Spatial Decision Tree: A Novel Approach to Land-Cover Classification

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Highlights

- Public engagement with science and technology :
  - Coursera MOOC, “From GPS and Google Maps to Spatial Computing”,
  - reached 21,844 participants across 182 countries

- Enhanced infrastructure for education
  - Interdisciplinary survey paper on spatiotemporal change footprint discovery
  - Encyclopedia of GIS (Springer, 2nd Edition): Multiple articles on climate change
  - APA/IEEE Computing in Sc. & Eng. special issue on “Computing and Climate”

- Enhanced infrastructure for research
  - Spatial decision trees can help improve wetland maps for climate models

Highlights

- Understanding
  - Large semantic gap between Data Science and Climate Science
    - Data Science results are hard to interpret in Climate Science
  - Data Science assumptions violate laws of physics
    - unnecessary errors, e.g., salt and pepper noise
- Concepts:
  - Physics-Guided Data Mining concepts are potentially transformative
  - Ex. Spatial Decision Trees: explicit physics (e.g., continuity) to wetland mapping
  - Ex. Intervals of Persistent Change detection uses Physics (e.g., violation of continuity)

Spatial Decision Tree: Motivation

- Wetland mapping:
  - Climate Change: wetlands – major source of methane[1]
  - manage natural disasters, defense against hurricanes, buffer of floods.
  - maintain biodiversity, habitats to wildlife species

Greenhouse Gas Methane

flood control

wildlife habitats

[1]Bryan Walsh, How Wetlands Worsen Climate Change, Time, Magazine, 2010

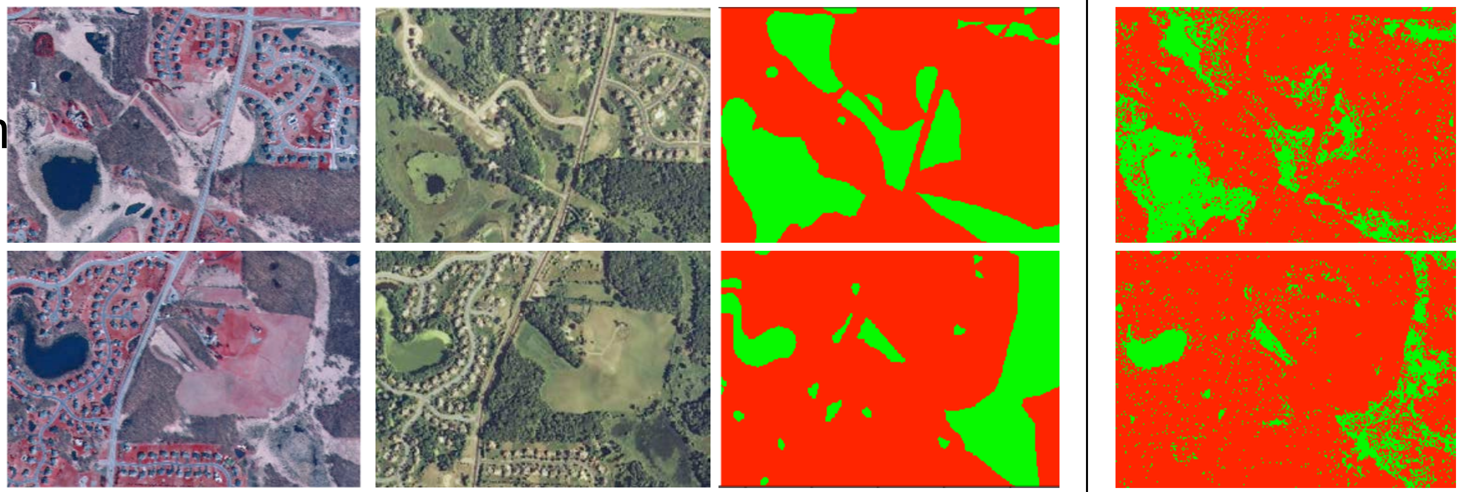
Wetland Mapping Example

Input:

Output:

train

test



(a) aerial photo (b) aerial photo (c) true classes (d) DT prediction

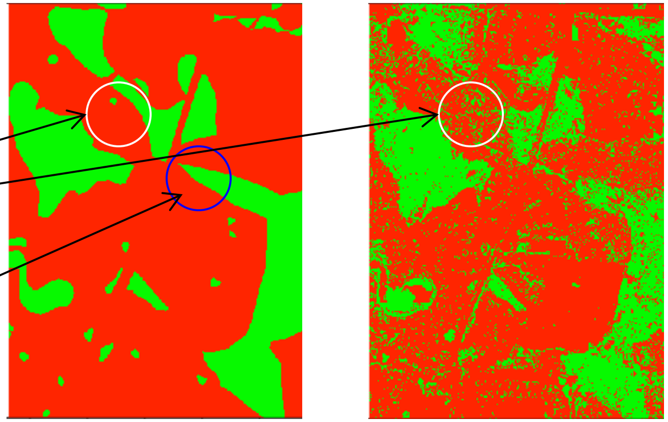
wetland dry land

Training samples: upper half
Test samples: lower half
Spatial neighborhood:

DT: decision tree

Challenges

- Spatial autocorrelation effect
  - samples violate i.i.d. assumption
  - salt-and-pepper noise (white circles)
- Spatial anisotropy
  - asymmetric spatial neighborhood (blue circle)
- Spatial heterogeneity
  - areas with the same features correspond to distinct class labels (white circle)
- High computational cost
  - large amount of focal computation with different spatial neighborhoods sizes



Ground truth classes Decision tree prediction

feature maps ground truth

wetland dry land

Problem Statement

- Given:
  - training & test samples from a raster spatial framework
  - spatial neighborhood, its maximum size
- Find:
  - a (spatial) decision tree
- Objective:
  - minimize classification error and salt-and-pepper noise
- Constraint:
  - training samples are contiguous patches
  - spatial autocorrelation, anisotropy, and heterogeneity exist
  - training dataset can be large with high computational cost

Example with Decision Tree

Input:

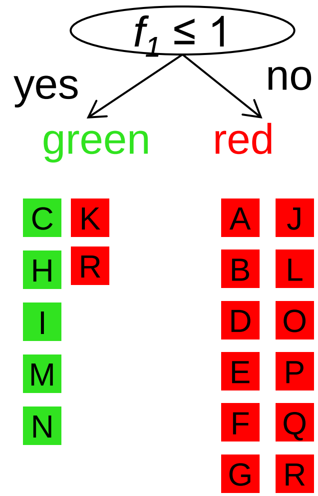
ID	f_1	f_2		class
A	3	3		red
B	3	3		red
C	1	2		green
D	3	1		red
E	3	1		red
F	3	1		red
G	3	3		red
H	1	2		green
I	1	2		green
J	3	1		red
K	1	1		red
L	3	1		red
M	1	2		green
N	1	2		green
O	3	1		red
P	3	1		red
Q	3	1		red
R	1	1		red

pixel id

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R

Output:

decision tree



predicted map

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R

salt-and-pepper noise pixel K from decision tree

In this example, Gamma index Γ_1 on feature f_1 is unique. Most often, Γ_1 is computed on the fly.

Related Work Summary

single decision tree

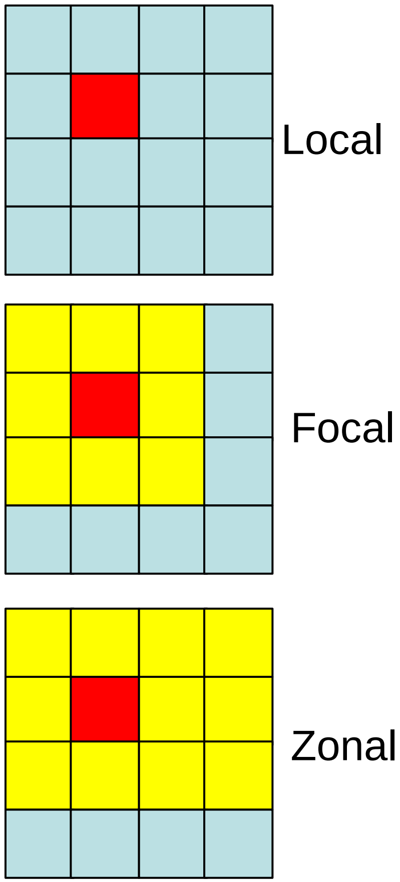
traditional decision tree **spatial decision tree**

	Existing Work	Proposed Work
Tree	local feature test & information gain:	focal feature test & spatial information gain:
Ensemble	bootstrap sampling:	geographic space partitioning:

random forest ensemble **spatial ensemble**

ensemble of decision trees

Proposed Approach – Focal Test



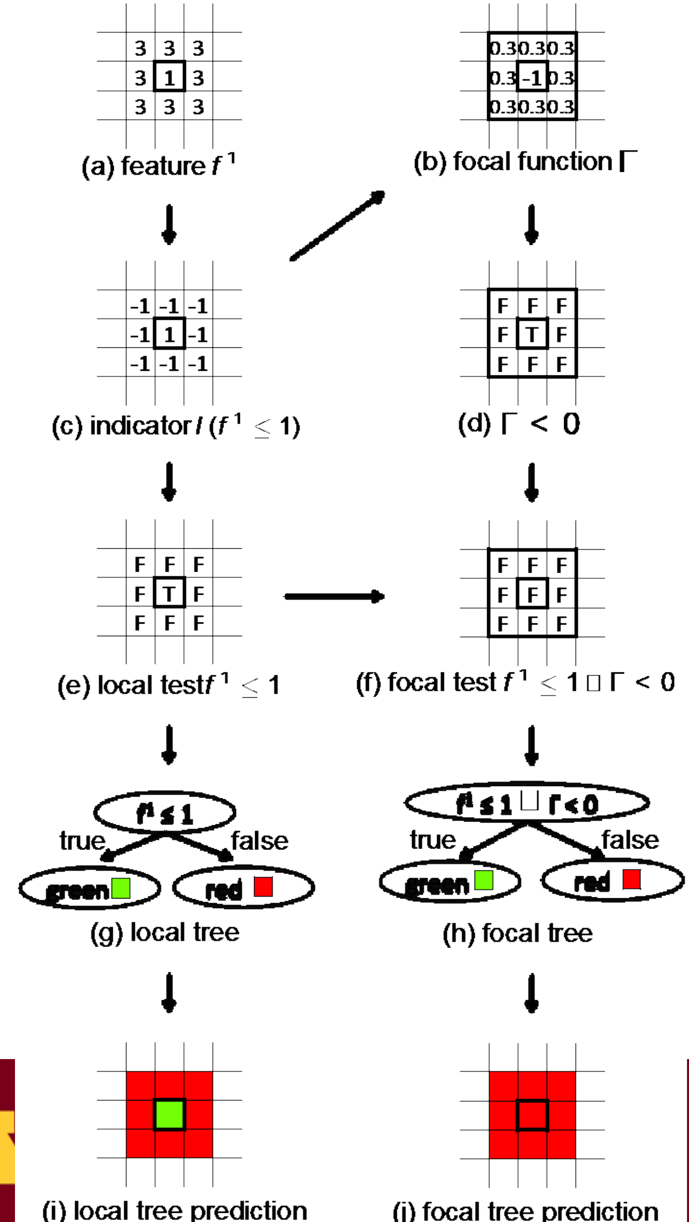
- Focal feature test
  - Test both *local* and *focal* (neighborhood) information
  - focal test uses local autocorrelation statistics, e.g., Gamma index

Proposed Approach - 2

- tree traversal direction depends on both *local* and *focal* (neighborhood) information
- focal test uses local autocorrelation statistics, e.g., Gamma index (Γ)
- neighborhood

$$\Gamma_i = \frac{\sum_j S_{i,j} W_{i,j}}{\sum_j W_{i,j}}$$

where:
i, j: pixel locations
$S_{i,j}$: similarity between location i and j
$W_{i,j}$ is adjacency matrix element

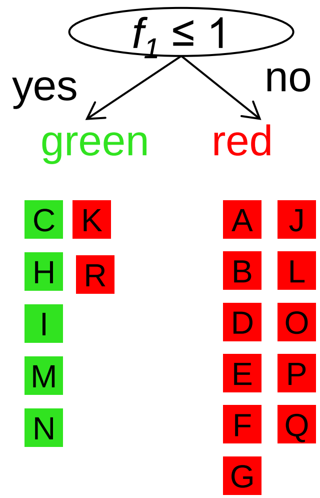


Example – Focal Tests

traditional decision tree

inputs: table of records

ID	f_1	f_2	Γ_1	class
C	1	2	1	green
H	1	2	1	green
I	1	2	1	green
K	1	1	-1	red
M	1	2	1	green
N	1	2	1	green
R	1	1	-1	red
A	3	3	1	red
B	3	3	1	red
D	3	1	1	red
E	3	1	1	red
F	3	1	1	red
G	3	3	1	red
J	3	1	1	red
L	3	1	1	red
O	3	1	1	red
P	3	1	1	red
Q	3	1	1	red



predicted map

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R

pixel id

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R

spatial decision tree

inputs: feature maps, class map

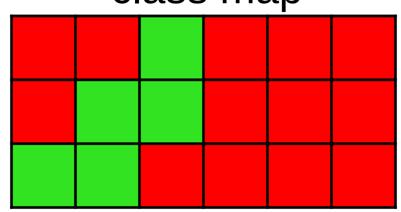
feature f_1

3	3	1	3	3	3
3	1	1	3	1	3
1	1	3	3	3	1

feature f_2

3	3	2	1	1	1
3	2	2	1	1	1
2	2	1	1	1	1

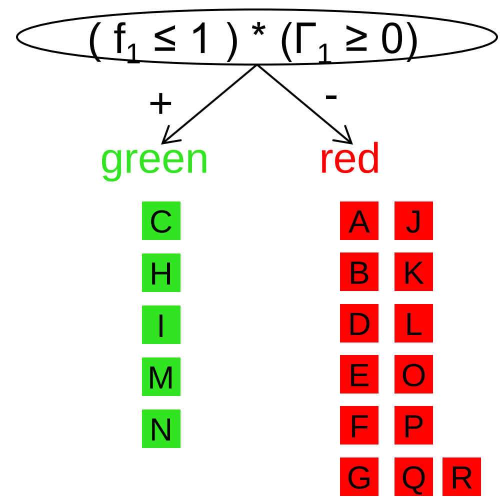
class map



adaptive neigh., 3 by 3

focal function Γ_1

1	1	1	1	1	1
1	1	1	1	-1	1
1	1	1	1	1	-1

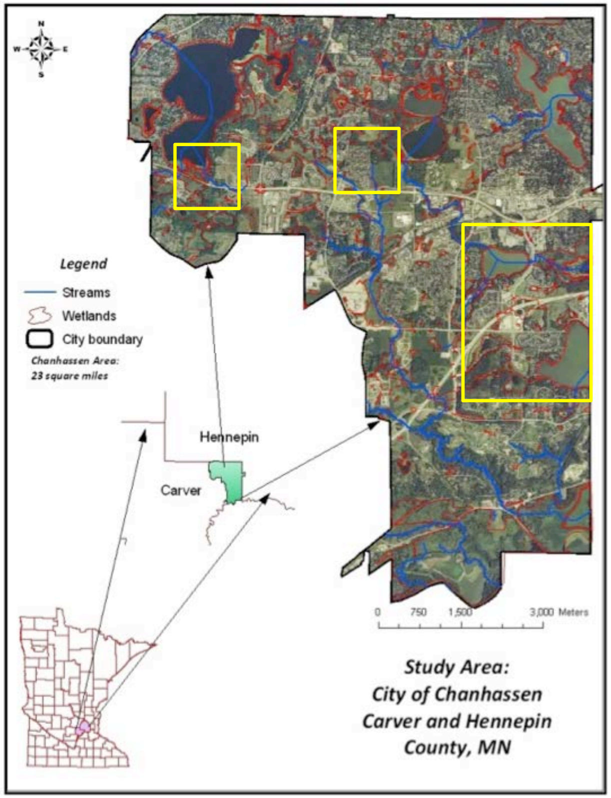


predicted map

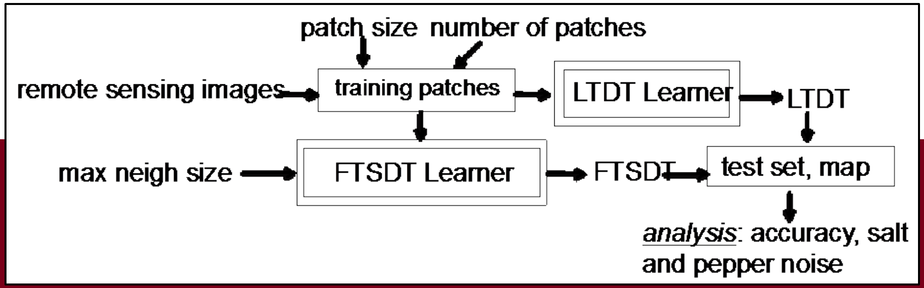
A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R

Evaluation: Case Study

- Questions to answer:
  - SDT v.s. DT - classification accuracy
  - SDT v.s. DT - salt-and-pepper noise
  - Computational scalability of SDT
- Dataset:
  - Chanhassen, MN (wetland mapping)
    - 2 classes: wetland, dry land
    - features: high resolution (3m*3m) aerial photos (RGB, NIR, NDVI) in 2003, 2005, 2008
    - Training set: randomly select circular patches; Test set: remaining pixels on the scene; Three scenes are used.
    - Max neighborhood size: 11 pixels by 11 pixels



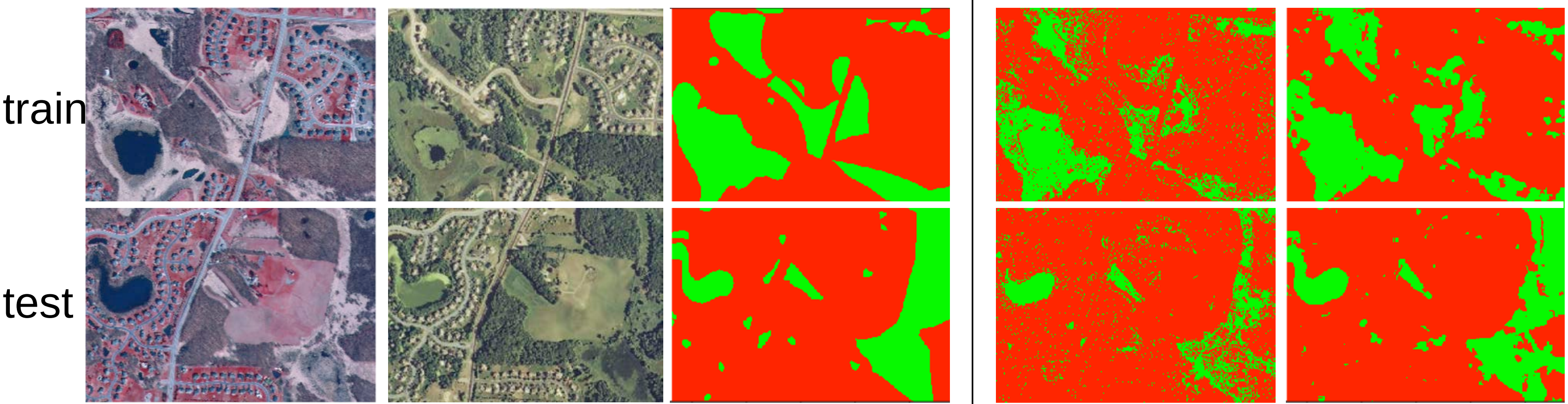
Chanhassen, MN



Wetland Mapping Comparison – Scene 1

Input:

Output:



(a) aerial photo (b) aerial photo (c) true classes (d) DT prediction (e) SDT prediction

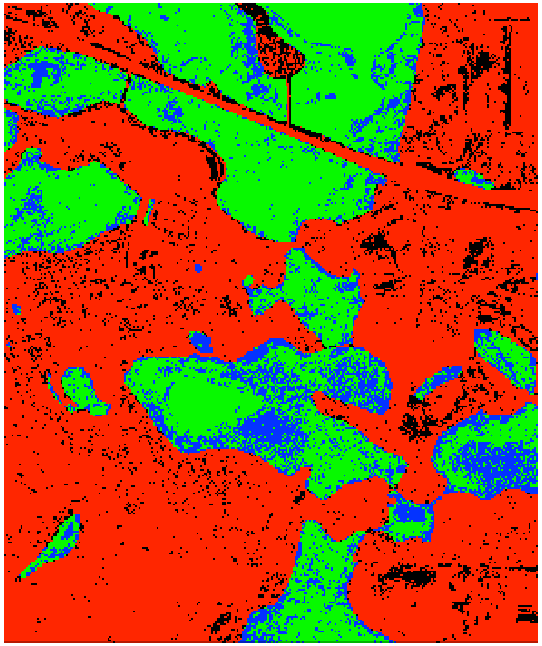
wetland dry land

Training samples: upper half
Test samples: lower half
Spatial neighborhood:

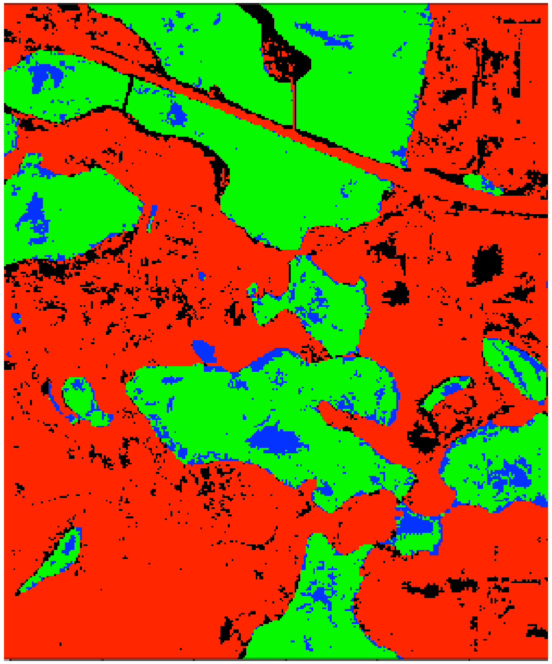
DT: decision tree
SDT: spatial decision tree
(11x11 neighborhood)

Classification Performance – Scene 2

decision tree (DT)



spatial decision tree (SDT)



true wetland
true dryland
false wetland
false dryland

Trends:

1. DT: salt-and-pepper noise
2. SDT improve accuracy, salt-and-pepper noise levels

Evaluation: Classification Performance

Classification accuracy and salt-and-pepper noise level

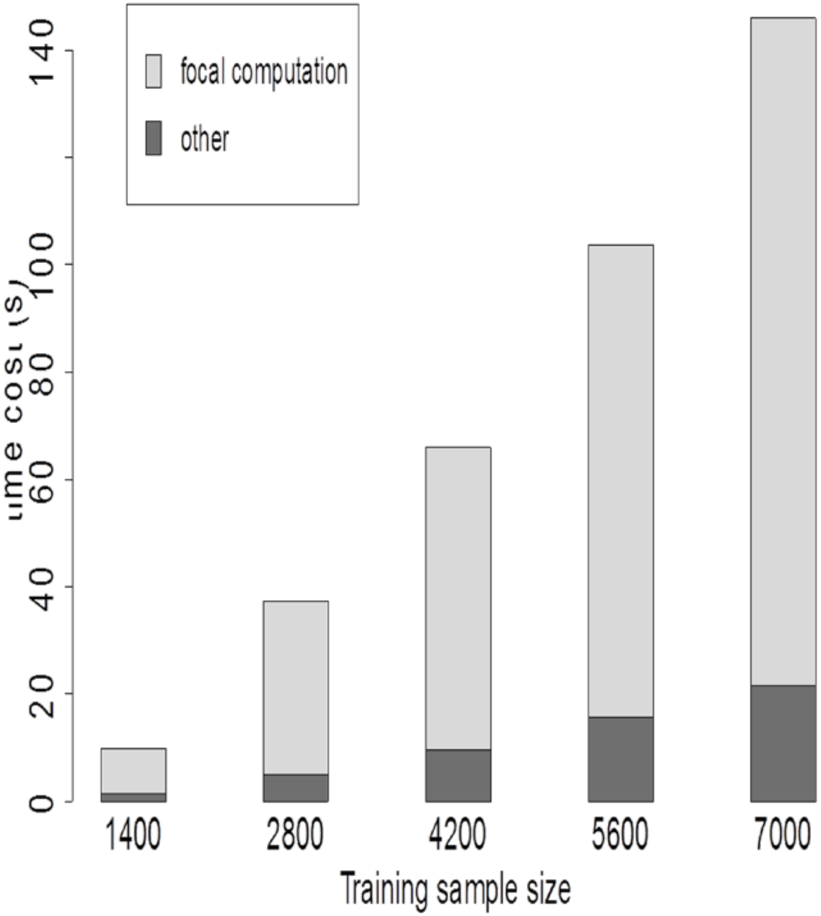
Model	Confusion Matrix		Prec.	Recall	F measure	Autocorrelation
DT	99,141	**10,688**	0.81	0.75	0.78	0.87
	15,346	45,805				
SDT	99,390	**10,439**	0.83	0.83	0.83	0.93
	10,618	50,533				

Significance test between confusion matrices:

Model	Khat	Khat Variance	Z-score	significance
DT	0.66	$3.6*10^{-6}$	26.8	significant
SDT	0.73	$3.0*10^{-6}$		

Spatial decision tree reduces salt-and-pepper noise and misclassification errors, compared with decision trees.

Computational Bottleneck Analysis



Analysis:

1. focal computation takes the vast majority of the time

2. focal computation cost increases faster with the training set size

Focal computation is the bottleneck!

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Incremental Update Approach

Key idea: reduce redundant focal computation by reusing results across candidate test thresholds Γ(f < δ)

1	9	9	9
2	9	9	9
3	8	7	6
4	5	5	5

(a) feature values

1	-1	-1	-1
-1	-1	-1	-1
-1	-1	-1	-1
-1	-1	-1	-1

-1	0.6	1	1
0.6	0.75	1	1
1	1	1	1
1	1	1	1

(b) indicators, focal values for δ=1

1	-1	-1	-1
1	-1	-1	-1
-1	-1	-1	-1
-1	-1	-1	-1

-0.33	0.2	1	1
-0.6	0.5	1	1
0.6	0.75	1	1
1	1	1	1

(c) indicators, focal values for δ=2

candidate δ
{1, 2, 3, 4, 5,
6, 7, 8}

$$\Gamma_i = \frac{\sum_j W_{i,j} I_i I_j}{\sum_j W_{i,j}}$$

1	-1	-1	-1
1	-1	-1	-1
1	-1	-1	-1
-1	-1	-1	-1

-0.33	0.2	1	1
-0.2	0.25	1	1
-0.6	0.5	1	1
0.33	0.6	1	1

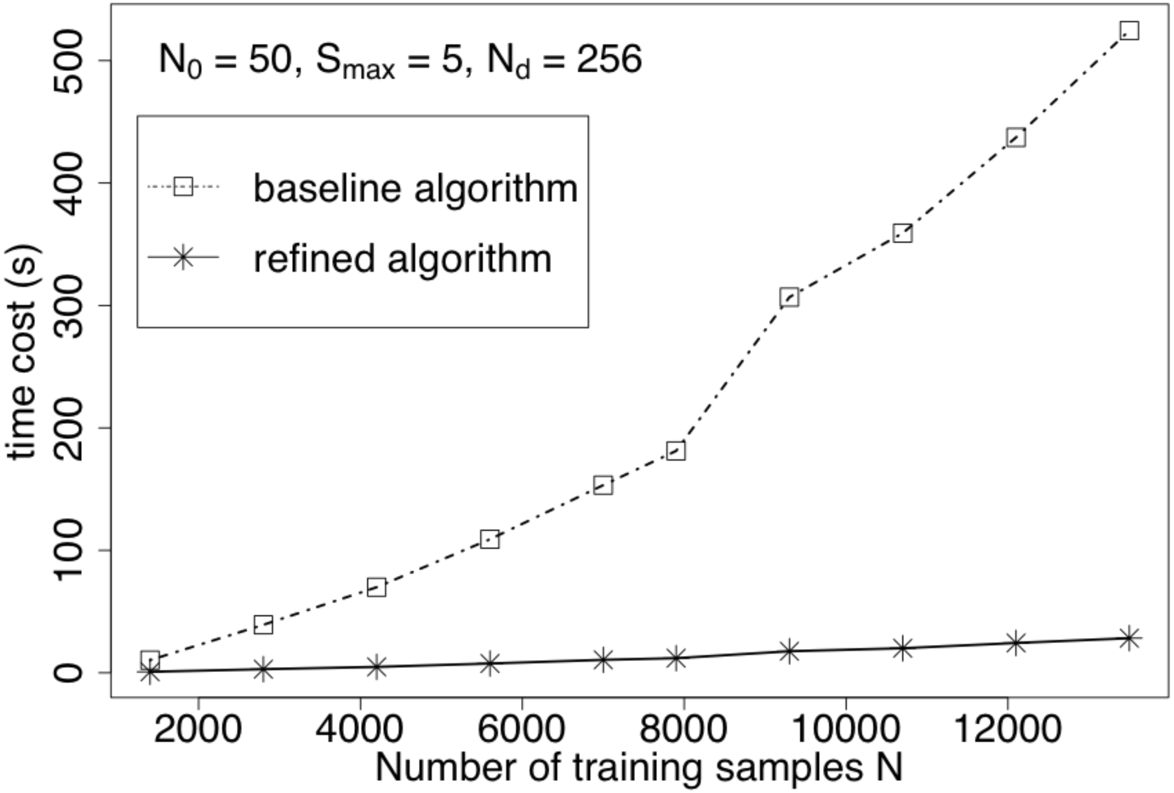
(d) indicators, focal values for δ=3

1	-1	-1	-1
1	-1	-1	-1
1	-1	-1	-1
1	-1	-1	-1

-0.33	0.2	1	1
-0.2	0.25	1	1
-0.2	0.25	1	1
-0.33	0.2	1	1

(e) indicators, focal values for δ=4

Evaluation of Computational Cost



Notation of symbols

F	# of features (12)
N	# of samples
N_d	# of distinct feature values
S_{max}	max neigh size
N_0	min node size

The refined algorithm significantly reduces computational cost.

Conclusions

- Ignoring auto-correlation leads to errors, e.g., salt-n-pepper noise
- Proposed a novel spatial decision tree approach with focal tests
- Evaluation shows that proposed method reduced salt-n-pepper noise
  - And improved classification accuracy
- Designed computational refinements to improve scalability

Publications on Spatial Decision Trees

[1] Z. Jiang, S. Shekhar, X. Zhou, J. Knight, J. Corcoran: Focal-Test-Based Spatial Decision Tree Learning. **IEEE Transactions on Knowledge and Data Engineering (TKDE)** 27(6): 1547-1559 (2015)

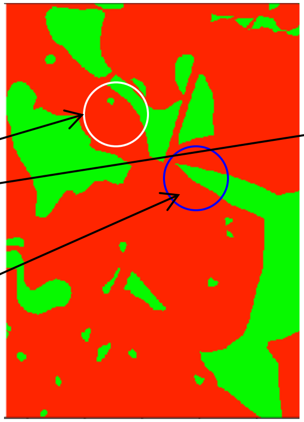
[2] Z. Jiang, S. Shekhar, X. Zhou, J. Knight, J. Corcoran: Focal-Test-Based Spatial Decision Tree Learning: A Summary of Results. **IEEE International Conference on Data Mining (ICDM)** 2013: 320-329

[3] Z. Jiang, S. Shekhar, P. Mohan, J. Knight, and J. Corcoran. "Learning spatial decision tree for geographical classification: a summary of results.” **International Conference on Advances in GIS**, pp. 390-393. ACM, 2012.

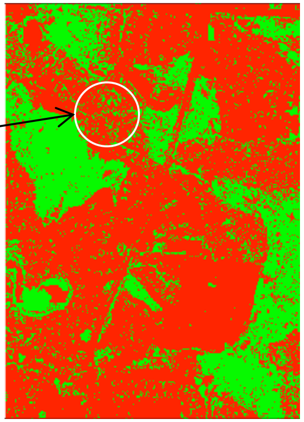
[4] Z. Jiang, S. Shekhar, A. Kamzin, and J. Knight. "Learning a Spatial Ensemble of Classifiers for Raster Classification: A Summary of Results.” **IEEE International Conference on Data Mining Workshop**, IEEE, 2014.

Challenges Revisited

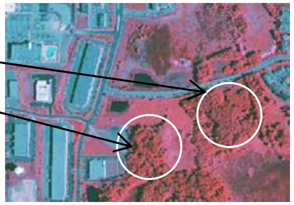
- Spatial autocorrelation effect
  - samples violate i.i.d. assumption
  - salt-and-pepper noise (white circles)
- Spatial anisotropy
  - asymmetric spatial neighborhood (blue circle)
- Spatial heterogeneity
  - areas with the same features correspond to distinct class labels (white circle)
- High computational cost
  - large amount of focal computation with different spatial neighborhoods sizes



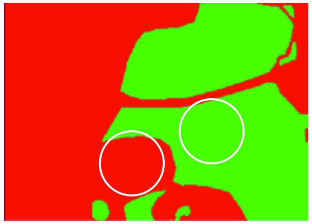
Ground truth classes



Decision tree prediction



feature maps



ground truth

wetland dry land

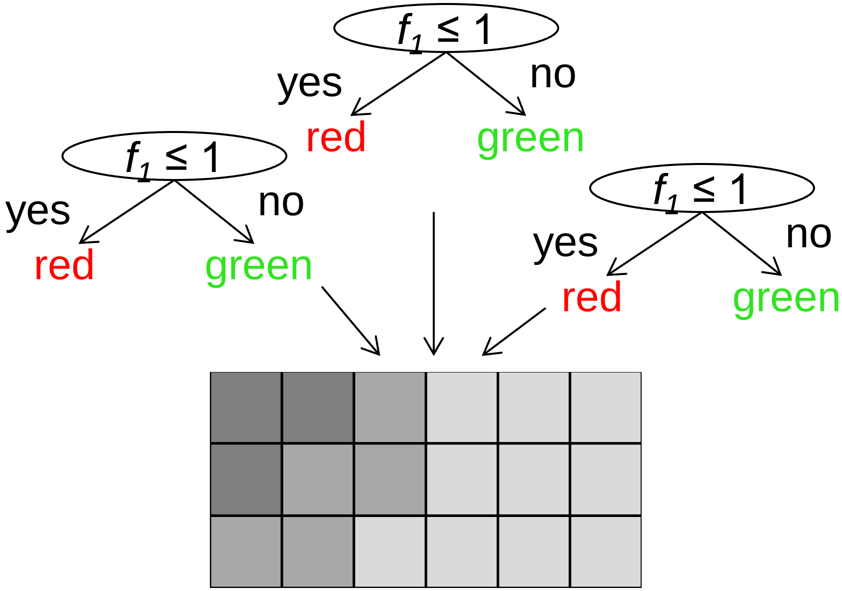
Future Work

- Key idea I: focal feature test
  - tree traversal direction depends on both *local* and *focal* (neighborhood) information
  - focal test uses local autocorrelation statistics, e.g., Gamma index
- Key idea II: spatial information gain (SIG)
  - SIG = Info. Gain * α + Spatial Autocorrelation * (1 – α)
  - tree node test selection depends on both *class purification* and *autocorrelation structure*
- Key idea III: spatial ensemble of local trees
  - geographic space partitioning, learn local classifiers

Proposed Approach: Spatial Ensemble

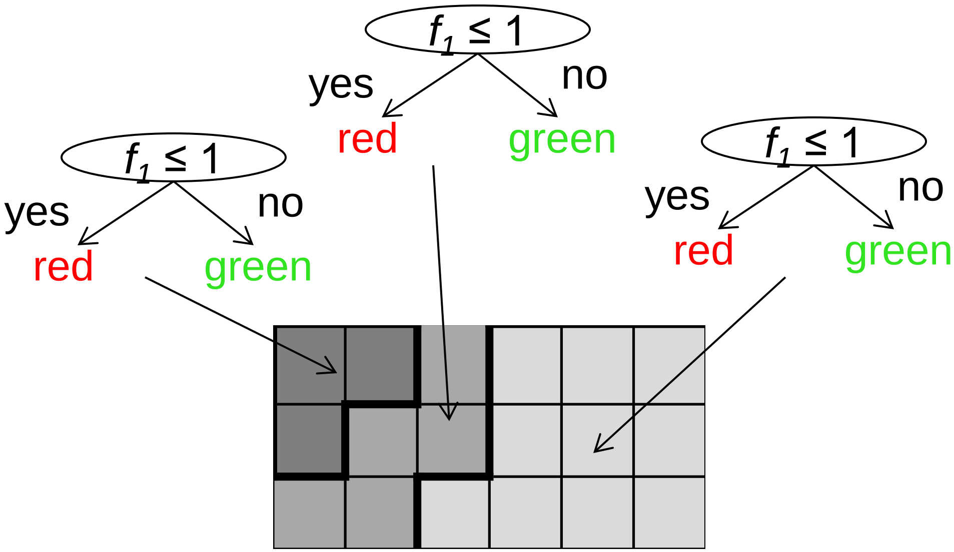
traditional ensemble
(random forest)

1. assume i.i.d. distribution
2. bootstrap sampling
3. learn a tree from one sampling
   with random feature subsets



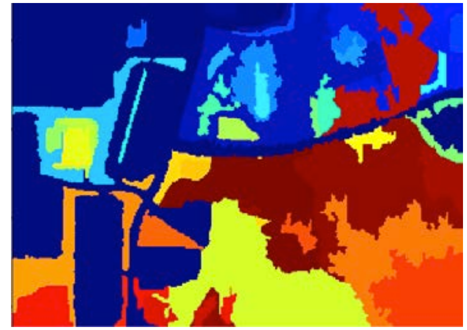
spatial ensemble
(spatial forest)

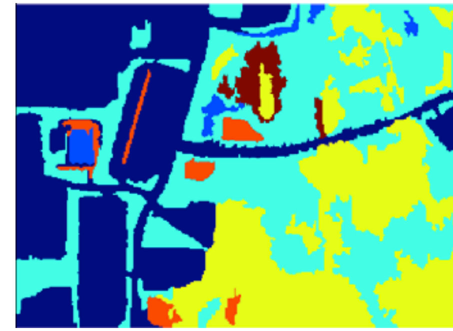
1. assume spatial heterogeneity
2. spatial partitioning
3. learn local tree model in each partition




one feature image

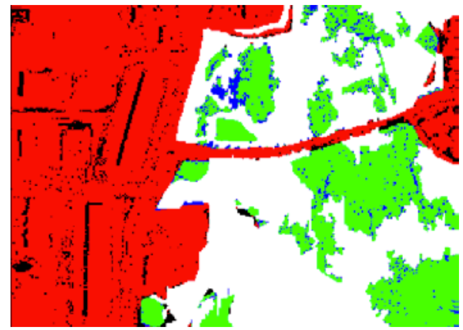

ground truth

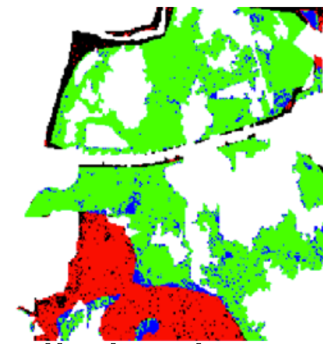

spatial cluster (islands)


archipelagos

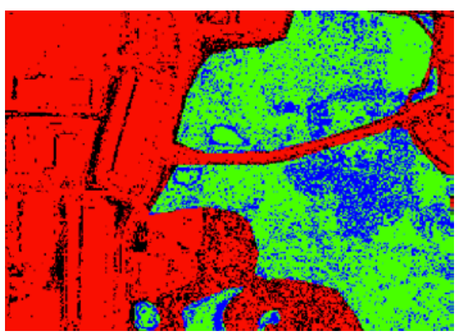

partition P1

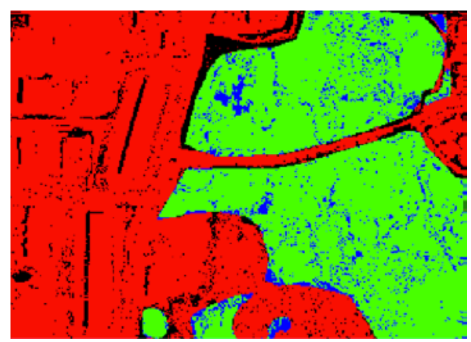

partition P2

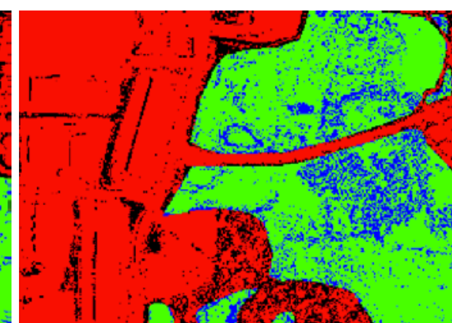

prediction in P1


prediction in P2


ground truth


single DT prediction


spatial ensemble


random forest