
>nibbled = Nibble("test", "<your raster file for nibbling that is an integer>", "DATA_ONLY")
```

***Remember to divide values by the factor used to multiply**

Resample Rasters

Resample (Data Management) tool, alters the raster dataset by changing the cell size and resampling method.

***Before you use resample make sure that your rasters line up.**

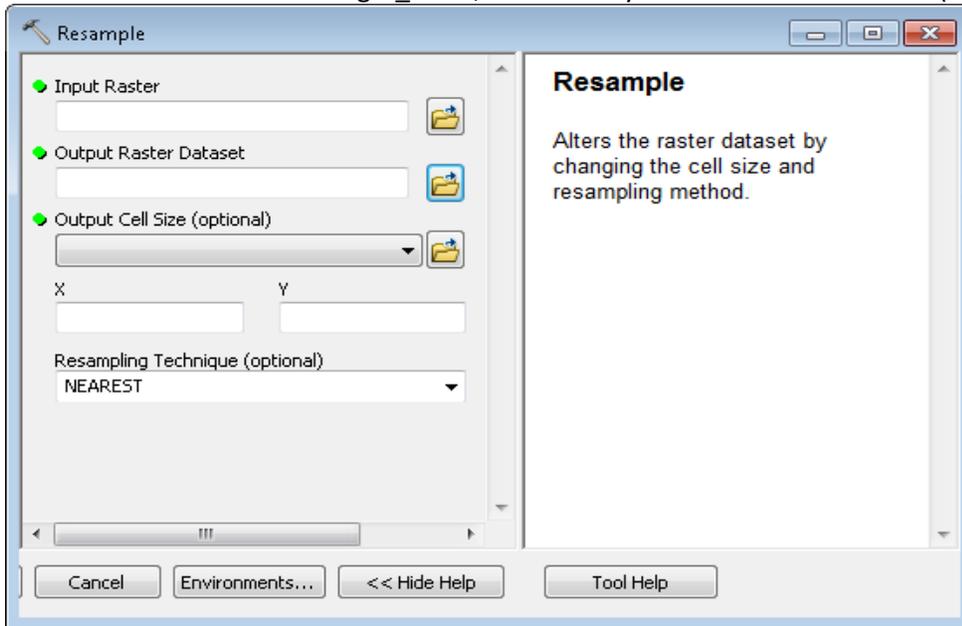
*If not use Raster Calculator and snap raster to 'realign' raster to Mask:

```
[Raster] * 1
```

Set Environments: Set Extent to "kenya_Mask" AND Snap Raster to "kenya_Mask"

Use *Resample* tool to get rasters to desired resolution (5 km). (ArcToolboxes\Data Management Tools.tbx\Raster\Raster Processing\Resample)

Set Environment: Extent to Niger_Mask; Raster Analysis Cell Size: 0.041667 dd (~5km)



Project Rasters

Make sure all rasters are in the same projection before aggregation. If not use Project Raster (Data Management) to project raster to desired projection. Project Raster tool transforms the raster dataset from one projection to another.

Tool Location: Toolboxes\System Toolboxes\Data Management Tools.tbx\Projections and Transformations\Raster\Project Raster

3.3. Converting to Tabular Data

In this session we will convert all raster files into tabular comma separated variable (CSV) format files using a common referencing system identified in day 1.

3.3.1 Extract Values to Point

Once all your data is in raster format you can use your centroids to extract the raster values to the centroids.

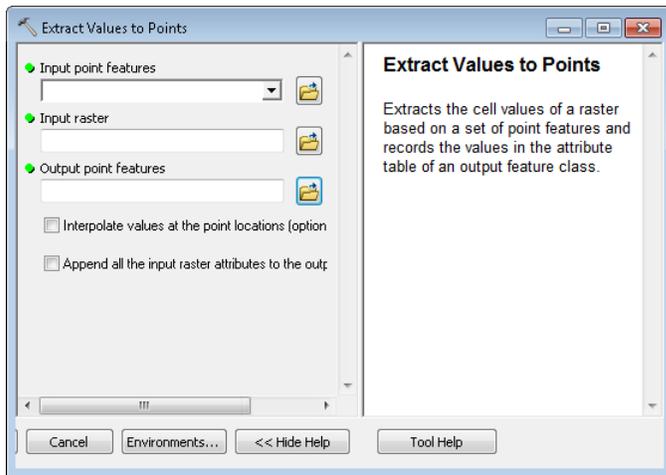
Extract the raster cell values from to the centroids using ArcGIS *Extract Values to Points* ArcToolbox\SpatialAnalyst\Extraction\Extract Values to Points tool

Input point features: Fishnet centroids

Input raster: [Raster] eg ACLED

Output point features: ACLED_Fishnet_Centroids

1. Add field to give field name according to CODE book
2. Choose correct data type
3. Calculate Field to RASTER_VALU
4. Remember to do any special calculations to undo factor multiplications or divisions



3.3.2 Export Values to Text Files

Add the point feature class to ArcMap and open the attribute table. Export table as text. In Windows you can change the file extension to .csv or write your R script to accept .txt

*Lecture 4. Introductions to R Statistics
Environment*

Contents

- What is R?
- Installing and configuring R
- Getting Help in R
- The CRAN R Project
- R Packages
 - What are packages?
 - How do you install and remove a package?
 - How do you load and unload an add-on package?

What is R?

- R is a language and environment for statistical computing and graphics.
- R provides a wide variety of statistical (linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering, ...) and graphical techniques
- R is highly extensible and compiles and runs on a wide variety of UNIX platforms and similar systems (including FreeBSD and Linux), Windows and Mac OS.
- R is available as Free Software under the terms of the Free Software Foundation's GNU General Public License in source code form.
- R was created by Ross Ihaka and Robert Gentleman at the University of Auckland, New Zealand, and is currently developed by the R Development Core Team.

Installing R

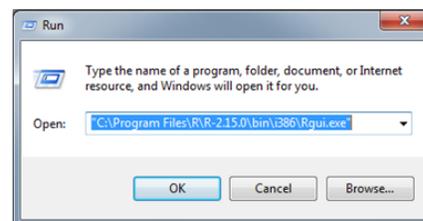
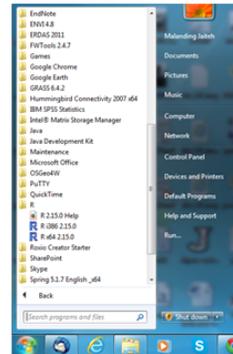
- To install use `R-2.15.0-win.exe`. Just double-click on the icon and follow the instructions.
- If you have an account with Administrator privileges you will be able to install R in the Program Files area and to set all the optional registry entries; otherwise you will only be able to install R in your own file area.
- After installation you should choose a working directory for R. You will have a shortcut to Rgui.exe on your desktop and/or somewhere on the Start menu file tree, and perhaps also in the Quick Launch part of the taskbar (Vista and earlier).
- Right-click each shortcut, select Properties... and change the `Start in` field to your working directory.
- On some systems you will have two shortcuts, one for 32-bit with a label starting R and one for 64-bit starting R x64
- It is also possible to install from an MSI file, which will be of interest only for system administrators.
- To learn how to build the MSI file, see the `R Installation and Administration Manual`.

32-bit or 64-bit?

- You can install both versions if OS is a 64-bit Windows.
- In general, use 32-bit R on 32-bit Windows and 64-bit R on 64-bit Windows
- The advantage of 64-bit R on 64-bit Windows is that it gets 64-bit 4GB address space. Allows single process access more than 4GB RAM
- Disadvantage is fewer third party tools and apps are available in 64-bit

Running R

- Double-click on the shortcut generated at installation.
- If you want to set up another project, make a new shortcut or use the existing one and change the 'Start in' field of the Properties.
- You may if you prefer run R from the command line by typing "C:\Program Files\R\R-2.15.0\bin\i386\Rgui.exe" in the



Update and UN-install R

- To update to a newer version, easy thing to do is to uninstall R, install the new version, copy any installed packages to the library folder in the new installation, run `update.packages(checkBuilt=TRUE, ask=FALSE)` in the new R and then delete anything left of the old installation.
- Different versions of R are installed in parallel folders so you can keep old versions around if you wish.
- For those with a personal library (folder `R\win-library\x.y` of your home directory, `R\win64-library\x.y` on 64-bit builds), you will need to update that too when the minor version of R changes (e.g. from 2.14.2 to 2.15.0). A simple way to do so is to copy (say) `R\win-library\2.14` to `R\win-library\2.15` before running `update.packages(checkBuilt=TRUE, ask=FALSE)`
- To Uninstall normally you uninstall through 'Add/Remove Programs' (XP) or 'Programs and Features' (Vista/7) group in the Control Panel. If it does not appear there, run `unins000.exe` in the top-level installation directory, e.g. `C:\Program Files\R\R-2.15.0`
- Uninstalling R only removes files from the initial installation, not (for example) packages you have installed or updated.
- If all else fails, you can just delete the whole directory in which R was installed.

Library vs Package

- A *library* is a place (directory) where R knows to find installed packages it can use
- A *package* is a standardized collection of material extending R, e.g. providing code, data, or documentation.
- R is told to use a package (to “load” it and add it to the search path) via calls to the function `library`.
- `library()` is employed to load a package from libraries containing packages.

Installing and removing *packages*

- In Window you use the following:
- `install.packages("ggplot2")` – Will download and install “ggplot2” package
- `update.packages("plyr")` - downloads the list of available packages and their current versions, compares it with those installed and offers to fetch and install any that have later versions on the repositories.
- Use `remove.packages()` to remove installed packages

R Workspace

- The workspace is the current R working environment. Includes any user-defined objects(vectors, data frames, lists and functions)
- Image of the current workspace can be stored any time during the session
- The current workspace is automatically reloaded the next time R is started
- Best practice is to have separate workspace for each project
- Some basic comments
 - `getwd()` # print the current working directory
 - `ls()` # list objects in the current workspace
 - `setwd("c:/doc/mydir")` # change to "c:/doc/mydir"
 - `save.image()`

Getting Help

- R FAQ - <http://cran.rstudio.com/> or `file:///../R/R-2.15.0/doc/html/rw-FAQ.html`
- R Manuals - `C:\Program Files\R\R-2.15.0\doc\manual`
- "Comprehensive R Archive Network" (CRAN) <http://CRAN.R-project.org/> - a collection of sites which carry identical material, consisting of the R distribution(s), the contributed extensions, documentation for R, and binaries.

Exercise 4. Installing and Configuring R Statistics

R is a language and environment for statistical computing and graphics. R provides a wide variety of statistical (linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering, ...) and graphical techniques, and is highly extensible. A major advantage of R over other statistical software is that it is freely available under the terms of the Free Software Foundation's GNU General Public License in the source code form, thus having fewer restrictions on who gets to use it for what. The Free Software status also allowed many users and developers to build a comprehensive library of functions and packages which are freely available at the Comprehensive R Archive Network (CRAN) <http://cran.r-project.org/>. CRAN is a network of ftp and web servers around the world that store identical, up-to-date, versions of code and documentation for R.

In this tutorial we will:

- Download the latest stable version of R from one of the many CRAN sites
- Install and configure the downloaded file
- Make sure the **Packages** we need for the next two days are all installed and updated

You will only need to perform the first part of this tutorial when you are installing R on your own, with administrative privileges. For most users in organizations installation, setting up environments and paths are done by the network administrator

4.1 Downloading R distribution

R distributions are available for Unix-like, Windows and Mac family of operating systems. The current release of the software is available via CRAN , <http://cran.r-project.org/>



CRAN
[Mirrors](#)
[What's new?](#)
[Task Views](#)
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[R Homepage](#)
[The R Journal](#)

Software
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[Manuals](#)
[FAQs](#)
[Contributed](#)

The Comprehensive R Archive Network

Download and Install R

Precompiled binary distributions of the base system and contributed packages, **Windows and Mac** users most likely want one of these versions of R:

- [Download R for Linux](#)
- [Download R for \(Mac\) OS X](#)
- [Download R for Windows](#)

R is part of many Linux distributions, you should check with your Linux package management system in addition to the link above.

Source Code for all Platforms

Windows and Mac users most likely want to download the precompiled binaries listed in the upper box, not the source code. The sources have to be compiled before you can use them. If you do not know what this means, you probably do not want to do it!

- The latest release (2013-09-25, Frisbee Sailing) [R-3.0.2.tar.gz](#), read [what's new](#) in the latest version.
- Sources of [R alpha and beta releases](#) (daily snapshots, created only in time periods before a planned release).
- Daily snapshots of current patched and development versions are [available here](#). Please read about [new features and bug fixes](#) before filing corresponding feature requests or bug reports.

The rest of this tutorial will be focused on R for Windows distribution. The latest release of the Windows distribution is [R 3.0.2 for Windows](#). For those installing R on Windows for the first time should download - <http://cran.r-project.org/bin/windows/base/R-3.0.2-win.exe>

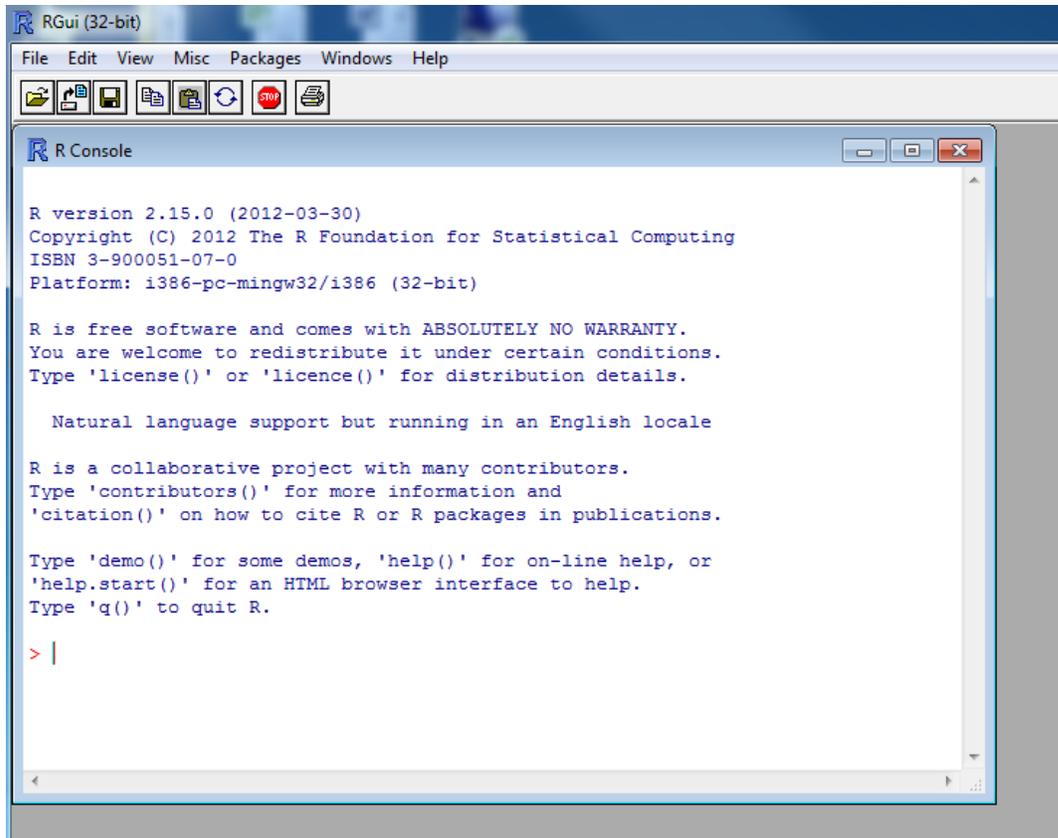
The download file, R-3.0.2-win.exe file size is 51.4MB. Depending on your internet connection, download could take only few minutes.

4.2 Installing R Installer

It is always ideal to install R with Administrator Privileges. This way the environment settings are done automatically and installed packages are available to all users.

1. To install, double-click on the downloaded file and follow the instructions to complete your installation. The installation process on Windows machines will install both the 32-bit and 64-bit R.
2. You should consider installing the open source version of [RStudio](#). This is a recently released IDE (Integrate Development Environment) for using R. RStudio includes a variety of features including editing and managing Codes, Commands, and Files.

For this training we will need the following packages installed. Before proceeding, start R with Administrator Privileges. This will enable you to install or update any package that may be needed.



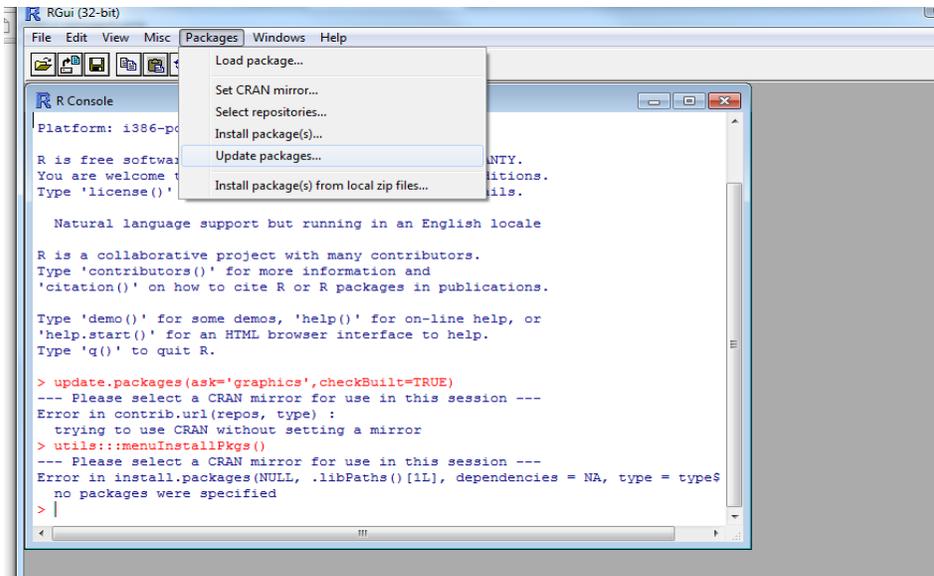
The following packages are essential for the completion of this training.

- ggplot2
- Plyr
- Foreign
- xlsReadWrite
- gridExtra
- lattice

4.2.1 Installing and updating packages

The current release includes most of the packages we need. It is good practice that we use package update to ensure that we have the most recent versions installed.

In the **Packages** menu, you have different options, select **Update packages**  to get the latest version of all installed packages (see below). The Default selection is all packages in need of update. You can narrow the selection by clearing default selection and selecting only those packages you want to update. This feature can be useful in situations where internet connectivity is poor.



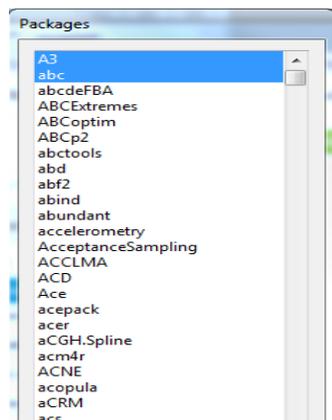
Load package - option will show all packages that are currently installed (see screenshot #). In the event that you cannot find your desired package, you can install packages using the **Install packages** option. The first time you select to install packages, you will get a list of CRAN mirror sites (screenshot #) where you can possibly download desired package; it is wise to download from closest mirror to your location. While it possible to download from any CRAN site, it is advised to download from mirror closest to you. Selecting CRAN site will open the Packages window. This has the list of all packages hosted at the CRAN site that are compatible with your OS. You can select multiple packages by holding Ctrl and select the packages. Installing in packages or updating packages require connection to the Internet.

Windows Installation on 64-bit Windows will result in the installation of both the R 32-bit and R 64-bit versions. The

installation process will place short-cuts for both the 32-bit



and the 64-bit versions on the Desktop. You can start R by double-clicking on the short-cuts on the Desktop or from the Start/All Programs/R



Exercise 5. Getting Started with R

Learning Objectives

Part II of vulnerability mapping is completed in R Statistics. The goal of this exercise is to introduce beginners to the R environment and how it works. By the end of the exercise you will learn ~~about R~~ how to:

- Start and exit the R environment
- Setup workspaces and navigate between directories
- Learn about the different data types
- Import and manipulate data frames
- Generate basic statistics and charts

Exercise data

Three data files used in this exercise are contained in the data.zip. You will need to uncompress the file into your ../VIA_R folder.

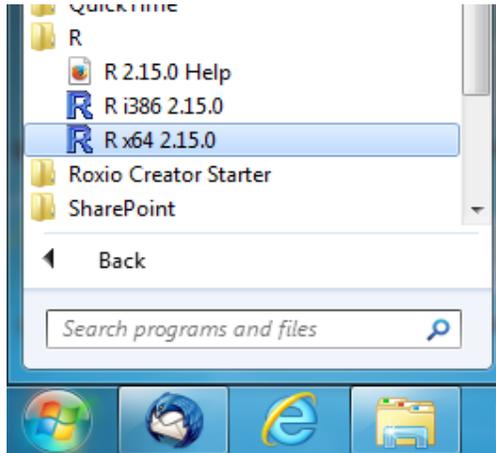
The files are:

- FEWSRFE.CSV .csv file
- FEWS.TXT Text file works very much like csv file.
- POP.XLS – Excel file

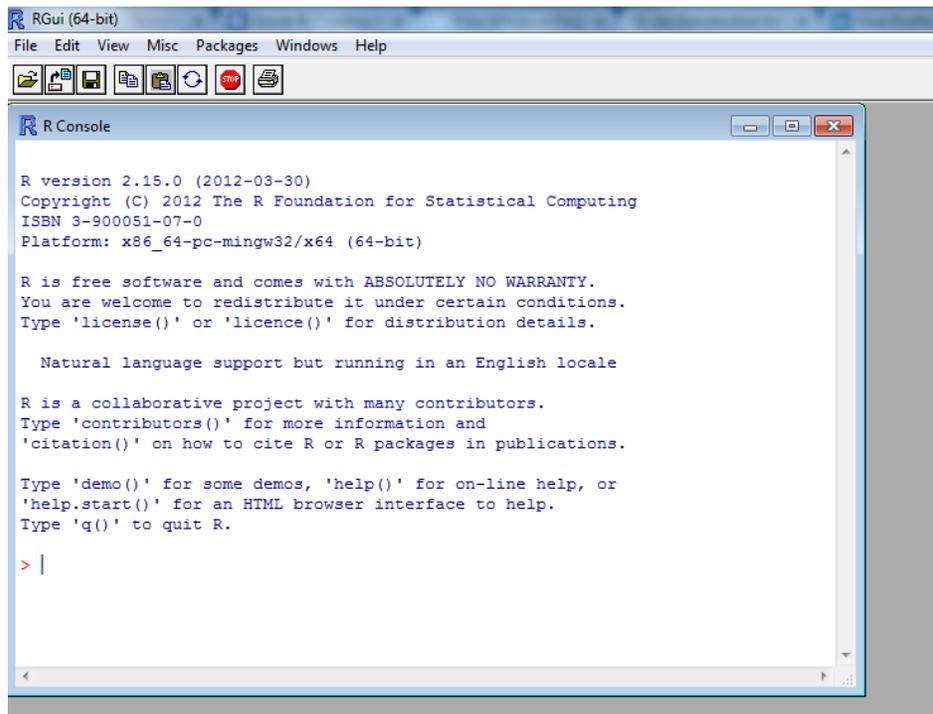
5.1 Start the R environment and setting up workspaces



1. Start R by either *double-clicking* on the  on your desktop or through the Start/All Programs/R/R x64 2.15.0



Starting R opens in the R Console window. The Console window is the default R Graphic User Interface (RGUI) allows interaction with the R environment. The '>' symbol by default indicates R is waiting for a command while '#' indicates the statement is a comment and not a command. R execute only a command not a comment!



2. To set your working directory:
 - Check your current directory with **getwd()**. If R is newly installed on a Windows machine, the default working directory is C:/Windows/systems32.
 - Change working directory to our project folder with **setwd("D:/VIA/VIA_R")**

Note: R writes path with forward slash '/' instead of backslash '\'. It is desirable to create a separate working directory for each new project. R is *case sensitive*. `getwd()` is not the same as `GETWD()`.

3. Next we will change working directory to our project folder. First, using Windows Explorer, create a new folder in the location you desire. Call it VIA_R. The path to the folder is "D:\VIA\VIA_R"

Type **setwd("D:/VIA/VIA_R")** to set working directory to the folder you just created. Use get working directory **function getwd()** to confirm the change in directory

Data Types

R has a wide variety of data types are scalars, vectors (numerical, character, logical), data frames, and lists.

Vectors

The simplest data type in R, are Vectors. There are three main types of vector data namely, numeric, character and logical. A vector assignment results in an **object** in R

4. To set up a vector named x, say consisting of one number, namely 5,

```
>x <- 5
```

The symbol '<-' denotes an assignment. Here **x** is assigned the value 5.

Type a and <enter> to confirm assignment

```
>a <enter>
```

R screen output

```
> a
```

```
[1] 5
```

output confirms **a** is now 5

[1], indicates the display starts at the first element of **a**

A vector can consist of a list of numbers. e.g. **y** consisting of all prime numbers between 0 and 10

```
>y <- c(2,3,5,7)
```

The function **c()** denotes concatenating list. **Concatenating list** is given list argument "2,3,5,7". The result is an object whose components are the argument list "2,3,5,7"

```
>y <enter>
```

```
> y
```

```
[1] 2 3 5 7
```

confirms **y** is a list of prime number between 0 and 10, "2,3,5,7"

Your turn.

Now try the following vector assignments:

```
a <- 5
```

```
b <- 6
```

```
c <- a * b # multiply a by b
d <- a / b
```

Q1. What is the value of a * b.....?

Q2. What is the value of c =.....?

We use the function **a[c(xxx)]** to refer to elements in a vector. For instance we can chose to display only the 1st and 4th elements in the vector **y <- c(2,3,5,7,)** by using:

- `y[c(1,4)]` # will display 1st and 4th elements (2 and 7) in the list
- `y[c(2,3)]` # will display the second and 3 elements in the list

Q3. Write the function to display only 3,5 and 7

Table. Types of vectors

Vector	Components	type
a <-	5	Numeric vector
b <-	c(2,3,5,7)	Numeric vector
c <-	c("Columbia","Brown", "Princeton")	Character vector
d <-	c(TRUE, FALSE, TRUE, TRUE)	Logical vector

Lists

In R, a *list* is an ordered collection of objects (components). A *list* allows us to gather a variety of (possibly unrelated) objects under one name. In GIS context a *list* refers to a record in an attribute data and the objects (components) are attributes (items). You can create as many attributes as you like for a record.

A *list* is created with the function **list()**. The object names must be specified when creating a list else the **names()** function will return NULL.

5. First create 2 vectors, x and y

```
x <- c(1:4) # creates a vector x <- c(1,2,3,4)
y <- c(2:4) # creates a vector y <- c(2,3,4,)
```

6. Using the following vectors, x <-(1:4) and b <-(2:4) create L1 and L2

```
L1 <- list(x,y)
L2 <- list(A=x, B=y)
```

Type L1 to see the content of the list

```
> L1 <enter>
• [[1]] #vector sequence number, 1
• [1] 1 2 3 4 # values in the vector
[[2]] # vector sequence number 2
[1] 2 3 4 # values in the vector
```

Type L2 to see content of the list

```
> L2 <enter>
$A #vector sequence number, 1
```

```
[1] 1 2 3 4
$B # vector sequence number 2
[1] 2 3 4
```

Names () is functions to get or set the names of an object. For further details, please see (<http://astrostatistics.psu.edu/su07/R/html/base/html/names.html>)

Q. Use **names()** function to list the labels for the vectors in each list

```
L1 .....
L2 .....
```

Data Frames

A data frame is more like an Excel spreadsheet, SAS or SPSS datasets. A data frame contains individual columns and rows. You can create a Data Frame by importing a table form another format using the `read.table` function.

The following example demonstrate working with data frames

5.2 Importing and Exporting Data Frames

Importing Files

R has specialized functions to import from and export data frames to other formats. Depending on the format you will need to load the **foreign** packages, you may need to download the needed packages as explain in the section 4.2.1. For Excel, you need the **xlsReadWrite** package. In the following steps we will import data from .TXT, .CSV and .XLS format.

7. Start a new R session and change working directory to "**../VIA/VIA_R**". The directory contains the following POP.XLS (Excel format), FEW.TXT, Text file and

Make sure to load the following packages:

```
Foreign
RODBC
xlsReadWrite
```

8. Import the FEWS.TXT data in R using the following:
> FEWS <- `read.table("FEWSRFE.TXT", header = TRUE, sep = ",", quote="\")`

Note: **header = TRUE** means there is a header in the table; **sep = ","** - denotes the separator in the data is a comma (,); and quotes are denoted by ""

This creates a data frame FEWS by importing the FEWS.TXT table
>View(FEWS) to view the imported table

9. Importing POP.XLS file entails the following steps:
 - a. call the RODBC library **Note: the RODBC library only works within the R 32-bit installation**
>library(RODBC)

- b. Assign the POP data frame equal to POP.XLS data:
 > POP = odbcConnectExcel(file.choose())
file.choose() function starts a add file dialog box to allow you navigate to the “../VIA” folder and select the POP.XLS
- c. Import the .CSV (comma separate variable) file using:
 > FEWSRFE<- read.csv("G:/PREPARED/VIA Workshop/FEWSRFE.CSV", header = TRUE, sep = ", ", quote="\")

You now have all three data frames imported in R. You can use the following functions to explore the content:

- names(data frame) - e.g. names(FEWS) -
- View(data_frame) # note use of Upper case V
- hist(data_frame\$column)
- quantile(POP\$, 0.025, c(0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9))

Now we will join the FEWS and POP data frames using the PixelID as the join field.

First use the name() function to list the fields in each of the tables. Note the sequencing of the fields.

This requires that you to download **plyr library**

>Install.package(“plyr”)

>library(plyr) – loads the plyr package

Then use the following line of code to join the tables:

```
>join1<-join(FEWS[,5:6],POP[,5:6],match="first", by="PixelID")
```

The newly created larger table is called join1

The join function joins columns 5 and 6 in the POP data frame to columns 5 and 6 in the FEWS data.

PixelID is used as the join field and joining starts with first pixel in each data frame. It is important to make sure that each of the files is of the same sequencing.

Exporting data

Like import, R allows us to export data frames to a number of formats. Use the following code to export the join1 table to a comma separated variable (.CSV) file.:

```
write.table(join1, file="g:/PREPARED/VIA Workshop/joinT.csv",append = TRUE, sep= ",")
```

5.3. Learning More

Other Useful Functions

Try out the following functions and note what they do.

str(object) # structure of an object

class(object) # class or type of an object

names(object) # names

c(object,object,...) # combine objects into a vector

cbind(object, object, ...) # combine objects as columns

rbind(object, object, ...) # combine objects as rows

object # prints the object e.g typing the name of variable b will print the values of b

ls() # list current objects

rm(object) # delete an object

rbind(object, object, ...) # combine objects as rows

fix(object) # edit in place

length(object) # number of elements or components

sum(object) # sums up all values in a data frame or column. Use `sum(data_frame$column)` to sum values in column

data.frame(object)

Online Tutorials

An Introduction to R- Notes on R: A Programming Environment for Data Analysis and Graphics-
<http://cran.r-project.org/doc/manuals/R-intro.pdf>

R for beginners by Emmanuel Paradis - http://cran.r-project.org/doc/contrib/Paradis-rdebuts_en.pdf

<http://www.statmethods.net/> - Site sun by Robert I. Kabacoff providing basics on working with R

<http://www.cyclismo.org/tutorial/R/genindex.html>

Exercise 6. Getting Started with R

In exercise 2-3 we have processed the various input layers using various GIS methods, converted them to raster and exported each individual raster to a comma separated variable table. Each table contains a field containing a raster sequence number and a column representing variable of interest. In this exercise we will:

- Setup a project and directories
- Import all the tables into data frames in R to create one large VIA data frame
- Use statistical data exploratory methods to determine statistical distribution of the raw data
- Variable transformations: clean, recode or winsorize
- Rescale each indicator to a 0-100 scale, where 0 equates to lower vulnerability and 100 equates to high vulnerability (invert the raw values from original data where necessary)
- Combine indicators to produce component scores
- Rescale component scores to 0-100
- Combine component scores to create final vulnerability map
- Principal Components Analysis and its interpretation

In exercises 4a and 4b we used command line RGui to handle vectors, list and data frames. In this exercise we will use RStudio IDE to implement the rest of the data processing.

6.1. R Studio Console

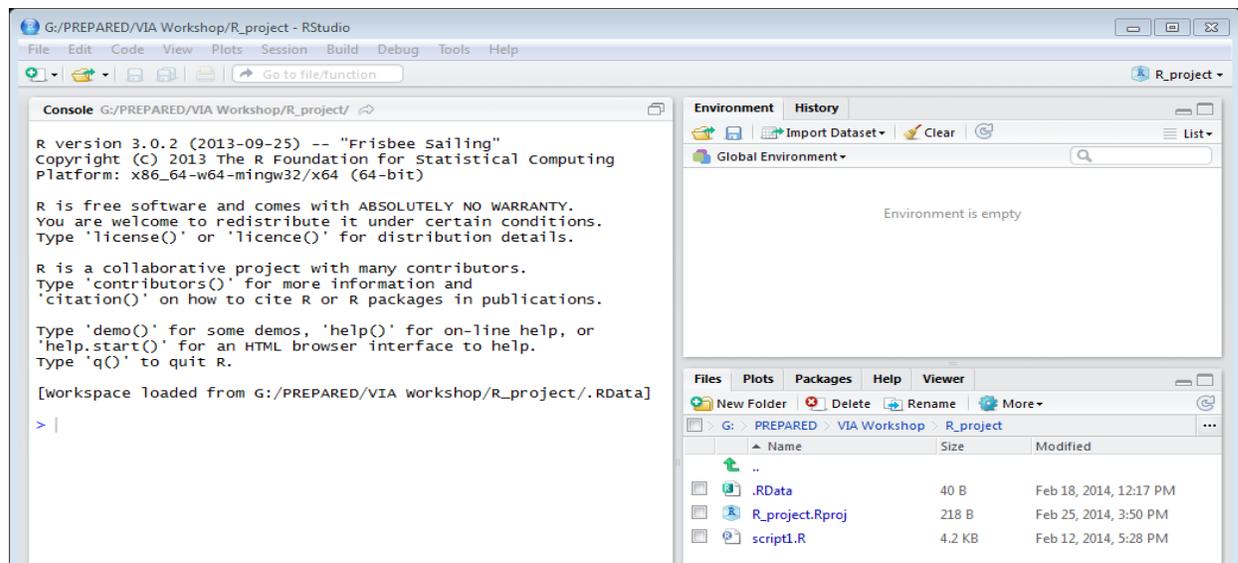
When started for the first time the RStudio GUI has three panels, namely Console, Environment/ History and Files/Plots/packages?Viewer/Help panel.

- The Console panel is the R command panel. This is where to type in commands such as `getwd()` to inquire about which folder R is using as Working Directory. The Console panel divides into 2 when a data is imported. The upper half of the panel turns into a data viewer (to help visualize the data frame active in the Environment panel. The lower part of the panel remains as the Console panel.
- The Environment /History panel – The Environment panel shows the data frames in the workspace. This panel allows us to open saved environments, or import data sets. The History panel contains the list of commands and functions used in the session. You can send commands from in this panel to the Console or to Source (new scripts).
- The Files/Plots/Packages/Help/Viewer panels – We manage files in the Files panel; Packages in Packages. Plots are drawn in the Plots panel.

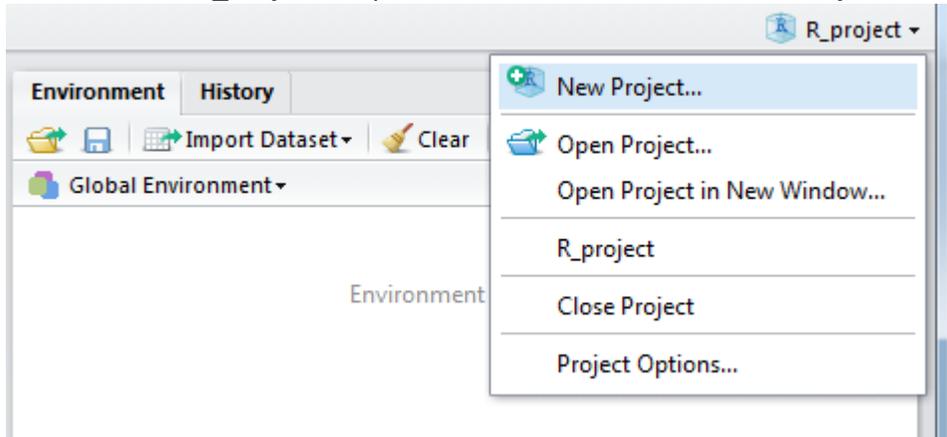
6.1.1 Create a new Project

Working in RStudio IDE allows you to create separate projects for your work. Projects make it easier to divide your work into multiple contexts each with their own working directory, workspace, history and source documents.

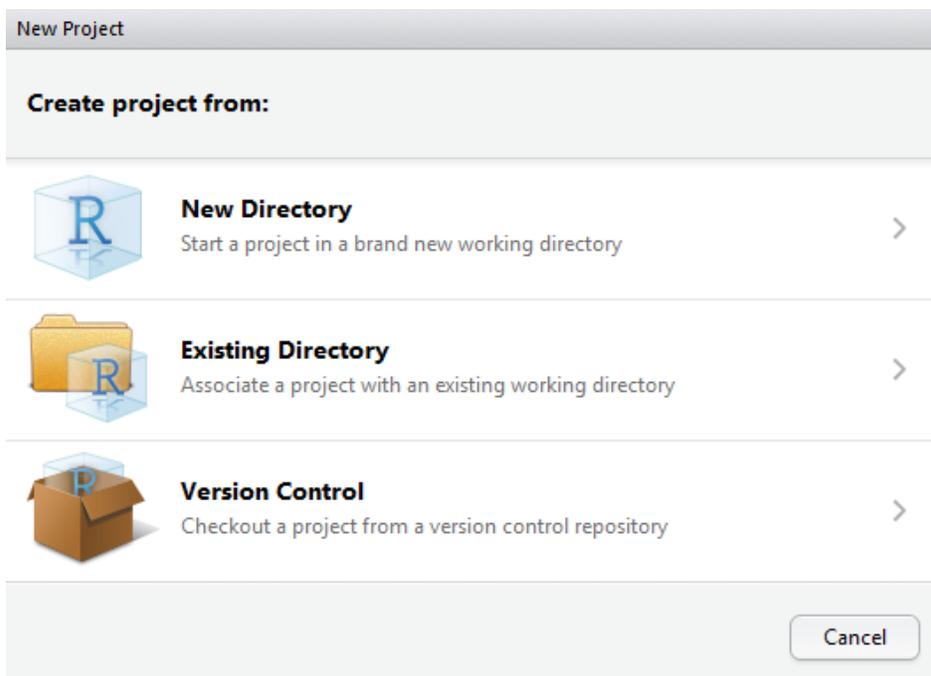
1. Start a new R Studio session from Start/All Programs/RStudio/



2. Click on the R_Project drop-down window and select New Project.



Select Create project from: Existing Directory. This will allow you to navigate to the CSV folder containing the .CSV files.



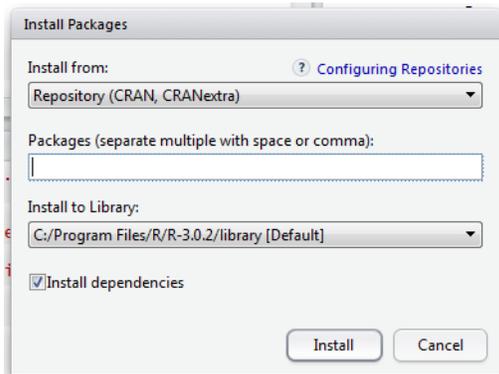
A new project in RStudio:

- Creates a project file with .Rproj extension with the directory chosen.
- Creates a hidden directory names .Rproj.user where project-specific temporary files are stored
- Loads the project into RStudio and displays its name in the Projects toolbar. In our case out new project is **CSV.Rproj**

3. In the **Packages** panel, check the box next to the following packages to load.

- plyr** - for join command
- ggplot2** - for nice graphics
- lattice** - for dotplots (in case you need PCA)
- stats** - prcomp(in case you need PCA)
- Hmisc** - for calculating correlations

If in the process you get an error that package failed to load as the dependencies are not found, you can search and install the dependencies by clicking on the Install Packages button in the panel.

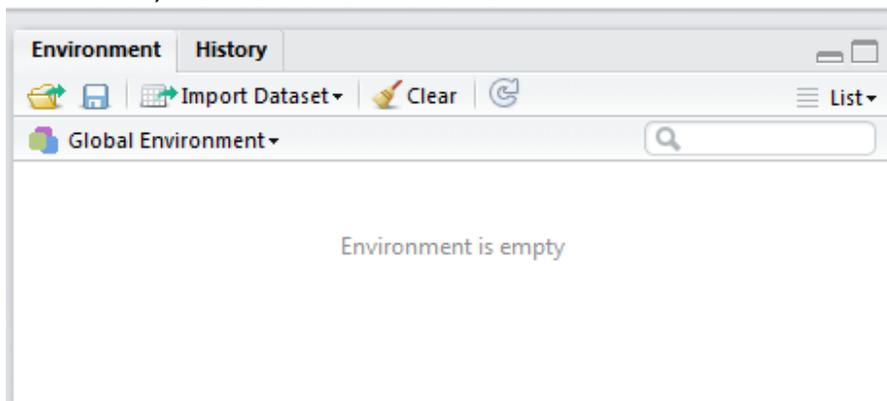


6.1.2 Reading CSV tables into R

Each variable considered for inclusion in the calculation of the vulnerability is available in CSV format. The variable tables include the point values of raster files created in exercise 2, and a raster sequence (PIXELID) field. We will use this field to merge the single variable data files into one data spreadsheet.

We are now ready to read in the .CSV files representing the input variables

1. Click on the **Import Dataset** button in the Environment panel to start the RStudio import wizard, then select from Text File



This opens the *Select File to Import Dataset* dialog window.

Import Dataset

Name: spi15dgt

Encoding: Automatic

Heading: Yes No

Row names: Automatic

Separator: Comma

Decimal: Period

Quote: Double quote (")

Comment: None

na.strings: NA

Strings as factors

Input File

```
OBJECTID_1,PIXELID,ISO,NAME_0,NAME_1,ENGTYP,NAME_2,N
1,5104,TZA,Tanzania,Ruvuma,Region,Mbinga,Kigonsera,Divi:
2,5105,TZA,Tanzania,Ruvuma,Region,Mbinga,Kigonsera,Divi:
3,5365,TZA,Tanzania,Ruvuma,Region,Mbinga,Kigonsera,Divi:
4,5366,TZA,Tanzania,Ruvuma,Region,Mbinga,Kigonsera,Divi:
5,5367,TZA,Tanzania,Ruvuma,Region,Mbinga,Kigonsera,Divi:
6,3792,TZA,Tanzania,Ruvuma,Region,Mbinga,Mbangamao,Divi:
7,3793,TZA,Tanzania,Ruvuma,Region,Mbinga,Mbangamao,Divi:
8,4054,TZA,Tanzania,Ruvuma,Region,Mbinga,Mbangamao,Divi:
9,4055,TZA,Tanzania,Ruvuma,Region,Mbinga,Mbangamao,Divi:
10,4056,TZA,Tanzania,Ruvuma,Region,Mbinga,Mbangamao,Divi:
11,4057,TZA,Tanzania,Ruvuma,Region,Mbinga,Mbangamao,Divi:
12,2553,TZA,Tanzania,Mtwara,Region,Masasi,Nanyumbu,Divi:
13,2812,TZA,Tanzania,Mtwara,Region,Masasi,Nanyumbu,Divi:
14,2814,TZA,Tanzania,Mtwara,Region,Masasi,Nanyumbu,Divi:
15,2815,TZA,Tanzania,Mtwara,Region,Masasi,Nanyumbu,Divi:
16,3074,TZA,Tanzania,Mtwara,Region,Masasi,Nanyumbu,Divi:
```

Data Frame

OBJECTID_1	PIXELID	ISO	NAME_0	NAME_1	ENGTYP
1	5104	TZA	Tanzania	Ruvuma	Region
2	5105	TZA	Tanzania	Ruvuma	Region
3	5365	TZA	Tanzania	Ruvuma	Region
4	5366	TZA	Tanzania	Ruvuma	Region
5	5367	TZA	Tanzania	Ruvuma	Region
6	3792	TZA	Tanzania	Ruvuma	Region
7	3793	TZA	Tanzania	Ruvuma	Region
8	4054	TZA	Tanzania	Ruvuma	Region
9	4055	TZA	Tanzania	Ruvuma	Region
10	4056	TZA	Tanzania	Ruvuma	Region
11	4057	TZA	Tanzania	Ruvuma	Region
12	2553	TZA	Tanzania	Mtwara	Region
13	2812	TZA	Tanzania	Mtwara	Region
14	2814	TZA	Tanzania	Mtwara	Region
15	2815	TZA	Tanzania	Mtwara	Region
16	3074	TZA	Tanzania	Mtwara	Region

Import Cancel

Make sure the dataset name in the Name field is correct, if there is Heading in the data or not and if the other variables (separator, Decimal and Quote) are correct.

The Import Dataset window also displays the Input File and the Output Data Frame. This allows you to confirm that all is well before hitting Import button to complete.

	OBJECTID_1	PIXELID	ISO	NAME_0	NAME_1	ENGTTYPE_1	NAME_2	NAME_3	ENGT
1	1	5104	TZA	Tanzania	Ruvuma	Region	Mbinga	Kigonsera	Div
2	2	5105	TZA	Tanzania	Ruvuma	Region	Mbinga	Kigonsera	Div
3	3	5365	TZA	Tanzania	Ruvuma	Region	Mbinga	Kigonsera	Div
4	4	5366	TZA	Tanzania	Ruvuma	Region	Mbinga	Kigonsera	Div
5	5	5367	TZA	Tanzania	Ruvuma	Region	Mbinga	Kigonsera	Div
6	6	3792	TZA	Tanzania	Ruvuma	Region	Mbinga	Mbangamao	Div
7	7	3793	TZA	Tanzania	Ruvuma	Region	Mbinga	Mbangamao	Div
8	8	4054	TZA	Tanzania	Ruvuma	Region	Mbinga	Mbangamao	Div
9	9	4055	TZA	Tanzania	Ruvuma	Region	Mbinga	Mbangamao	Div
10	10	4056	TZA	Tanzania	Ruvuma	Region	Mbinga	Mbangamao	Div
11	11	4057	TZA	Tanzania	Ruvuma	Region	Mbinga	Mbangamao	Div
12	12	2553	TZA	Tanzania	Mtwara	Region	Masasi	Nanyumbu	Div
13	13	2812	TZA	Tanzania	Mtwara	Region	Masasi	Nanyumbu	Div
14	14	2814	TZA	Tanzania	Mtwara	Region	Masasi	Nanyumbu	Div

The imported data will be displayed in the panel on the left. You can view the first 1000 rows of your document as well as the total number of rows in the dataset in this case 1,538,278.

Your Turn: Using the same approach to import the remaining CSV files into R.

6.1.3 Joining Imported Data Frames

We will need to join the individual data frames to create one large data frame. We will use the PIXELID field to JOIN. We can **only** join two tables at a time.

To begin, type the following in the command line console:

```
join1 <- join(variable dataset 1,variable dataset2, match="first", by="PIXELID")
```

For example, to join the Biomes (ANTH) and soil carbon (CARB) datasets, the following command was used:

```
join1 <- join(ANTH, CARB, match="first", by="PIXELID")
```

Join1 is the data frame to be created by the join
match="first" parameters tells R to start joining in the first row of the input files
by= "PIXELID" sets PIXELID as the join field

Now join the rest of the data frames, beginning with the second data set in the list to join1 to create join2, then third to join2 to create join3, and so on.

```
join2 <- join(join1, EDUC, match="first", by="PIXELID")
```

Name the final join data frame **via_data**

We need to clean up our workspace of unnecessary data frames. This means removing all joined files except the last, **via_data**

To remove objects from a workspace, use the **rm()** function:

```
rm(join1, join2, join3, ..., joinX)
```

6.2 Data Exploration

It is general practice in statistics to employ exploratory data analysis tools to check for missing data and determine central tendency of input variables.

In this step we will use the following data exploration techniques to examine each of our variables.

We begin by displaying the list of variable names in the `via_data` frame using the command:

```
names(via_data)
```

Numerical measures including:

- `mean(dataframe$field)`
- `median(dataframe$field)`
- `quartile(dataframe$field)`
- `percentile(dataframe$field)` - percentile of fields
- `sd(dataframe$field)` - standard deviation,
- `summary(dataframe$field)` – displays summary statistics (min, 1st Qu., Mean, 3rd Qu., Max) of the field in question.

Graphical methods for exploring data include,

- `hist(dataframe$field)` - histograms
- `(dataframe$field)` - Scatter plots
- `(dataframe$field)` - Box plots

6.2.1 Numerical measures

1. The **mean** of an observation variable is a numerical measure of the central location of the data values. The mean is the arithmetic average of a set of values ~~that is~~; the sum of ~~its~~ data values divided by data count. For variable like with n number of pixels, the mean is given by:

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n}$$

We use the function, `mean(dataframe$field)` to calculate the mean.

```
> mean(join3$ANTH) - computes the mean of the ANTH field in the join3 data frame
```

```
> mean(join3$DCVAR, na.rm=TRUE)
```

```
[1] 25.3434?
```

```
na.rm=TRUE - removes missing values from the mean calculation
```

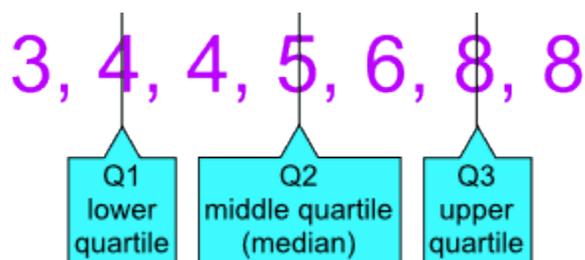
2. **Median** - The **median** of an observation variable is the value at the middle when the data is sorted in ascending order. It is an ordinal measure of the central location of the data values. The median of a few data points is the value of the middle observation when all the observations are lineup from lowest to highest value.

We use the function

```
> median(via_data$ANTH, na.rm=TRUE)
```

```
[1] 25.34643
```

3. **Quartile** – Quartiles divide data values in to 4 equal groups. The first quartile(Q1), or lower quartile is the value that cuts off 25% of the data when it is sorted in ascending order. The second quartile (Q₂) is the median of the data. The third quartile (Q₃) is the middle value between the median and the highest value of the data set, the 75%.



We apply the quantile function to compute the quartiles of eruptions.

```
> quantile(join3$DCVAR, na.rm=TRUE)
```

```
0% 25% 50% 75% 100%
2.378686 22.357409 25.346428 28.378949 38.683297
```

You can specify the break points using the concatenation function,
`(c(0, 0.1, 0.25, 0.5, 0.75, 1.0))`

```
> quantile(via_data$DCVAR, c(0, 0.1, 0.25, 0.5, 0.75, 1.0), na.rm=TRUE)

0% 10% 25% 50% 75% 100%
2.378686 19.316085 22.357409 25.346428 28.378949 38.683297
```

4. Percentile – The n^{th} percentile of an observation variable is that cuts off the first n percent of the data values when it is sorted in ascending order. For instance when we sort a variable from lowest to highest observation, the 66th percentile is the that value that cuts of the first 66 percent data observation points. The **quantile()** function is used to compute the percentiles by using the concatenate, `c()` function.
5. The **standard deviation (SD)** shows how much dispersion from the average exists. It is mathematically expressed as the square root of its variance.

We apply the **sd** function to compute the standard deviation of a variable.

```
> sd(via_data$CARB, na.rm=-9999)
[1] 4807.659
```

The `sd(via_data$CARB, na.rm=-9999)` function above computes standard deviation of CARB variable in join3 data frame.

`na.rm=-9999 Removed -9999`, the no data values from the dataset in order to calculate it.If the missing datais not coded (appear as NA in the dataset), the argument is: `na.rm=TRUE`)

6. Summary statistics. Summary statistics are used to summarize a set of observations. The function **summary()** displays the minimum, 1st Quartile, Mean, 3rd Quartile and Max.

```
> summary(via_data$ANTH)
Min. 1st Qu. Median Mean 3rd Qu. Max.
11.00 41.00 43.00 47.15 63.00 63.00
```

Your turn: Now use the functions above and explore each of the variables in the `via_data` data frame.

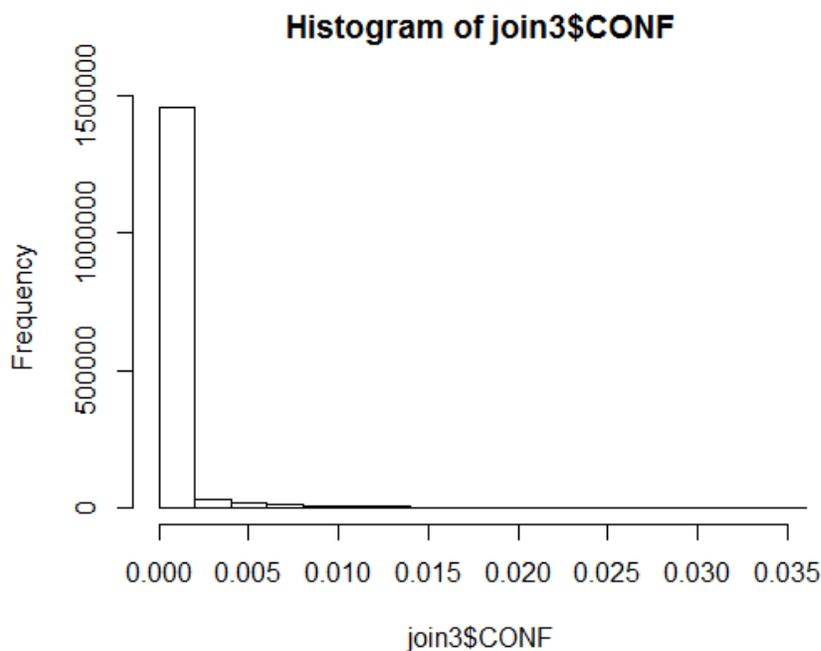
6.2.2 Graphical Methods

R statistics contain a number of tools for graphical methods for exploratory data analysis including:

- histograms
- Scatter plots
- Box plots

1. Histograms - a **histogram** consists of parallel vertical bars that graphically show the frequency distribution of a quantitative variable. A histogram is a graphical representation of the data in which the area of each bar is equal to the frequency of items found in each class.

```
> hist(via_data$CONF, main="Conflict", xlab="Ratio", ylab="Number of grids")
```



We can use the **ggplot()** function to make elaborate histograms with labels.

```
> plot_anth <- ggplot(via_data, aes(x=ANTH))+geom_histogram(colour = "darkgreen", fill = "white")+scale_x_continuous("name of x axis")+scale_y_continuous("name of y axis")+ggtitle("ANTH graph")
```

`plot anth` – the name of your plot

ggplot() function used to declare the input data frame for a graphic and to specify the set of plot aesthetics intended to be common throughout all subsequent layers unless specifically overridden

`aes()` aesthetics function describes how variables in the data are mapped to visual properties of geometries.

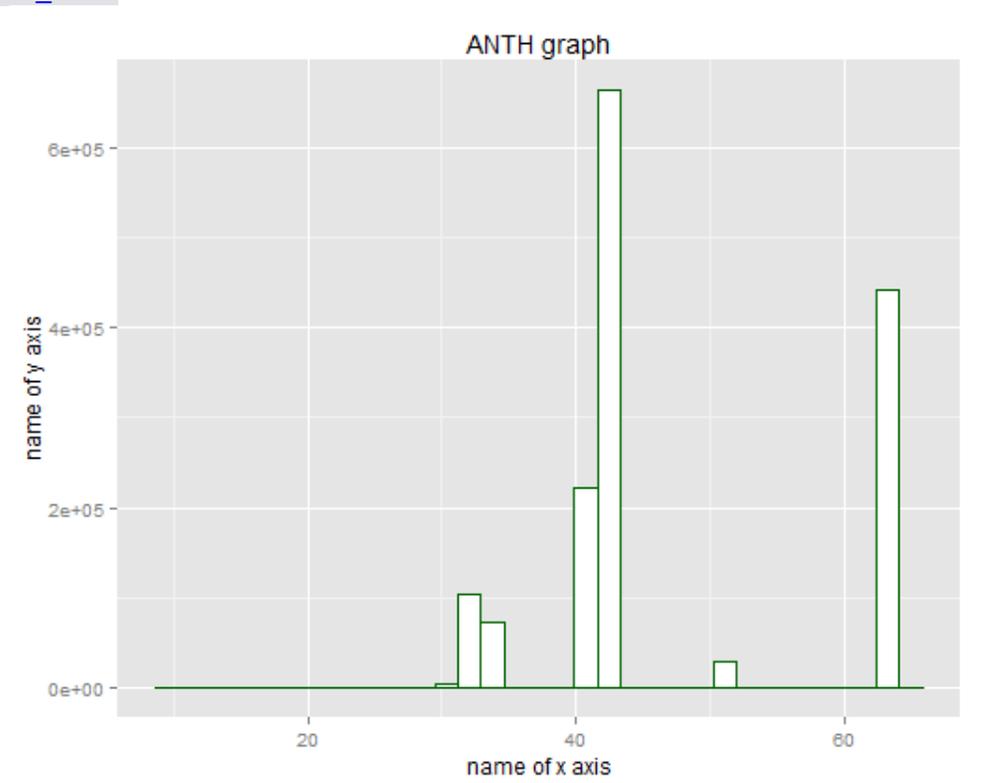
`X=ANTH` – states the x-axis variable

`geom_histogram()` function sets line and fill color

`scale_x_continuous` and `scale_y_continuous` sets labels for the x- and y- axis

`ggtitle()` sets graph title

`> plot_anth`

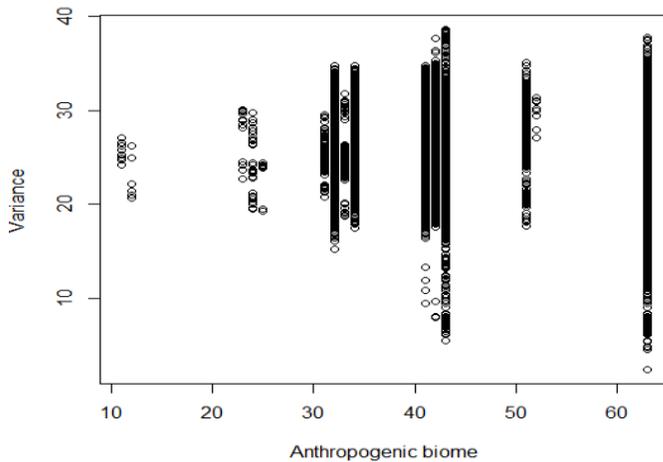


2. Scatter plots . A scatter plot provides a graphical view of the relationship between two variables. The data is displayed as a collection of points, each having the value of one variable determining the position on the horizontal axis and the value of the other variable determining the position on the vertical axis.

For instance the scatter plot of ANTH and DCVAR variables is:

```
> plot(via_data$ANTH, via_data$DCVAR, xlab="Anthropogenic biome", ylab="Variance ")
```

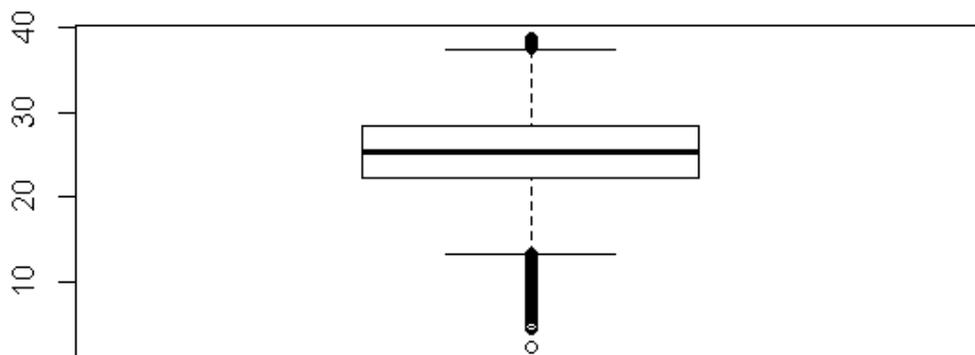
```
>
```



3. Box plots - A boxplot provides a graphical view of the median, quartiles, maximum, and minimum of a data set. Box plots display differences between groups without making any assumptions of the underlying statistical distribution, and are most useful for identification of outliers.

Example below applies `boxplot()` function to generate the boxplot graphics

```
> boxplot(join3$DCVAR)
```



6.3 Winsorization

Extreme values sometimes have a big effect on statistical operations. Extreme values can have positive or negative effect. Winsorization is the transformation of statistics by limiting extreme values in the statistical data to reduce the effect of possibly spurious outliers. A common method to deal with outliers is to trim or truncate the data. A 90% Winsorisation would see all data below the 5th percentile set to the 5th percentile and data above the 95th percentile set to above 95th percentile. We usually do the winsorization at one end, where we observe the presence of outliers, i.e. data is usually highly skewed to the left or to the right.

Example of Winsorization

- Order the observations by value
 - $X_{i1}, X_{i2}, X_{i3}, X_{i4}, X_{i5} \dots X_{i95}, X_{i96}, X_{i97}, X_{i98}, X_{i99}, X_{i100}$, where i denotes the i^{th} regressor
 - If Winsorizing at 5% and 95%, also called 10% Winsorization, then
 - The value for $X_{i1}, X_{i2}, X_{i3}, X_{i4}$, will be replaced by the value for X_{i5}
 - The value for $X_{i96}, X_{i97}, X_{i98}, X_{i99}, X_{i100}$, will be replaced by the value for X_{i95}
 - $X_{i5}, X_{i5}, X_{i5}, X_{i5}, X_{i5} \dots X_{i95}, X_{i96}, X_{i96}, X_{i96}, X_{i96}, X_{i96}$, **new values**

We use the function **recode()** to set the new values below 5th and above 95th percentile to new values.

To do a 10% Winsorization we:

1. Use the `> quantile(via_data$ANTH,c(0.05, 0.95))` to determine the 5th and 95th percentile values. In this case its 32 and 63

```
5% 95%
32 63
```

2. Recode all values below 5th percentile (32) in the ANTH field to 32. This creates a new field called ANTHr1

```
> via_data$ANTH1r <-[via_data$ANTH < 32] <-32
```

3. Recode all values above 95th percentile (63) in the ANTHr1 to 32. This creates a new field called ANTHr2

```
> via_data$ANTH2r[a_data$ANTHr1 > 63] <-63
```

The resultant data frame contains original ANTH field and ANTHr1 field with values less than 32 (5th percentile) recoded to 32 and ANTHr2 field with values greater than 95th percentile (63) recoded to 63.

6.4 Rescale variable values to 0-100

The variables have different units of measurements, and the next step in the analysis is to bring all the data to a common 0-100 scale, where 0 equates to lower vulnerability and 100 equates to high vulnerability. For variables where *larger values represent low vulnerability* (i.e. years for education), we invert the data.

Data rescaling for variable where low values indicates low vulnerability: example= conflict

- 1) `min_conf<-min(via_data$CONF)1`
- 2) `max_conf<-max(via_data$CONF)2`
- 3) `via_data$var_pct<-(via_data$CONF-min_conf)/(max_conf-min_conf)*1003`

The command number (1) created a new field (min_conf) and sets value to the minimum value in the CONF field.

Command (2) creates a new field (max_conf) and computes value to maximum value in the CONF field.

Command (3) subtract the minimum value created in (1) from the CONF field and divide it by maximum minus minimum.

Data rescaling for variable where low values indicates high vulnerability: example= education

- 4) `min_educ<-min(via_data$EDUC)1`
- 5) `max_conf<-max(via_data$EDUC).....2`
- 6) `via_data$var_pct<-(via_data$EDUC-max_conf)/(min_conf-max_conf)*100.....3`

6.5 Calculate composites using weighted averages, and rescale to 0-100

The input variables included in our spreadsheet are measures of three dimensions of vulnerability: adaptive capacity, exposure and sensitivity. In the following step, we will use the clean and transformed data generated in the previous steps to calculate these composites.

The calculation of the composites is based on average. If you think that some of the variables have a larger importance within the vulnerability dimension, wither because of data quality, resolution or conceptual meaning, weights are assigned to the variables to account for this.

This can be done in three steps:

1. Sum all the importance value for each of the variable. For example, if we have 5 variables, and the first 2 have double the importance of the rest of the variables, we calculate the sum of the importance as follows: $2+2+1+1+1=7$ Calculate the weights:
 - o for variable with 1 importance: $1/7=0.1428$
 - o for variables with double importance: $0.1428*2=0.2857$
2. The sum of all the weights is equal to 1.
3. Calculate the weighted composite

```
via_data$adaptive<-(via_data$var1*0.2857+ via_data$var2*0.2857+
via_data$var3*0.1428+ via_data$var4*0.1428+ via_data$var5*0.1428)/5
```

The rescaling to 0-100 range is done similarly as the variable rescaling, renaming the variable adaptive_prc.

6.6 Calculate vulnerability, and rescaling to 0-100

The overall vulnerability is calculated using simple average of the three composites calculated in the previous step:

```
via_data$vulnerability <-(via_data$adaptive_prc+ via_data$exposure_prc+  
via_data$sensitivity_prc)/3
```

The rescaling to 0-100 range is done similarly as the variable and composite rescaling, renaming the index vulnerability_prc.

Exercise 7. Mapping Results in ArcMap

1. In ArcCatalog import table generated from R “composites_for_mapping_table”, as a table in geodatabase.
2. In ArcMap join “composite table” by PixelID field to a copy of the “centroids” feature class.
3. If the analysis area is smaller or a subset of the “mask” then create a query by using “Select By Attributes” where PixelID IS NOT NULL.
4. Export new point feature class with the attributes from composite table
“composite_table_points”
5. Rasters were created for each component and each PCA in the “composite_table_point” using ArcGIS Point to Raster tool (ArcToolbox\Conversion Tools\Raster\Point To Raster)