

# Characterizing analyst bias in unsupervised classification of Landsat images

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# Water and Its Importance

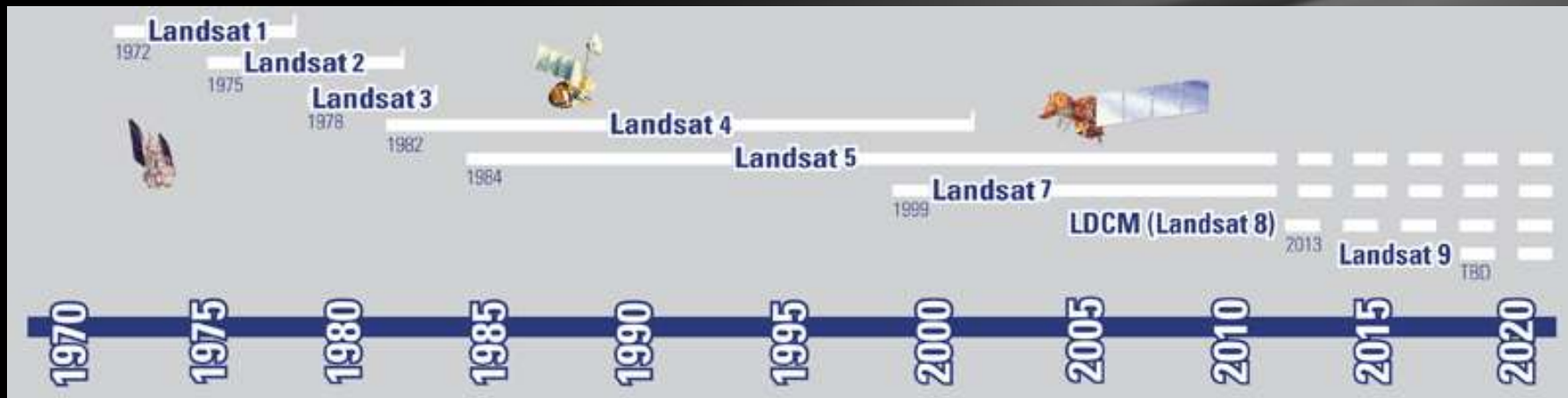
- Life
- Agriculture
- Recreation
- Aesthetics
- Power
- Dry states



# Remote Sensing Data

## Landsat 5

- 6 Bands
- Every 16 days



# Advantages and Limitations to Remote Sensing

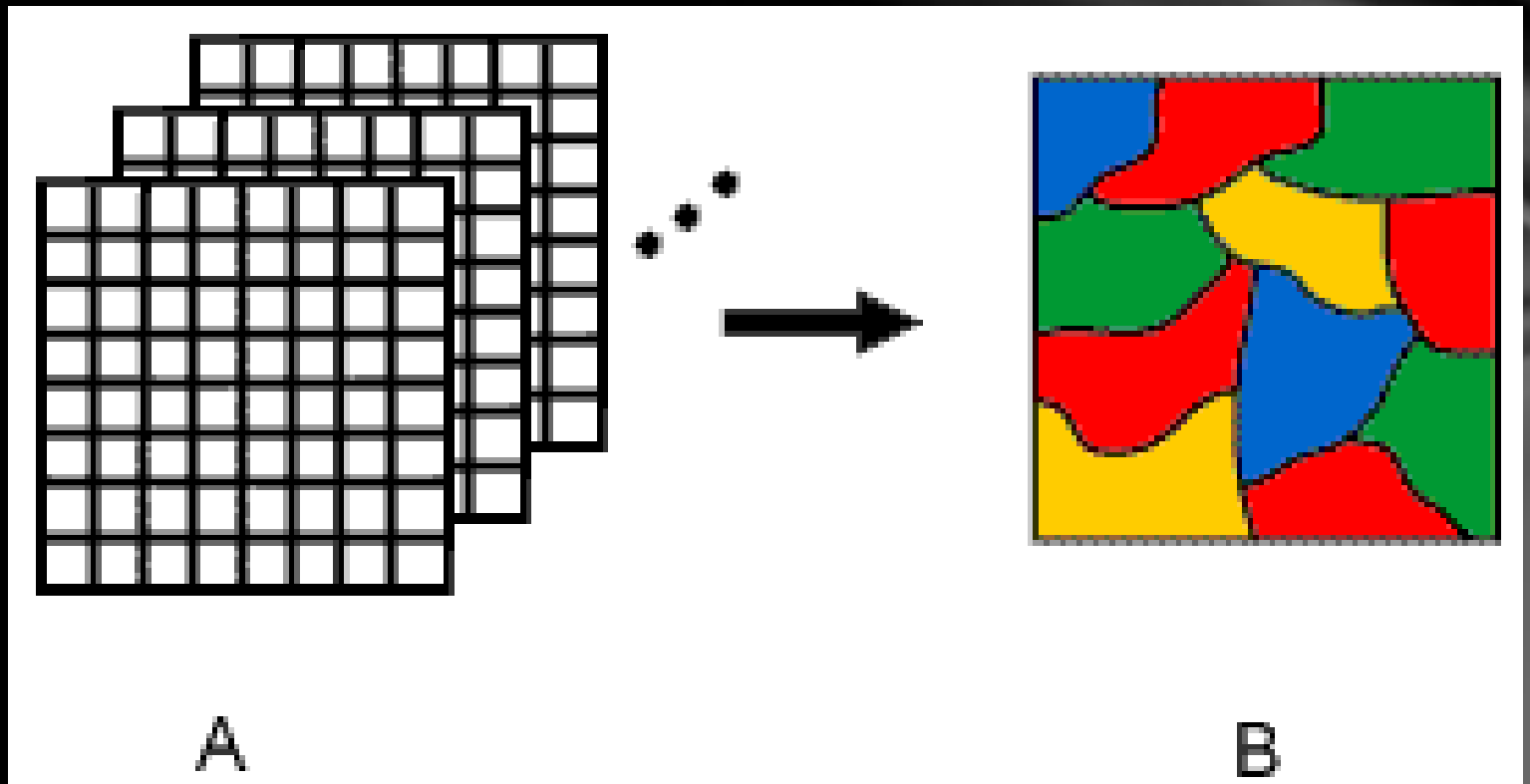
## Advantages

- Relatively easier than going to field
- Process large areas relatively fast

## Limitations

- Obtain right type of Data
- Cloud-free images may not be available at desired dates

# Goal: data in pixels -> information



Data in several bands are processed to create a map of classes (clusters)

# Image classification

## Several techniques

- Unsupervised, supervised, several advanced techniques

## Unsupervised

- Advantages
  - Limited knowledge of ground to start
  - Spectral signatures and ancillary data from ground can be used to assign clusters to classes
- Disadvantages
  - Operator bias
    - Training, knowledge of the area, consistency

# Study objectives

Assess operator bias in classifying the surface area of Keyhole Reservoir

Landsat data

- Two operators classified them independently
  - More or less same amount of training
  - Did not consult with each other
  - Used unsupervised classification
    - Exact number of bins, iterations, and convergence
  - Exact dates were masked to minimize potential bias

# Landsat image – infrared band combination



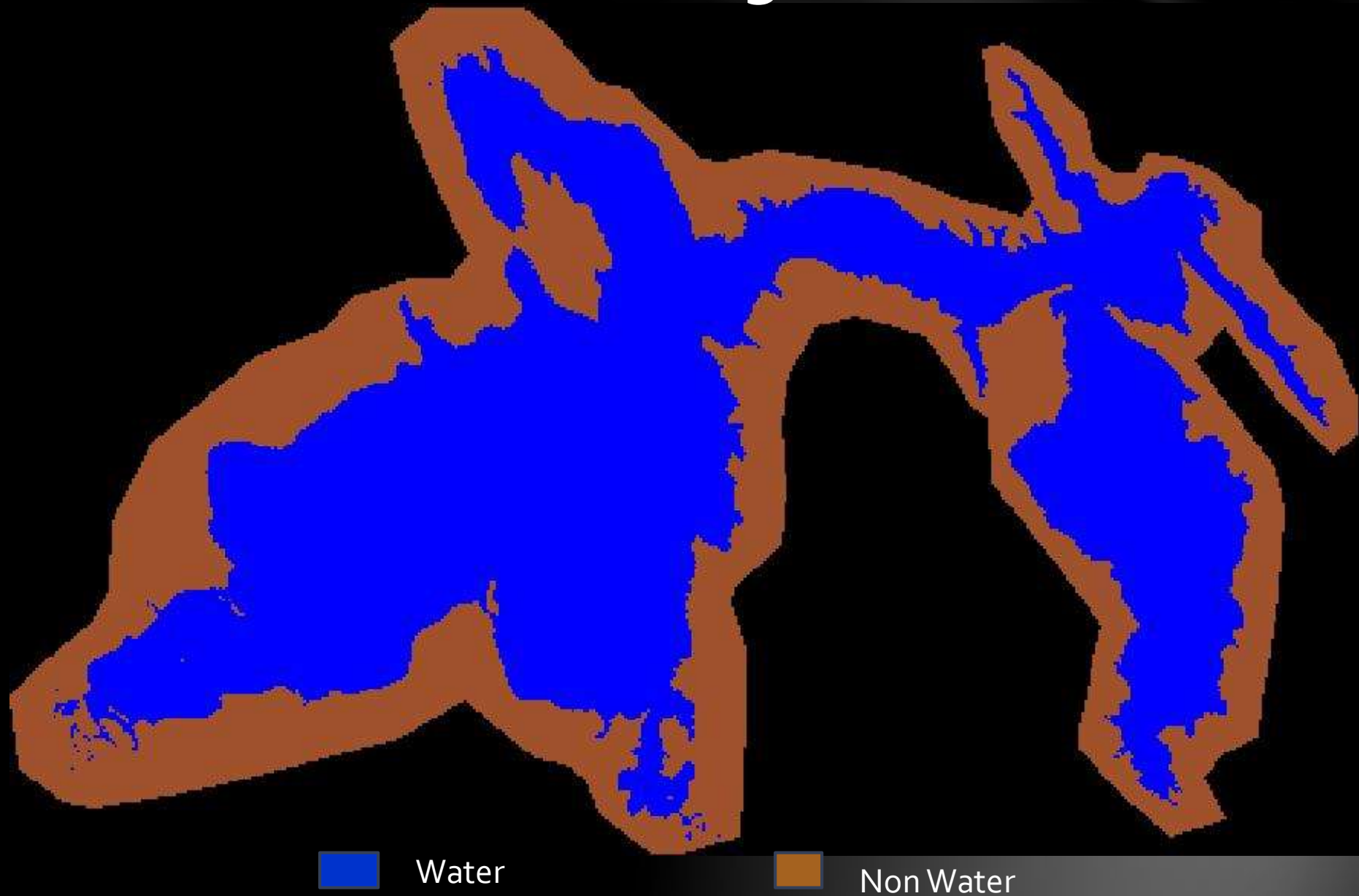


# Methods

8 Landsat images were between 1989- were classified

- Unsupervised Classification
  - 100 Bins (clusters), 500 Iterations, and .995 Convergence threshold
- Clusters were assigned to classes water or non-water
- Recoded to 1 (water) and 2 (non-water)
- 2 images for each year

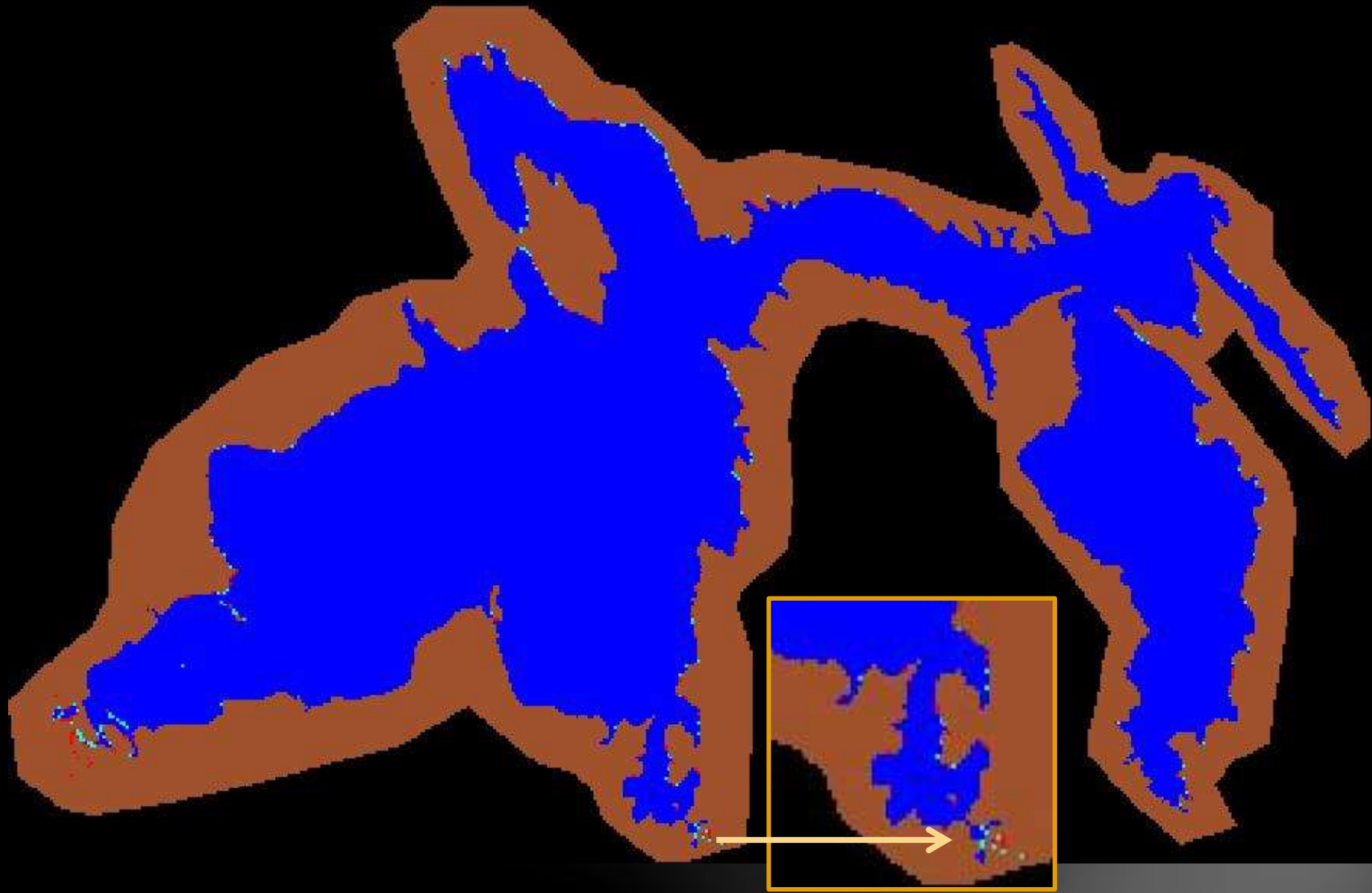
# Classified Landsat image



# Methods

## Comparison of each map pair

- If both maps agreed:
  - 1: it was water
  - 2: it was non-water
- If maps had disagreement
  - 3: non-water in map 1, water in map 2
  - 4: water in map 1, non-water in map 2
- Spatial modeler in ERDAS Imagine was used for this comparison
  - Output: new (agreement/disagreement) map



Water

Non Water

Bias #1

Bias #2

# Result – Contingency matrix for each agreement/disagreement map

		User 2 (area in ha)	
		Water	Non-water
User 1	Water	3422	17 (Bias #2)
	Non-water	18 (Bias #1)	2757

# Kappa agreement index

Measure of agreement between 2 maps

Value ranges between -1 and +1

+1: complete agreement (positive)

-1: complete agreement (negative)

For year 2000: Kappa value was 0.989

Most of the disagreement were confined to the edges

# Results: Kappa agreement values

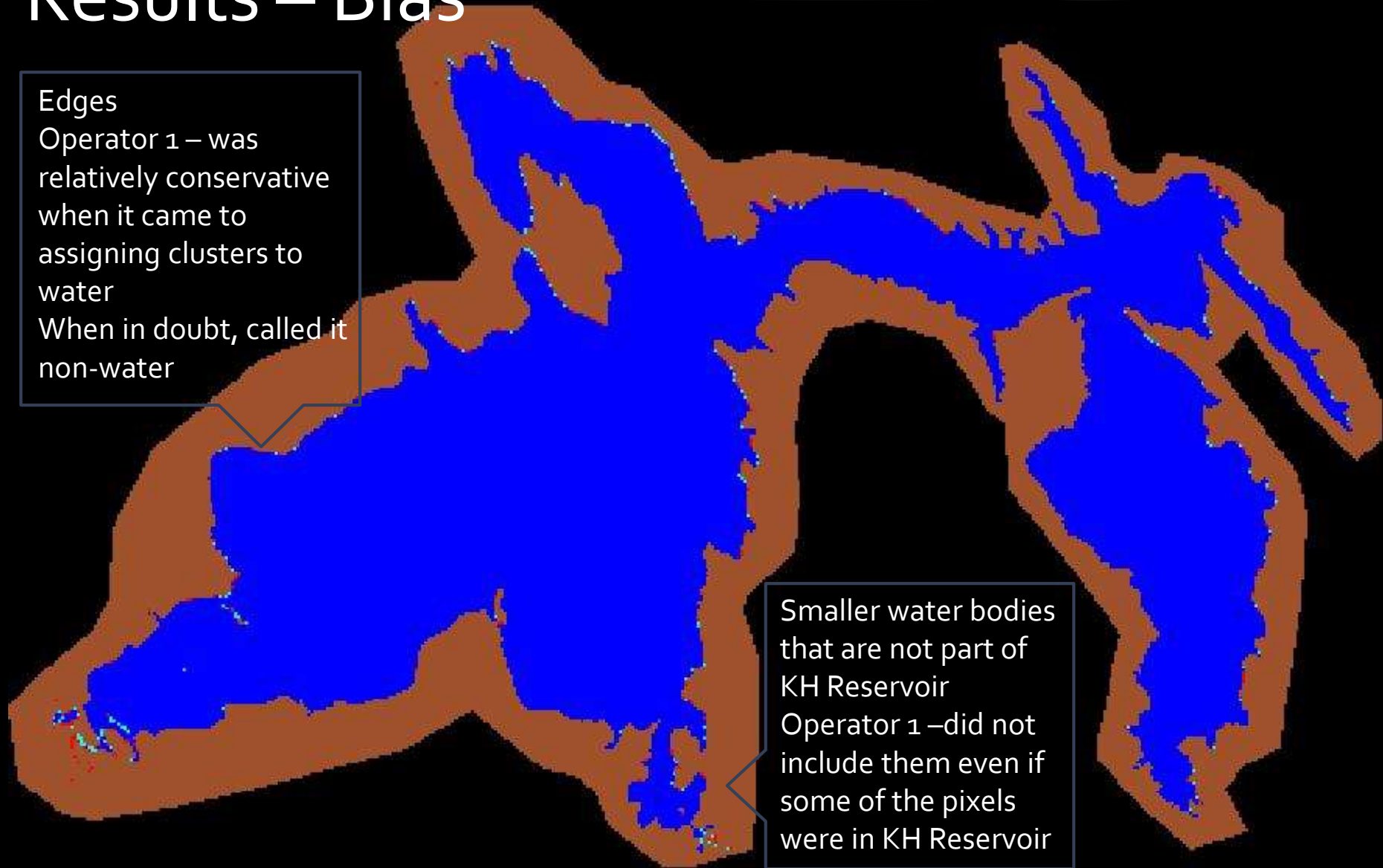
ba	8/15/1995	0.945
bb	8/17/1996	0.963
bc	8/20/1997	0.985
bd	8/23/1998	0.98
be	8/26/1999	0.989
ca	8/21/2000	0.989
cc	8/18/2002	0.982
cd	8/21/2003	0.98

# Results – Bias

## Edges

Operator 1 – was relatively conservative when it came to assigning clusters to water

When in doubt, called it non-water



Smaller water bodies that are not part of KH Reservoir

Operator 1 –did not include them even if some of the pixels were in KH Reservoir

 Water

 Non Water

 Bias #1

 Bias #2



# Discussion

## Lessons learned

- Interpreting deeper and clear part of the Key Hole Reservoir was consistent
  - Edges were problematic

## How to minimize bias in future work?

- Define a standard on what is to be classified as “water”
  - Use defined spectral values of riparian veg and water
- Inclusion of edges can be determined by use
  - Water allocations for irrigation activities

# Acknowledgement

WyomingView scholarship

Funded by AmericaView/USGS

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