Aggregation of Indicators for Vulnerability & Risk Assessment

Today’s Goals

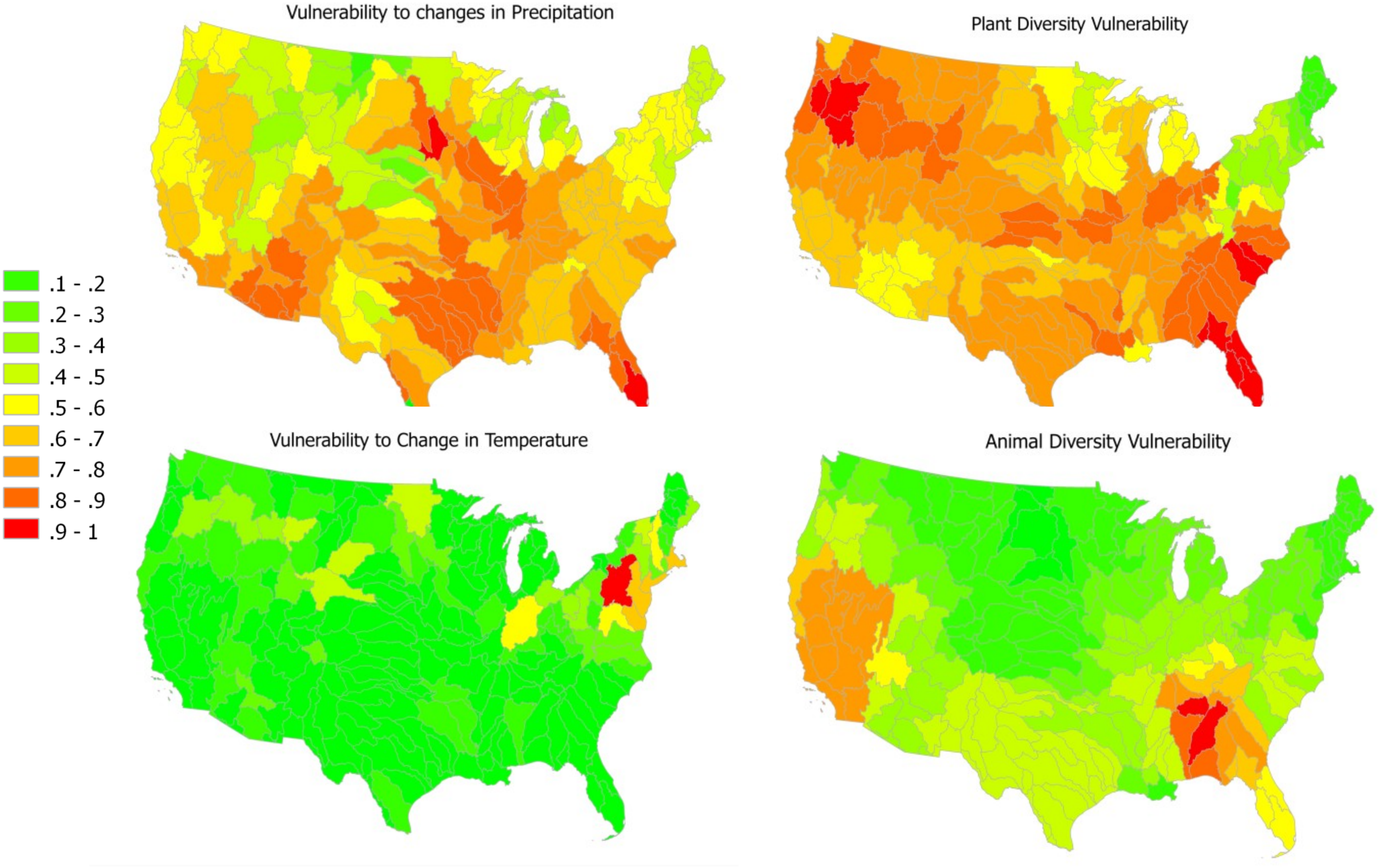
- What is data aggregation? Why use it?
- What is an example of data aggregation?
- What else should I know?

Index Creation & Data Aggregation

- Take multiple datasets in different units (e.g., precipitation; temperature) and aggregate them into one single indicator.
- E.g., Temperature + Precipitation = Vulnerability

- What’s wrong with the above example?

Which areas do we need to fund?



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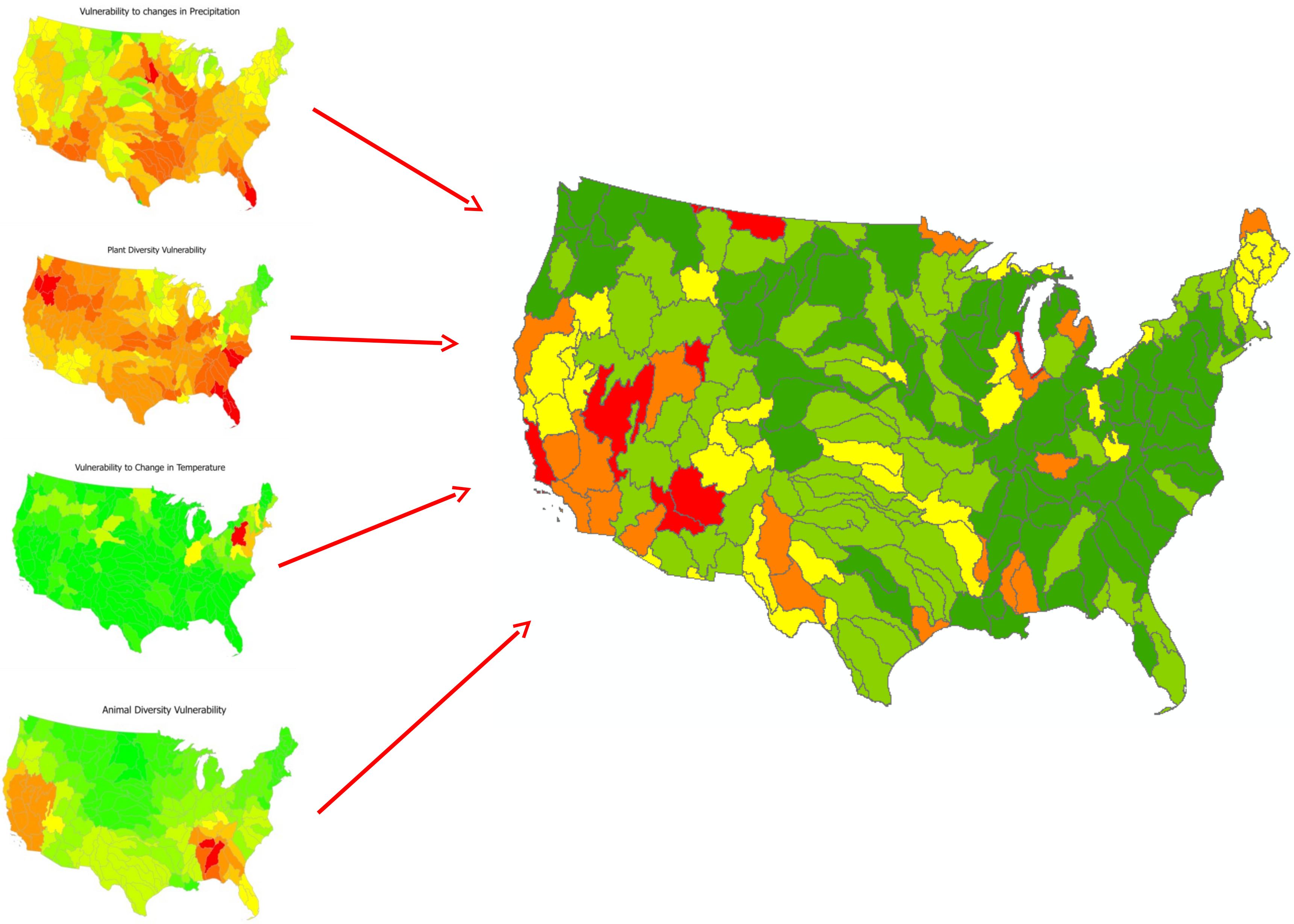

Today’s Goals

- What is data aggregation? Why use it?
- What is an example of data aggregation?
- What else should I know?

Steps!

(1) Data Selection

(2) Data Creation / Identification / Integration

(3) Multivariate Analysis

(4) Standardization

(5) Weighting

(6) Aggregation

(7) Sensitivity / Uncertainty

(8) Analysis / Visualization

Getting Started

- Data Selection: Theoretically driven.
  - What is your research question?
  - What data might be relevant to get at it?
- Data Creation / Identification / Integration
  - Is the data you need already available?
  - Do you have it in a Geodatabase?
- Multivariate Analysis
  - Is your data measuring unique aspects of the system, or is it all measuring the same thing?

Excel Example

Steps!

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Standardization

- Attributes in different units need to be standardized so they are comparable.
- E.g., adding the number of people living in an area to the annual temperature make no sense, conceptually or mathematically.

Techniques for Standardization

Data Standardization Approach	Short Summary	Sources
Quantile	Data are grouped into quantiles, then scaled from 0-1 based on which quantile they fall into. $$\frac{(MAX_k - k)}{(MAX_k - MIN_k)}$$	(Hurd, Leary et al. 1999; Alessa, Kliskey et al. 2008; Perch-Nielsen 2010)
Human Development Index	$$\frac{k}{MAX_k}$$	(Sharma and Patwardhan 2008)
Division by Max (Theoretical Max can be substituted)		(Cutter, Mitchell et al. 2000; Wu, Yarnal et al. 2002; SDI 2010)
Z-Scores	The number of standard deviations the indicator value is from the mean.	(Wood, Burton et al. 2010)
As a proportion of an external indicator	Dataset normalized by an external dataset (e.g., monetary values in terms of 1990 dollars)	(Auerbach 1981; Moss, Brenkert et al. 2002; Cutter, Boruff et al. 2003; Brooks, Neil Adger et al. 2005)
Thresholding	Either survey design or post-hoc thresholds are determined to separate datasets into comparable sets (e.g., expert decision on what threshold for heat indicates "high vulnerability")	(Shoaf, Seligson et al. 2006; Aceves-Quesada, Diaz-Salgado et al. 2007; López-Marrero and Yarnal 2010; NOAA 2010)

When to use each Technique

- Quantile
  - Indicator has limited precision or accuracy
  - Groupings are more interesting than actual values

EXAMPLE:

Data on economic welfare for countries around the world.

Biggest Disadvantage:

You do not retain information on the absolute differences between different values.

When to use each Technique

- Human Development Index
  - Differences between scores within the indicator are very important
  - Effectively “stretches” the values from 0 to 1.

EXAMPLE:

Stream Flow Variability

Biggest Disadvantage:

Stretching can suggest larger differences than actually exist.

When to use each Technique

- Division by Max
  - Absolute values are important
  - Data is very precise

EXAMPLE:

Precipitation if the goal is to estimate absolute risk of flooding.

Biggest Disadvantage:

Very data-reliant!

When to use each Technique

- Z-Scores
  - Interested in how unusual a unit is compared to the mean

EXAMPLE:

Precipitation if the goal is to estimate relative risk of flooding events.

Biggest Disadvantage:

Only helpful for relative studies (cannot be used to determine absolute risk)

When to use each Technique

- Proportion of an external indicator
  - Mostly done to compare economic outputs

<u>EXAMPLE:</u>

The GDP of Great Britain in 1990 as a proportion of the US's GDP

<u>Biggest Disadvantage:</u>

Only makes sense if you have a relevant external indicator.

When to use each Technique

- Thresholding
  - Can help to group areas into different levels of vulnerability when you have a great deal of knowledge about the indicator

EXAMPLE:

CO2 emissions – Levels below ~200PPM may not be concerning, levels from 200-400PPM are of some concern, 400PPM + are very concerning.

Biggest Disadvantage:

You have to know your indicator VERY well. Very labor intensive.

When to use each Technique

Rank-Order

Very helpful if you cannot threshold, and have limited information about the accuracy of your data.

For Each Attribute, you:

(1) Determine the rank of each unit of analysis (in our case, Hydrologic Unit Codes [HUCs]). Make sure to rank in the right order – more vulnerable areas need to have a lower rank, while less vulnerable areas should have smaller values / higher ranks (closer to 1).
(2) Divide each value by the maximum rank.

Flood Risk Example (more rain = more risk)

HUC ID	Precip (mm/week)	Rank-Order	Rank / Max Rank
100	**1.1**	1	(1/10) = 0.1
101	**2.3**	5	(5/10) = 0.5
102	**3.1**	7	0.7
103	**3.3**	8	0.8
201	**2.5**	6	0.6
202	**1.7**	4	0.4
203	**1.6**	3	0.3
965	**1.5**	2	0.2
1810	**13**	10	1.0
1805	**5**	9	0.9

Vörösmarty, C., P. McIntyre, et al. (2010). "Global threats to human water security and river biodiversity." Nature **467(7315): 555-561.**

[EXCEL EXAMPLE OF STANDARDIZATION]

Steps!

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(2) Data Creation / Identification / Integration

(3) Multivariate Analysis

(4) Standardization

(5) Weighting

(6) Aggregation

(7) Sensitivity / Uncertainty

(8) Analysis / Visualization

Many methods for weighting…

- You already learned:
  - Relative to minimum
    - What is the least important attribute? How many times more important are other attributes than it?
  - Swing Weighting
    - How important is a swing from the worst outcome to the best for a given indicator?

Many methods for weighting…

- Most commonly applied weighting approach in risk assessment is “Equal Weights”, in which every attribute receives the same weight (generally 1 / the number of attributes).

- This assumes that all indicators are equally important!

- AHP will be our next tool.

Considerations when you weight

- Multicollinearity! If two indicators have the same data in them, giving them a lot of weight can lead to “double counting”.
- Sensitivity! Even if you choose not to weight (aka Equal Weighting), your results still might be sensitive to that decision.

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Aggregation Strategies

- Weighted Linear Combination (WLC)
- Data Envelopment Analysis (DEA)
- Pareto Rank Order (PAR)
- Ordered Weighted Average (OWA)
- Weighted Ordered Weighted Average (WOWA)

Weighted Linear Combination

- Establish weights based on some method (e.g., swing weighting).
- Multiply each weight by the attribute value.

$$Y = (b_0 * x_0) + (b_1 * x_1) + (b_2 * x_2) + \cdots + (b_n * x_n)$$

Examples: Rank Order Standardization

HUC ID	Precip (mm/week)	Rank-Order	Rank / Max Rank
100	**1.1**	1	(1/10) = 0.1
101	**2.3**	5	(5/10) = 0.5
102	**3.1**	7	0.7
103	**3.3**	8	0.8
201	**2.5**	6	0.6
202	**1.7**	4	0.4
203	**1.6**	3	0.3
965	**1.5**	2	0.2
1810	**13**	10	1.0
1805	**5**	9	0.9

HUC ID	People in Flood Plain	Rank-Order	Rank / Max Rank
100	**110**	4	(4/10) = 0.4
101	**200**	7	(7/10) = 0.7
102	**150**	5	0.5
103	**175**	6	0.6
201	**300**	8	0.8
202	**350**	9	0.9
203	**12500**	10	1.0
965	**100**	3	0.3
1810	**50**	2	0.2
1805	**10**	1	0.1

Examples: Weighted Linear Combination

<u>Weights:</u>
Precip = 0.4
People in Flood Plain = 0.6

HUC ID	Standardized Precipitation	**Standardized People in Flood Plain**	**Weighted Linear Combination**
100	0.1	0.4	=(0.4 * 0.1) + (0.6 * 0.4) = 0.28
101	0.5	0.7	=(0.4 * 0.5) + (0.6 * 0.7) = 0.62
102	0.7	0.5	???
103	0.8	0.6	
201	0.6	0.8	
202	0.4	0.9	
203	0.3	1.0	
965	0.2	0.3	
1810	1.0	0.2	
180			

Examples: Weighted Linear Combination

Weights:
Precip = 0.4
People in Flood Plain = 0.6

HUC ID	Standardized Precipitation	Standardized People in Flood Plain	Weighted Linear Combination
100	0.1	0.4	=(0.4 * 0.1) + (0.6 * 0.4) = 0.28
101	0.5	0.7	=(0.4 * 0.5) + (0.6 * 0.7) = 0.62
102	0.7	0.5	0.58
103	0.8	0.6	0.68
201	0.6	0.8	0.72
202	0.4	0.9	0.7
203	0.3	1.0	0.72
965	0.2	0.3	0.26
1810	1.0	0.2	0.58
1805	0.9	0.1	0.42

Examples: WLC

<u>Weights:</u>
Precip = 0.4
People in Flood Plain = 0.6

HUC ID	Standardized Precipitation	Standardized People in Flood Plain	Weighted Linear Combination
100	0.1	0.4	=(0.4 * 0.1)
101	0.5	0.7	=(0.4 * 0.5)
102	0.7	0.5	0.58
103	0.8	0.6	0.68
201	0.6	0.8	0.72
202	0.4	0.9	0.7
203	0.3	1.0	0.72
965	0.2	0.3	0.26
1810	1.0	0.2	0.58
1805	0.9	0.1	0.42

If we used these values to determine which HUCs to fund, we would potentially ignore an area that is highly likely to flood due to precipitation, just because it has less people that are at risk!

In other words: The low number of people has *averaged out* the high precipitation chance.

The OWA offers a solution to this.

What is an Ordered Weighted Average (OWA)?

OWA is a method to aggregate data which weights based on *rank order*. Constituent Indicator values for each HUC are ranked largest to smallest.

Example

Weights are assigned to a *rank* in OWA. This example will assign:

Rank 1: *.6*

Rank 2: *.4*

HUC-ID	Indicator 1	Indicator 2
1	**10**	**30**
2	**20**	**5**

Given the data to the left….

HUC-ID 1 would have a final value of:

(10 * ***.4***) + (30 * ***.6***) = **22**

HUC-ID 2 would have a final value of:

(20 * ***.6***) + (5 *** .4***) = **14**

In this example weighting scheme, the larger values in each row are given more weight, but the rank weights can be distributed to give a range of weighting schemes.

Yager, R. (1988). On ordered weighted averaging aggregation operators in multicriteria decisionmaking. IEEE transactions on Systems, Man and Cybernetics *18, 183-190.*

Examples: OWA

Rank Weights:

Rank 1 = 0.8

Rank 2 = 0.2

HUC ID	Standardized Precipitation	Standardized People in Flood Plain	Ordered Weighted Average
100	0.1	0.4	= (0.2 * 0.1) + (0.8 * 0.4) = 0.34
101	0.5	0.7	
102	0.7	0.5	
103	0.8	0.6	
201	0.6	0.8	
202	0.4	0.9	
203	0.3	1.0	
965	0.2	0.3	
1810	1.0	0.2	

First, the two attributes are ranked: in this case, the number of people in the flood plain is larger than the standardized precipitation (0.4 > 0.1), so it received rank 1. Precipitation received rank 2. We then multiple by the appropriate rank weight to get our final valuation.

Examples: OWA

Rank Weights:

Rank 1 = 0.8

Rank 2 = 0.2

HUC ID	Standardized Precipitation	Standardized People in Flood Plain	Ordered Weighted Average
100	0.1	0.4	= (0.2 * 0.1) + (0.8 * 0.4) = 0.34
101	0.5	0.7	= (0.2 * 0.5) + (0.8 * 0.7) = 0.66
102	0.7	0.5	???
103	0.8	0.6	
201	0.6	0.8	
202	0.4	0.9	
203	0.3	1.0	
965	0.2	0.3	
1810	1.0	0.2	
180			

Examples: OWA

Rank Weights:
Rank 1 = 0.8
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HUC ID	Standardized Precipitation	Standardized People in Flood Plain	Ordered Weighted Average
100	0.1	0.4	= (0.2 * 0.1) + (0.8 * 0.4) = 0.34
101	0.5	0.7	= (0.2 * 0.5) + (0.8 * 0.7) = 0.66
102	0.7	0.5	0.66
103	0.8	0.6	0.76
201	0.6	0.8	0.76
202	0.4	0.9	0.8
203	0.3	1.0	0.86
965	0.2	0.3	0.28
1810	1.0	0.2	0.84
1805	0.9	0.1	0.74

Examples: OWA

Rank Weights:
Rank 1 = 0.8
Rank 2 = 0.2

HUC ID	Standardized Precipitation	Standardized People in Flood Plain	Ordered Weighted Average
100	0.1	0.4	= (0.2 * 0.1) + (0.8 * 0.4) = 0.34
101	0.5	0.7	= (0.2 * 0.5) + (0.8 * 0.7) = 0.66
102	0.7	0.5	0.66
103	0.8	0.6	0.76
201	0.6	0.8	0.76
202	0.4	0.9	0.8
203	0.3	1.0	0.86
965	0.2	0.3	0.28
1810	1.0	0.2	0.84
1805	0.9	0.1	0.74

Using this approach, the small number in the number of people in the flood plain is not allowed to average out *as much* of the high value in precipitation as it used too. Thus, this HUC that is at a high chance for flooding is ranked high using the WOWA.

The degree to which averaging out is allowed to occur is called "ORness" in the OWA.

Optimistic / Pessimistic Outlooks and assigning the OWA Rank Weights

The degree of “ORness” chosen allows for the selection of Rank Weights based on an ***optimistic or pessimistic outlook.***

For an **optimistic outlook full trade-off** is allowed - low values can compensate for (or “average out”) high values.

Orness = .95	
Rank	**Weight**
1	.830
2	.140
3	.020
4	.010
5	**.001**

Orness = .75	
Rank	Weight
1	.460
2	.260
3	.140
4	.080
5	**.050**

Orness = .5	
Rank	Weight
1	.20
2	.20
3	.20
4	.20
5	**.20**

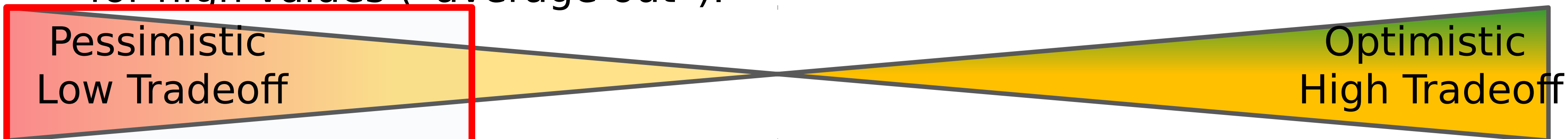
Malczewski, J., Chapman, T., Flegel, C., Walters, D., Shrubsole, D., and Healy, M. (2003). GIS-multicriteria evaluation with ordered weighted averaging (OWA): case study of developing watershed management strategies. Environment and Planning A *35, 1769-1784.*

Jiang, H. & Eastman, J. (2000). Application of Fuzzy Measures in Multi-Criteria Evaluation in GIS. Int. J. Geographical Information Science. 14(2): 173-184.

Optimistic / Pessimistic Outlooks and assigning the OWA Rank Weights

The degree of “ORness” chosen allows for the selection of Rank Weights based on an ***optimistic or pessimistic outlook.***

For a **pessimistic decision strategy** a **low degree of tradeoff** is allowed: low values are not able to compensate for high values (“average out”).



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1	.460
2	.260
3	.140
4	.080
5	**.050**

Orness = .5	
Rank	Weight
1	.20
2	.20
3	.20
4	.20
5	**.20**

Weighted OWA

<u>Weights:</u>
Precip = 0.4
People in Flood Plain = 0.6

<u>Rank Weights:</u>
Rank 1 = 0.8
Rank 2 = 0.2

HUC ID	Standardized Precipitation	Standardized People in Flood Plain	Weighted Precip	Weighted People	Weighted Linear Combination
100	0.1	0.4	=0.1 * 0.4	=0.4 * 0.6	
101	0.5	0.7			
102	0.7	0.5			
103	0.8	0.6			
201	0.6	0.8			
202	0.4	0.9			
203	0.3	1.0			
965	0.2	0.3			
1810	1.0	0.2			
1805	[illegible]	0.1			

Weighted OWA

Weights:
Precip = 0.4
People in Flood Plain = 0.6

Rank Weights:
Rank 1 = 0.8
Rank 2 = 0.2

HUC ID	Standardized Precipitation	**Standardized People in Flood Plain**	**Weighted Precip**	**Weighted People**	**Weighted Linear Combination**
100	0.1	0.4	=0.1 * 0.4	=0.4 * 0.6	
101	0.5	0.7	??	??	
102	0.7	0.5			
103	0.8	0.6			
201	0.6	0.8			
202	0.4	0.9			
203	0.3	1.0			
965	0.2	0.3			
1810	1.0	0.2			
1805	0.9	0.1			

Weighted OWA

Weights:
Precip = 0.4
People in Flood Plain = 0.6

Rank Weights:
Rank 1 = 0.8
Rank 2 = 0.2

HUC ID	Standardized Precipitation	Standardized People in Flood Plain	Weighted Precip	Weighted People	Weighted Ordered Weighted Average
100	0.1	0.4	.04	.24	=(.24 * 0.8) + (.04 * 0.2)
101	0.5	0.7	.2	.42	??
102	0.7	0.5	.28	.3	
103	0.8	0.6	.32	.36	
201	0.6	0.8	.24	.48	
202	0.4	0.9	.16	.54	
203	0.3	1.0	.12	.6	
965	0.2	0.3	.08	.18	
1810	1.0	0.2	.4	.12	
1805	0.9	0.1	.36	.06	

Weighted OWA

Weights:
Precip = 0.4
People in Flood Plain = 0.6

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HUC ID	Standardized Precipitation	Standardized People in Flood Plain	Weighted Precip	Weighted People	Weighted Ordered Weighted Average
100	0.1	0.4	.04	.24	.2
101	0.5	0.7	.2	.42	.37
102	0.7	0.5	.28	.3	.29
103	0.8	0.6	.32	.36	.35
201	0.6	0.8	.24	.48	.43
202	0.4	0.9	.16	.54	.46
203	0.3	1.0	.12	.6	.50
965	0.2	0.3	.08	.18	.16
1810	1.0	0.2	.4	.12	.34
1805	0.9	0.1	.36	.06	.3

Weighted OWA

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201	0.6	0.8	.24	.48	
202	0.4	0.9	.16	.54	
203	0.3	1.0	.12	.6	
965	0.2	0.3	.08	.18	
1810	1.0	0.2	.4	.12	

In WOWA it is important to apply the weights FIRST, then rank for the rank weights SECOND. Look at this example: if you applied rank weights before weighting, you would get a different ranking of attributes than you do after you apply the weights.

Comparing All Results

Weights:
Precip = 0.4
People in Flood Plain = 0.6

Rank Weights:
Rank 1 = 0.8
Rank 2 = 0.2

HUC ID	Standardized Precipitation	Standardized People in Flood Plain	WLC	OWA	WOWA
100	0.1	0.4	0.28	0.34	.2
101	0.5	0.7	0.62	0.66	.37
102	0.7	0.5	0.58	0.66	.29
103	0.8	0.6	0.68	0.76	.35
201	0.6	0.8	0.72	0.76	.43
202	0.4	0.9	0.7	0.8	.46
203	0.3	1.0	0.72	0.86	.50
965	0.2	0.3	0.26	0.28	.16
1810	1.0	0.2	0.58	0.84	.34
1805	0.9	0.1	0.42	0.74	.3

Weighted OWA

<u>Weights:</u>
Precip = 0.4
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<u>Rank Weights:</u>
Rank 1 = 0.8
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HUC ID	Standardized Precipitation	Standardized People in Flood Plain	Weighted Precip	Weighted People	Weighted Linear Combination
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101	0.5	0.7			
102	0.7	0.5			
103	0.8	0.6			
201	0.6	0.8			
202	0.4	0.9			
203	0.3	1.0			
965	0.2	0.3			
1810	1.0	0.2			
1805	0.9	0.1			

[EXCEL EXAMPLE]

Steps!

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(7) Sensitivity / Uncertainty

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Definitions

- Sensitivity
- Uncertainty

Definitions

- Sensitivity – How were the results influenced by decisions YOU made (e.g., weighting, aggregation technique, standardization technique, Orness values…)
- Uncertainty – How were the results influenced by potential error or lack of precision in the data?

Sensitivity / Uncertainty

- Implemented in a very similar fashion to how we implemented sensitivity in the SMART process.
- How frequently would your ranking of risk / vulnerability change? Do your most-vulnerable areas change frequently?
- More on this for Problem Set 3!

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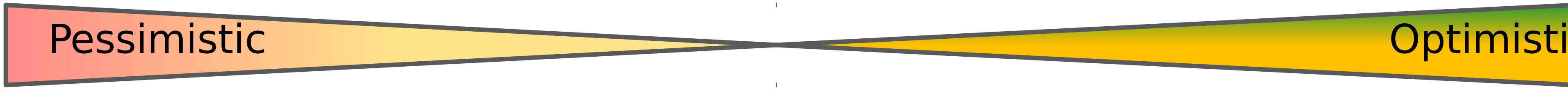
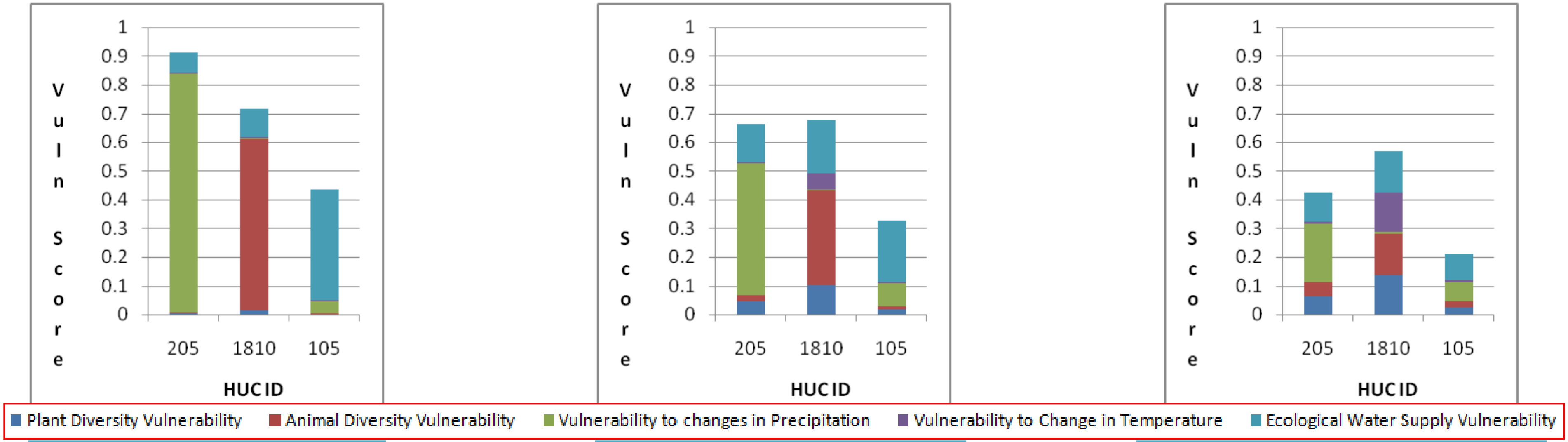
Contribution of Constituent Indicators

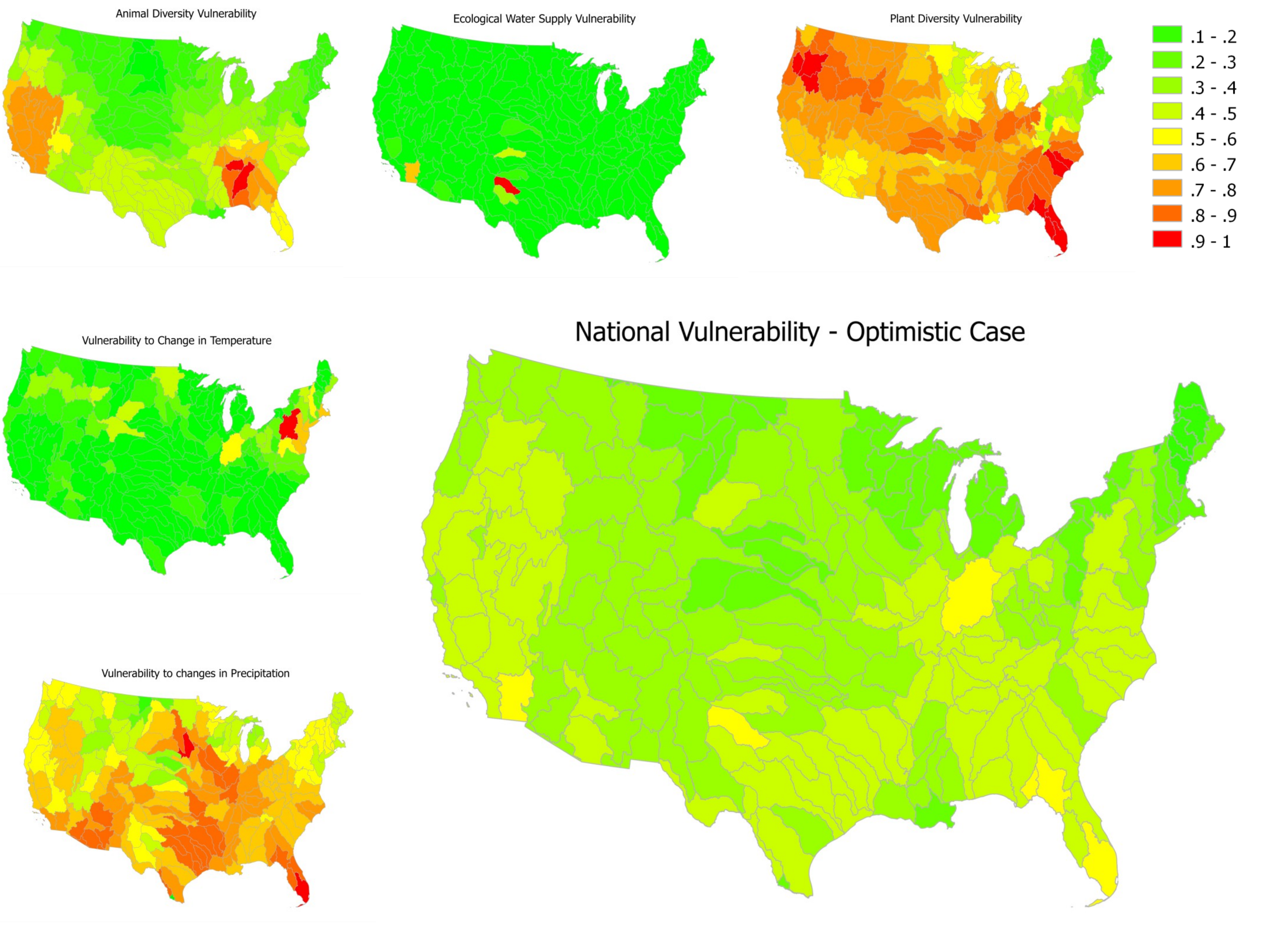




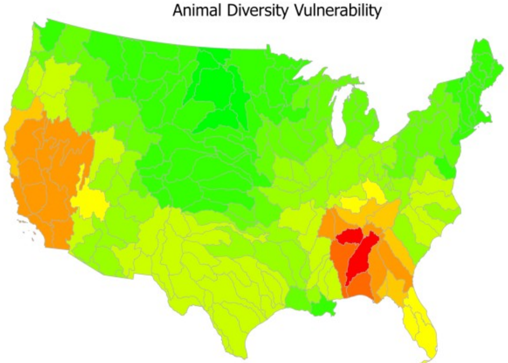
Pessimistic Outlook
ORness = .95 High attribute values will contribute the most
Tradeoff = .23 Lower values contribute very little to the score

Intermediate
ORness = .75 More lower-ranked variables contribute to the composite score
Tradeoff = .65 Lower values contribute more to the composite score

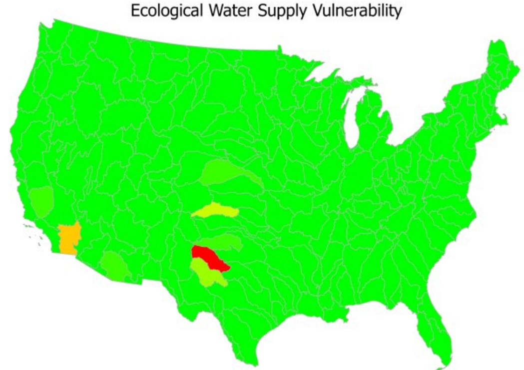
Optimistic Outlook
ORness = .50 Weights are equally spread across variables (Average)
Tradeoff = 1 Low values contribute equally with high values


Animal Diversity Vulnerability
Ecological Water Supply Vulnerability
Plant Diversity Vulnerability
.1 - .2
.2 - .3
.3 - .4
.4 - .5
.5 - .6
.6 - .7
.7 - .8
.8 - .9
.9 - 1
Vulnerability to Change in Temperature
National Vulnerability - Optimistic Case
Vulnerability to changes in Precipitation

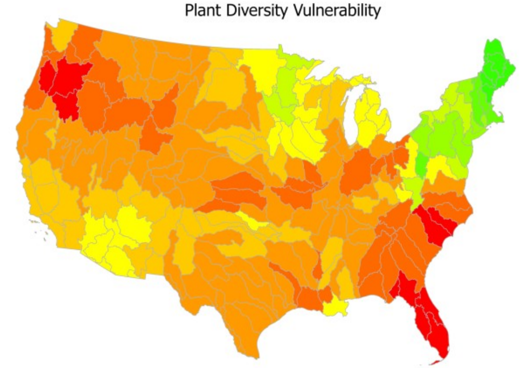
Animal Diversity Vulnerability

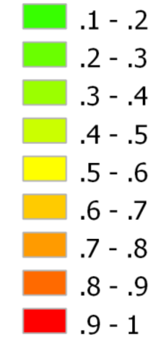


Ecological Water Supply Vulnerability

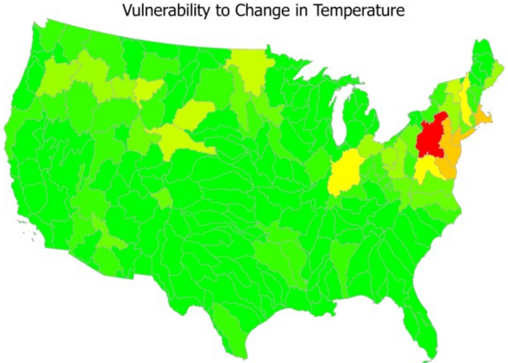


Plant Diversity Vulnerability

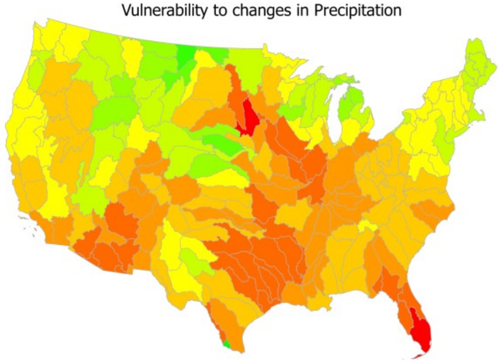




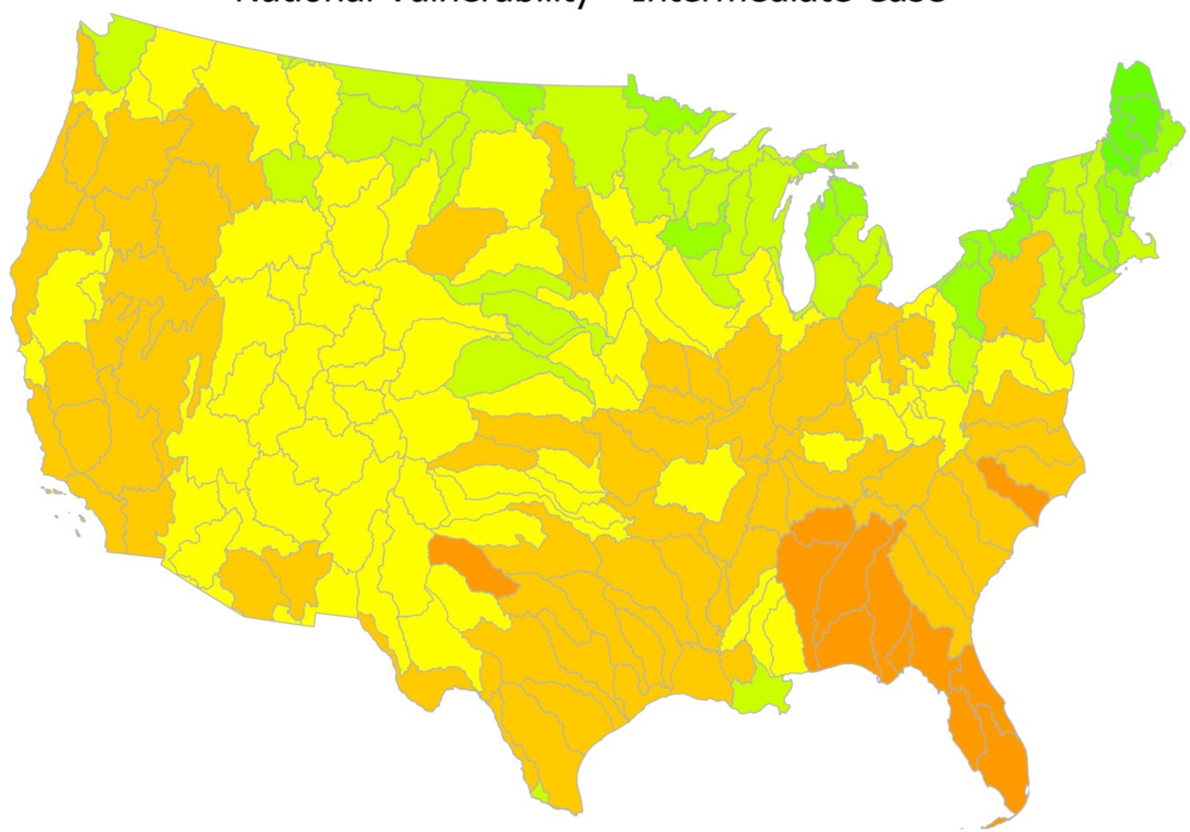
Vulnerability to Change in Temperature

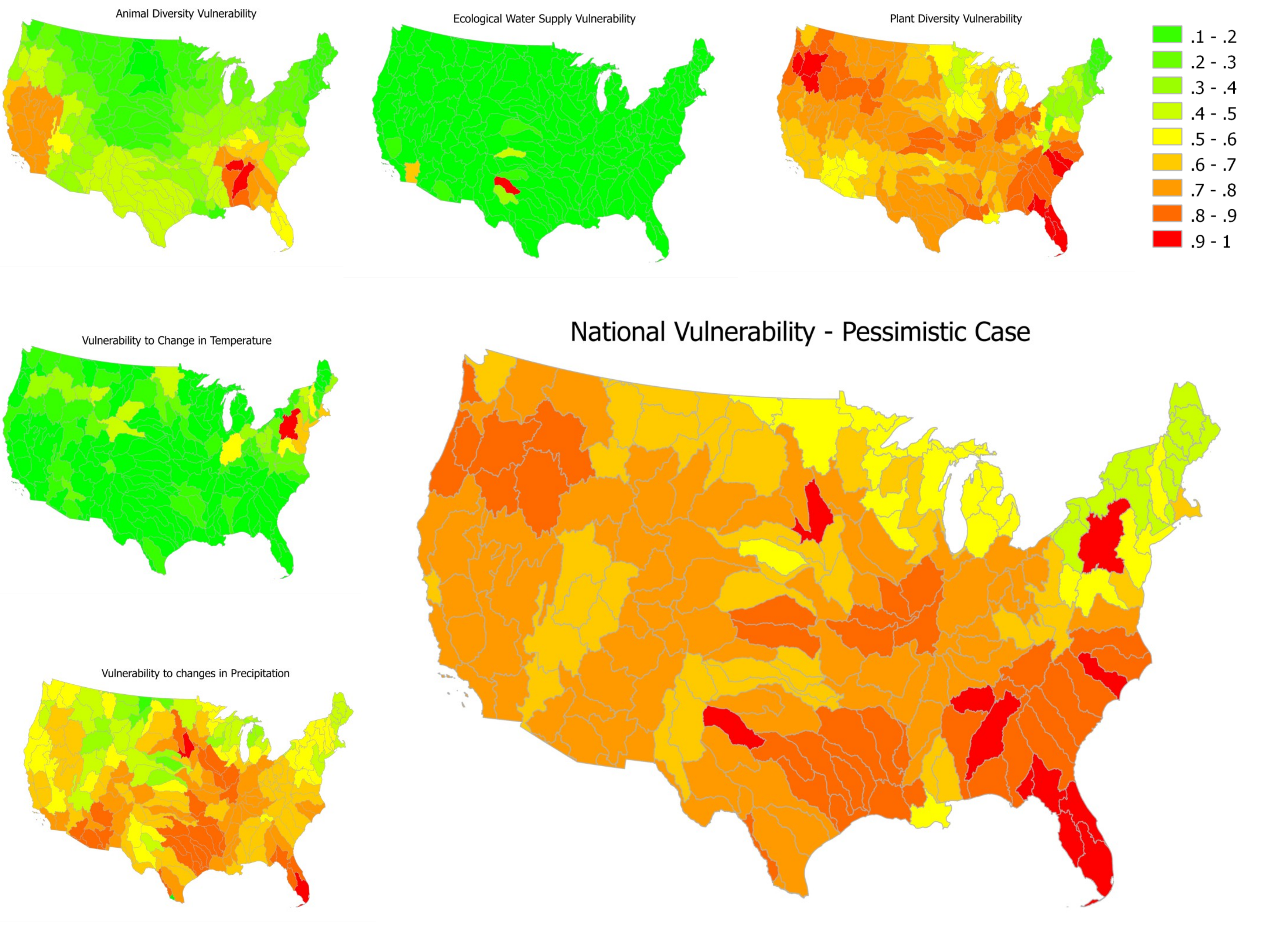


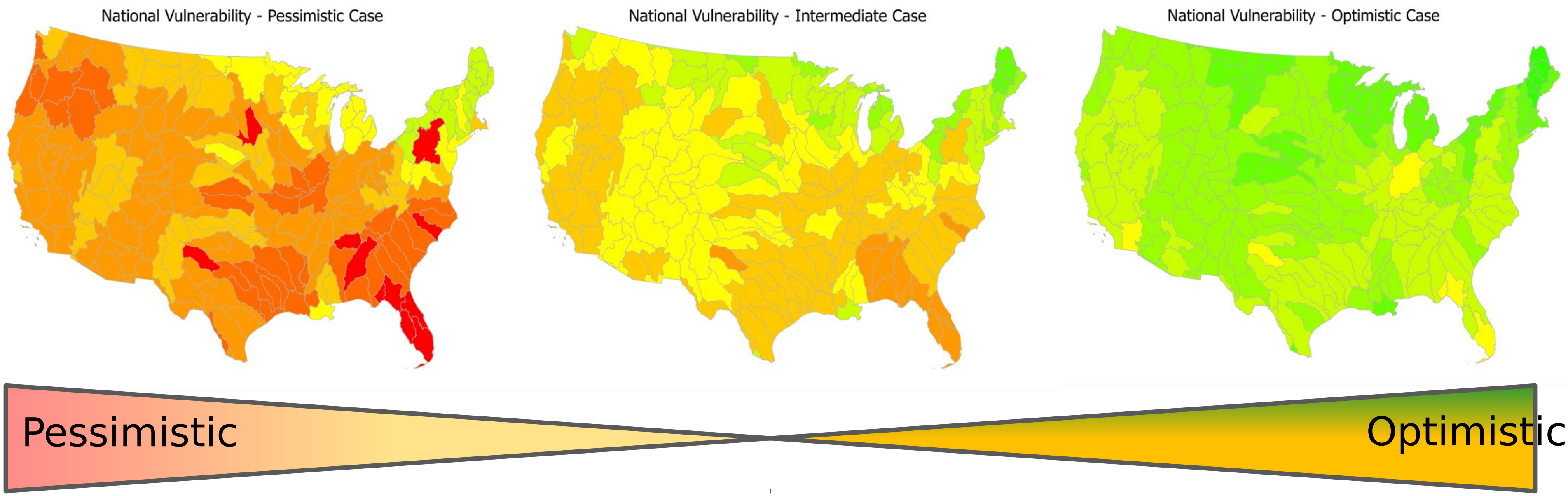
Vulnerability to changes in Precipitation



National Vulnerability - Intermediate Case




Animal Diversity Vulnerability
Ecological Water Supply Vulnerability
Plant Diversity Vulnerability
.1 - .2
.2 - .3
.3 - .4
.4 - .5
.5 - .6
.6 - .7
.7 - .8
.8 - .9
.9 - 1
Vulnerability to Change in Temperature
National Vulnerability - Pessimistic Case
Vulnerability to changes in Precipitation



Pessimistic Outlook

ORness = .95
Much more weight is given to high attribute values

Tradeoff = .23
Low Values are less able to
average out high values

Mean Score = .71
Higher ORness and lower tradeoff will lead to higher scores.

Intermediate Case

“Or”ness = .75
More weight is given to high
attribute values

Tradeoff = .65
Low Values are somewhat able to average out high values

Mean Score = .56
Decreasing ORness and increasing tradeoff will lead to decreasing

Optimistic Outlook

“Or”ness = .50
Equally weights all variables (Takes an average).

Tradeoff = 1
Low Values are able to average out high values

Mean Score = .36
Smaller ORness and high tradeoff will lead to lower scores.

Today’s Goals

- What is data aggregation? Why use it?
- What is an example of data aggregation?
- What else should I know?

Many Different Types of Aggregation

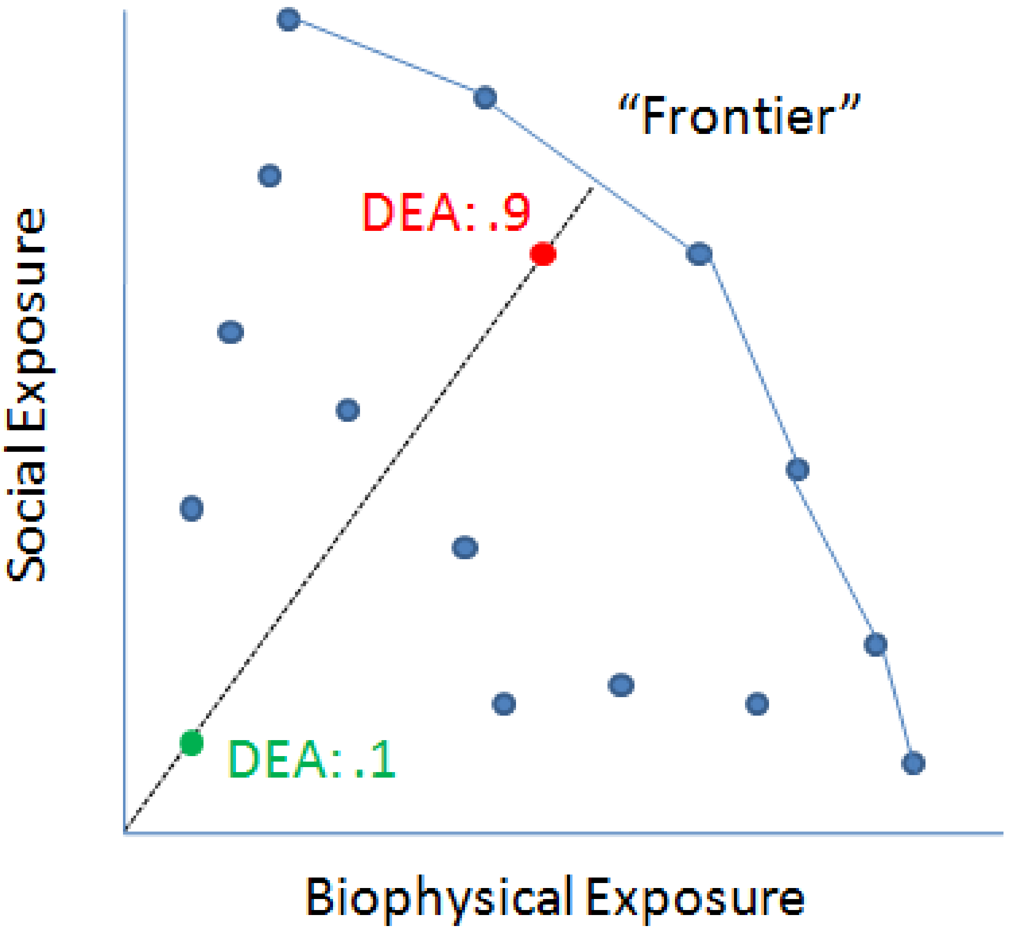
- I suggest you use OWA, as you can control the degree of tradeoff. Alternatives other than WLC include:
  - Data Envelopment Analysis
  - Pareto Rank Order
  - Weighted Ordered Weighted Average

Data Envelopment Analysis

First, establish the frontier of options. Second, from the origin, determine how far a given point lays on a straight line from the origin to the frontier.

This has the characteristic of placing a great deal of weight on the highest scoring indicator (similar to an OWA where Orness = 1).

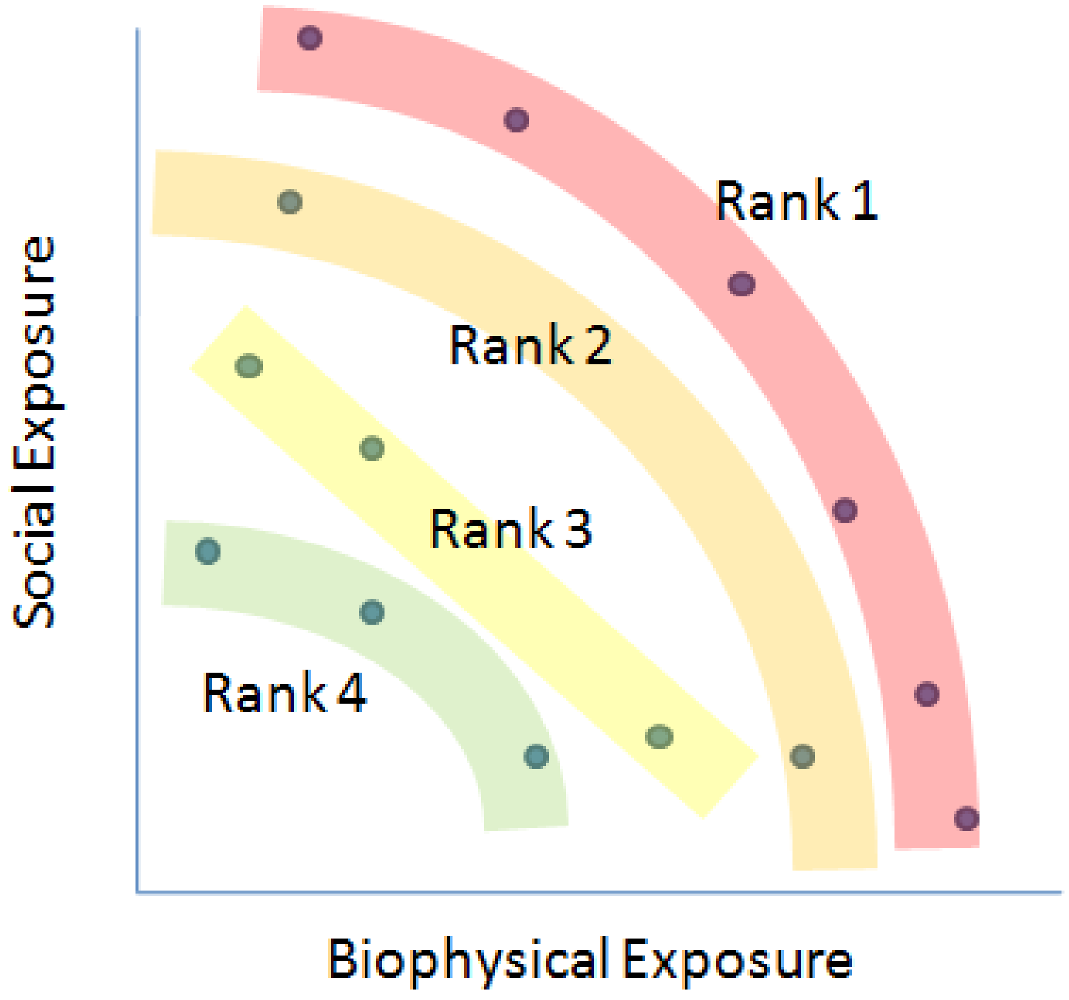
If a new point is added which moves the frontier, the analysis has to be re-run.



Pareto Rank Order

First, establish what units of analysis fall on the frontier. Label these as the highest rank of vulnerability.

Remove them from the analysis, and identify the next frontier, and rank them as the second highest. Repeat this until no further observations exist.



Comparison to other aggregation techniques

All the aggregation methods have their strengths and drawbacks. OWA has a variety of advantages similar to some of the other techniques reviewed. These drawbacks may be addressed in the techniques compared below but may require more adjustment than using OWA.

	Weighted Linear Combination	Frontier Methods	Clustering	OWA
Tradeoff	High values can be averaged out by low values (High tradeoff)	Too many indicators can lead to all attributes being rated as highly vulnerable.	N/A, Numerical Scores are not assigned	Tradeoff can be selected
Weighting	Requires Subjective Weighting	Weighting makes no difference in results	Weighting makes no difference in results	Subjective weighting can be implemented, but is optional
Data Scaling	Sensitive to Scaling Techniques Adding additional areas of analysis will not change all results	Not Sensitive to Scaling Techniques Adding additional areas of analysis can change all results	Not Sensitive to Scaling Techniques Adding additional areas of analysis can change all results	Sensitive to Scaling Techniques Adding additional areas of analysis will not change all results

Important Caveats

- Methods are almost always RELATIVE: You can only say “According to the method, HUC 1 is more vulnerable than HUC 2”.
- Absolute statements can almost never be made: You can NOT say “HUC 1 is 10 times more vulnerable than HUC 2”.
- These methods can be very sensitive to assumptions: Importance weights, standardization methods, normality of data.

Appendix

Why OWA?

- **Flexible:** The technique is flexible allowing for a range of aggregation solutions ranging from *optimistic* outlooks (full trade-off among constituent indicators, perhaps overlooking some HUCs that are vulnerable) to *pessimistic* outlooks (no trade-off among constituent indicators, likely not omitting any HUC that may be vulnerable) through the choice of order weights. The solution with all order weights equal (optimistic outlook, full trade-off is allowed) results in the Equal-Weights Weighted Linear Combination (WLC) widely used in the extant literature on Vulnerability Indicators.

- **Consistent/Reproducible:** a consistent and reproducible method for obtaining the order weights can be selected. There are a number of methods in the literature, we have chosen to use the maximum entropy method which tries to equalize weights for the constituent indicators for any chosen decision strategy

Why OWA?

- **“Importance” Weights:** If some constituent indicators are deemed more important to the vulnerability assessment, this preference can be incorporated by using the importance weights (pre-conditioning) before using the order weights, and renormalizing.

- **Use with other techniques:** The large number of constituent indicators being developed for each Corps business line may prescribe the use of a data reduction technique such as principal Component Analysis (PCA). The OWA aggregation method can be used to combine the PCA indicators.

Obtaining The Maximum Entropy Rank Weights

While each value of ORness has multiple potential sets of weights, the weights chosen in these examples are based on the principal of maximum dispersion. **For a given level of ORness (Trade-off, Decision Strategy)**, a unique set of weights that is the most **'equal'** across the constituent indicators is obtained through the solution of a non-linear constrained optimization problem. Spreading the weights as much as possible given the decision strategy uses as much information in the constituent indicators for that level of ORness.

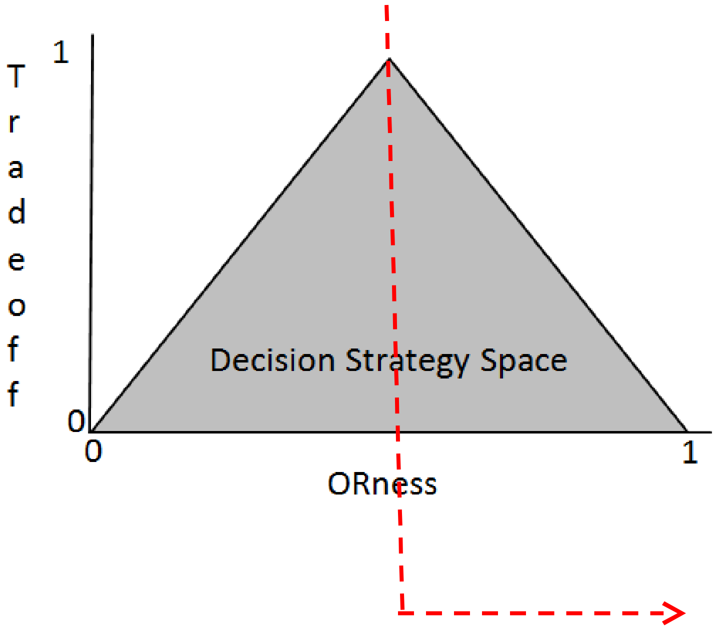
$$Maximize\ Entropy\,(dispersion) = -\sum_{i=1}^{n} W_{order\,i} \ln W_{order\,i}$$

$$Subject\ to: \frac{1}{(n-1)} \sum_{i=1}^{n} (n-i) W_{order\,i} = Chosen\ ORness\ level\ (trade-off)$$

Obtaining The Maximum Entropy Rank Weights

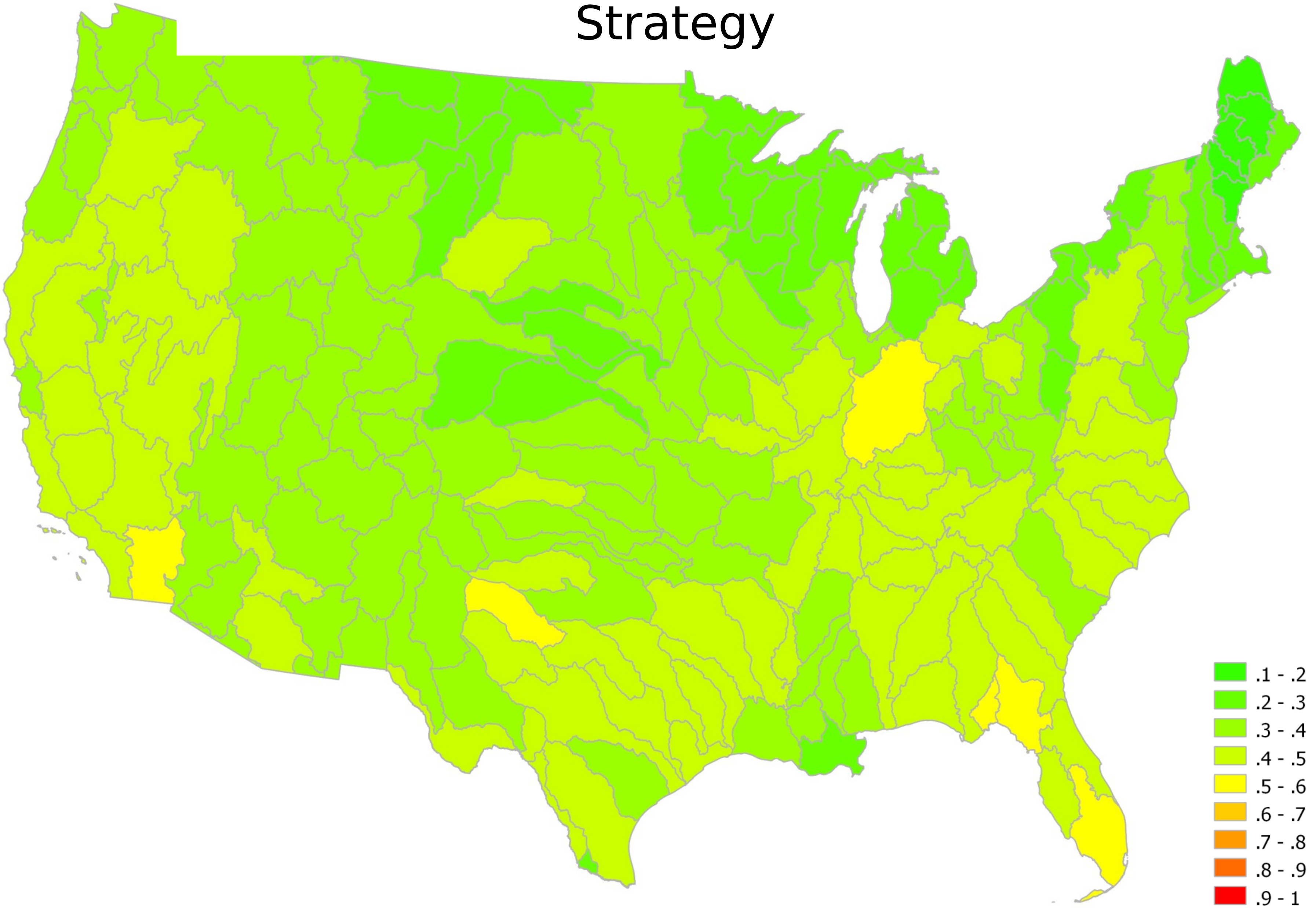
$$Maximize\ \ Entropy\,(dispersion\,) = -\sum_{i=1}^{n} W_{order\,i}\,\ln W_{order\,i}$$

$$Subject\ to:\ \frac{1}{(n-1)}\sum_{i=1}^{n}(n-i)W_{order\,i} = Chosen\,ORness\,level\,(trade-off\,)$$

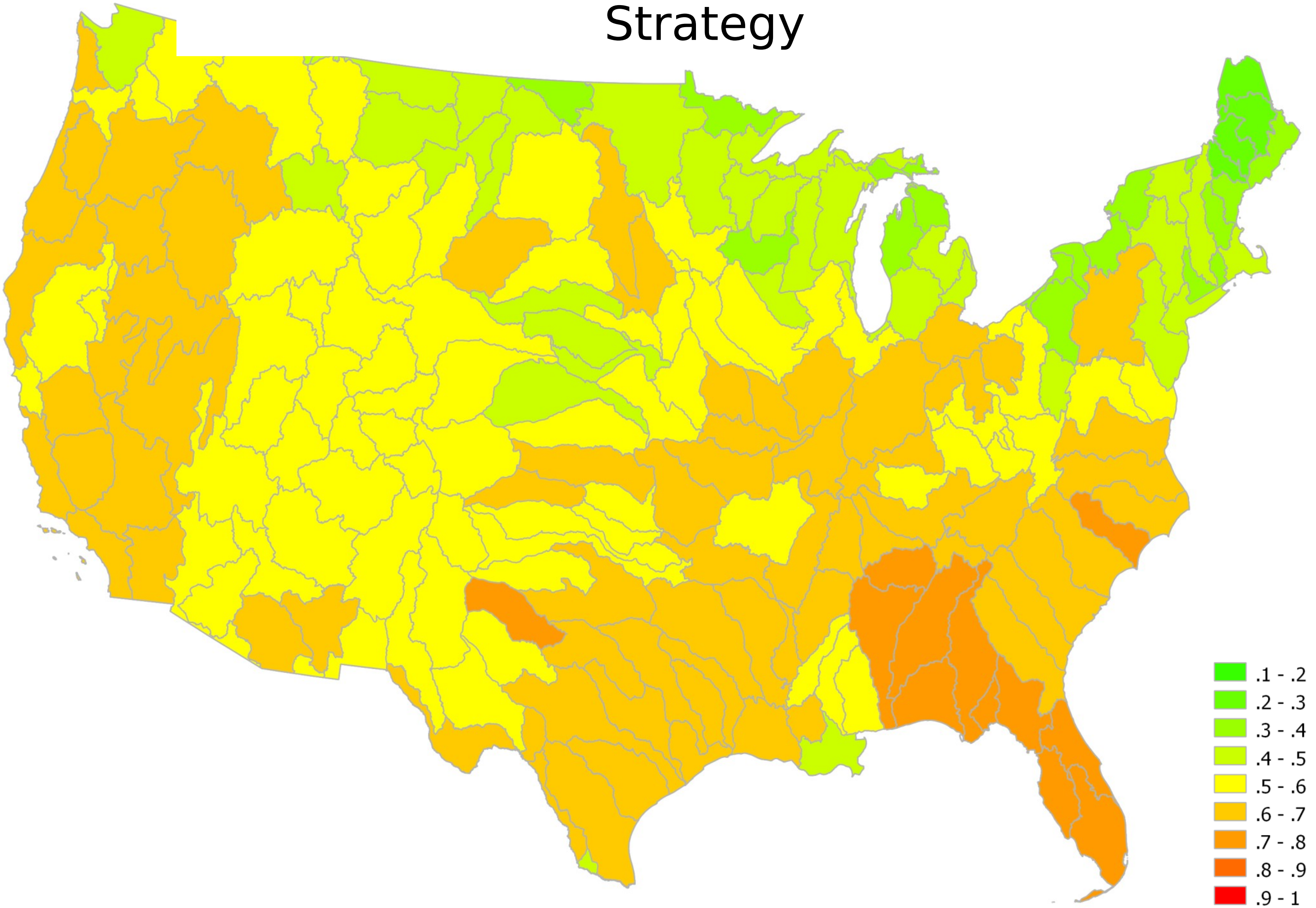


The solution to the constrained optimization finds the order weights that guarantees the weights chosen will have the highest level of Trade-off (the Y axis) for that level of ORness (points on the outer edge of the Decision Strategy Triangle). We are only using the right half of the triangle, where the ORness level goes from 0.5 (full trade-off), to 1.0 (highest constituent indicator given all the weight, trade-off).

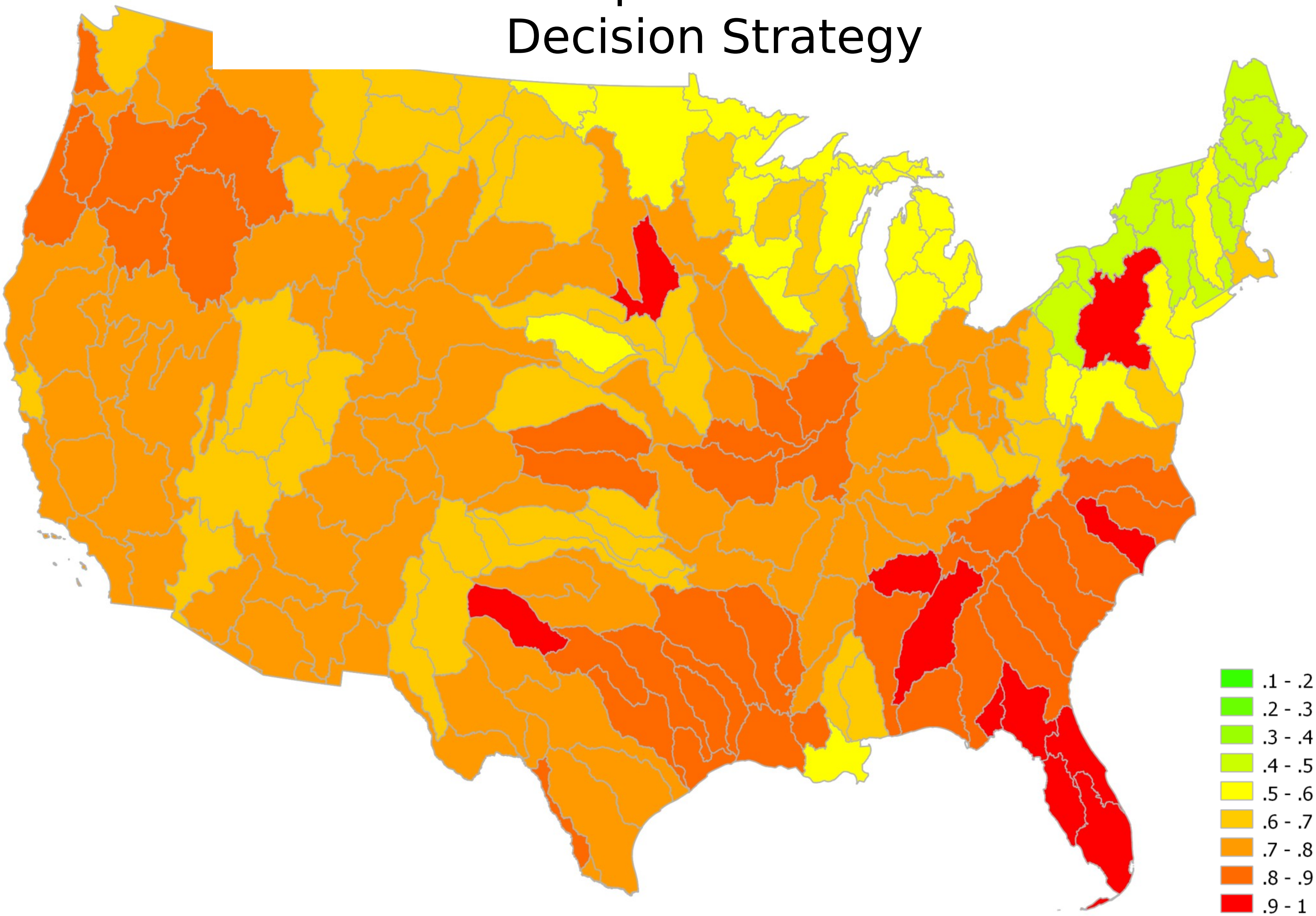
National Map HUC 4: Optimistic Decision Strategy



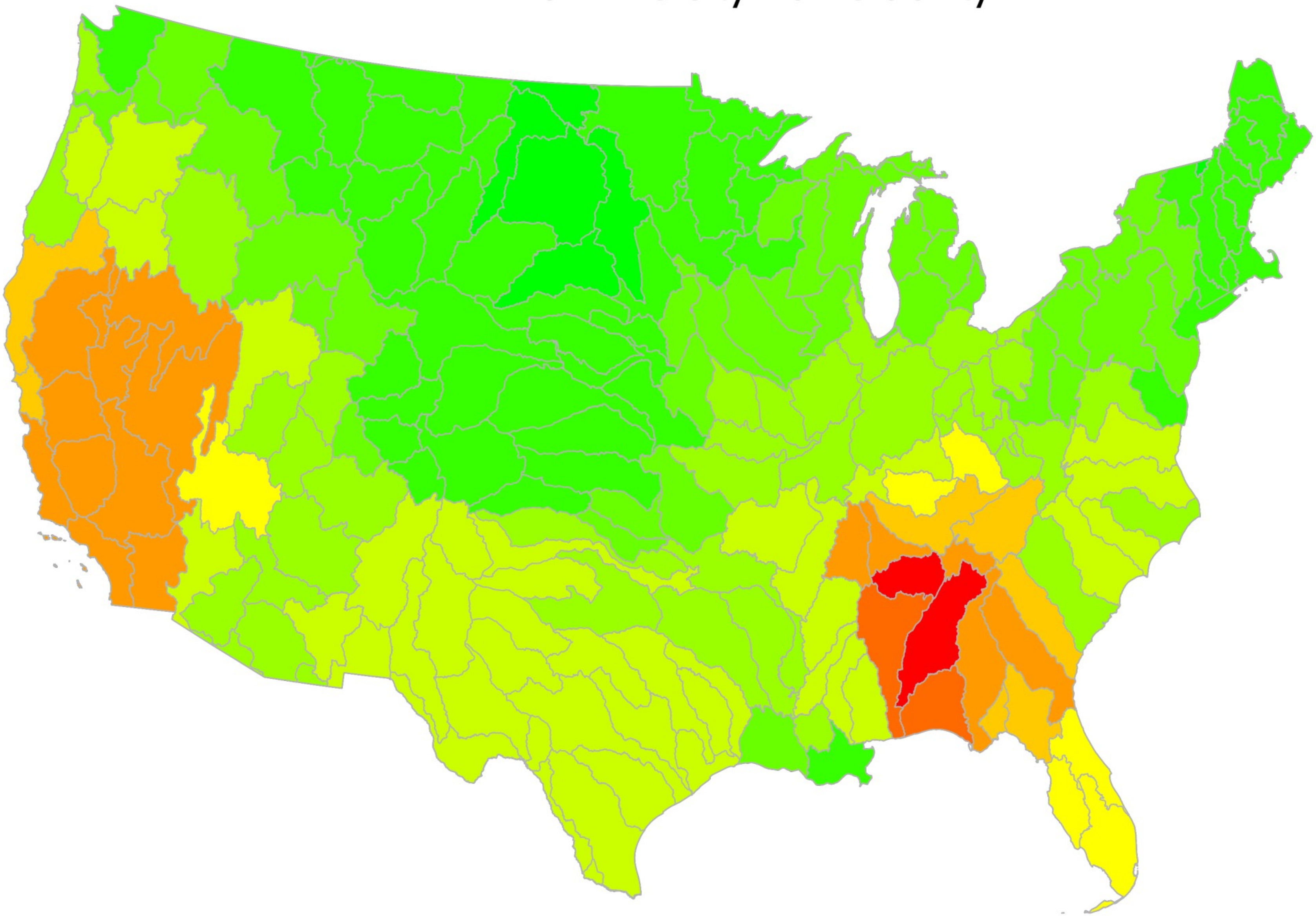
National Map HUC 4: Intermediate Decision Strategy



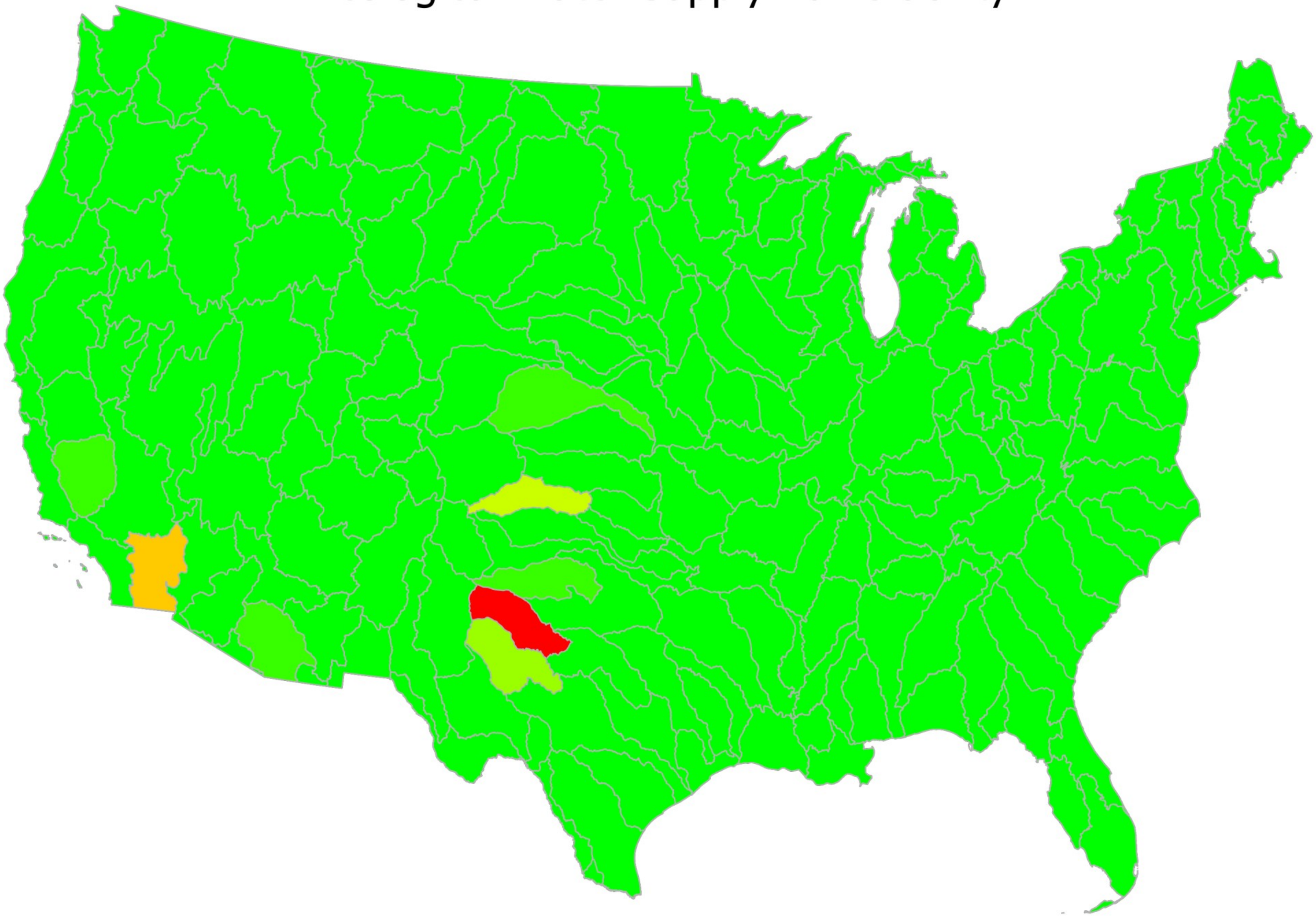
National Map HUC 4: Pessimistic Decision Strategy



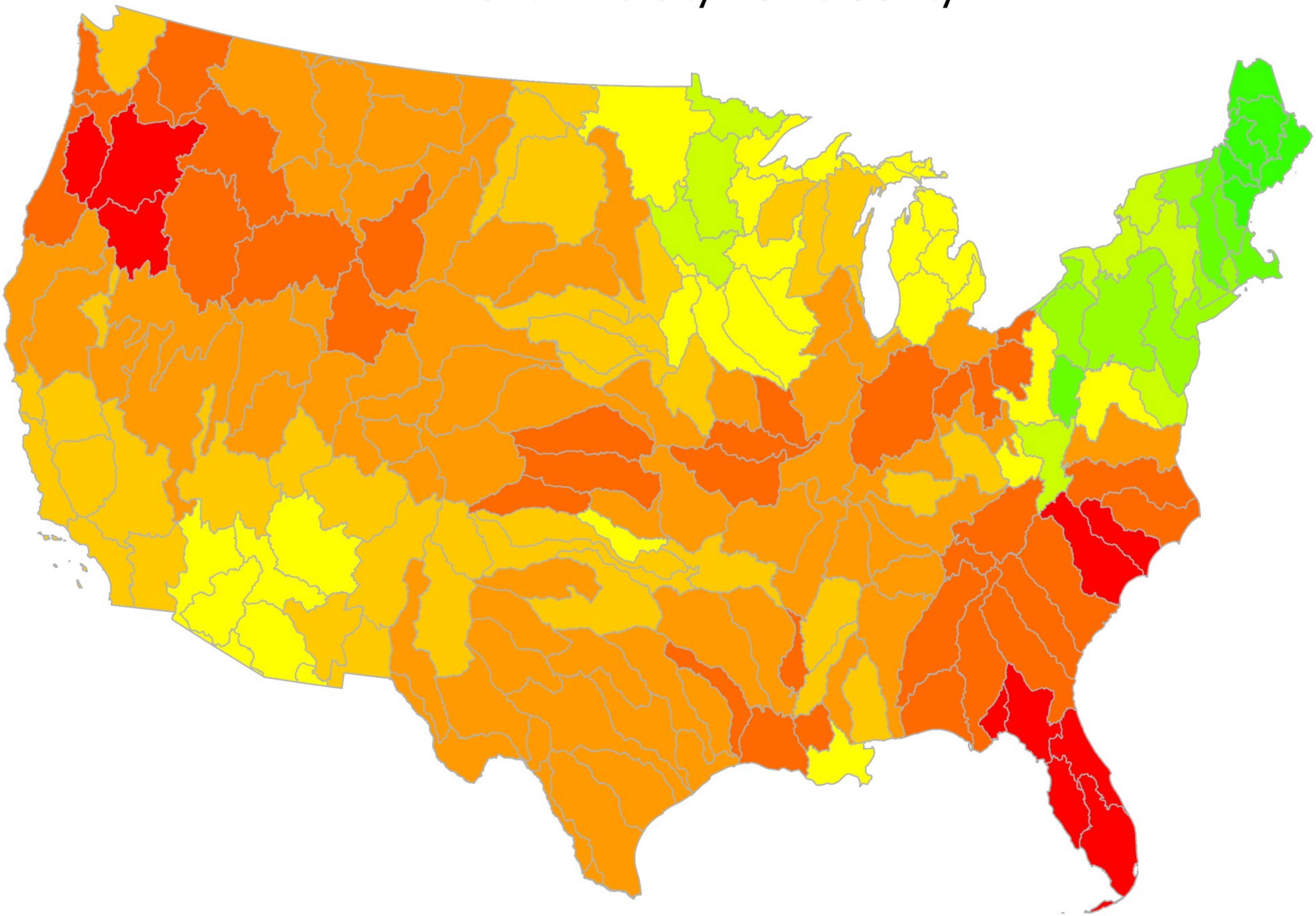
Animal Diversity Vulnerability



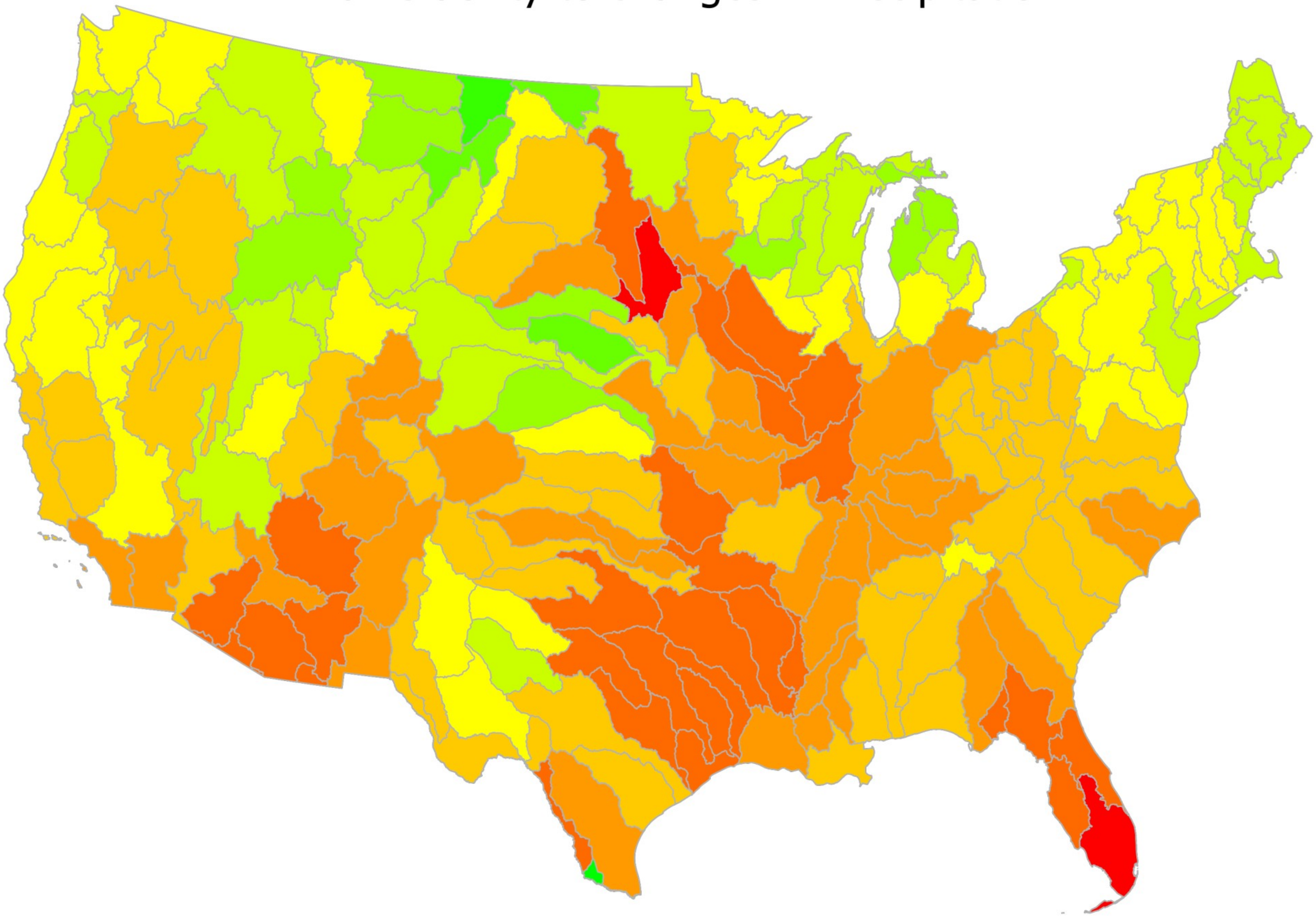
Ecological Water Supply Vulnerability



Plant Diversity Vulnerability



Vulnerability to changes in Precipitation



Vulnerability to Change in Temperature