

Lessons and challenges in land change modeling as revealed by map comparisons

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Master of Applied Statistics, The Ohio State University

PhD, State University of New York / College of Environmental Science and Forestry



Major Points

1. We analyzed results of thirteen cases of model applications.
2. We solicited responses in a variety of ways.
3. This presentations summarizes the nine most important lessons.

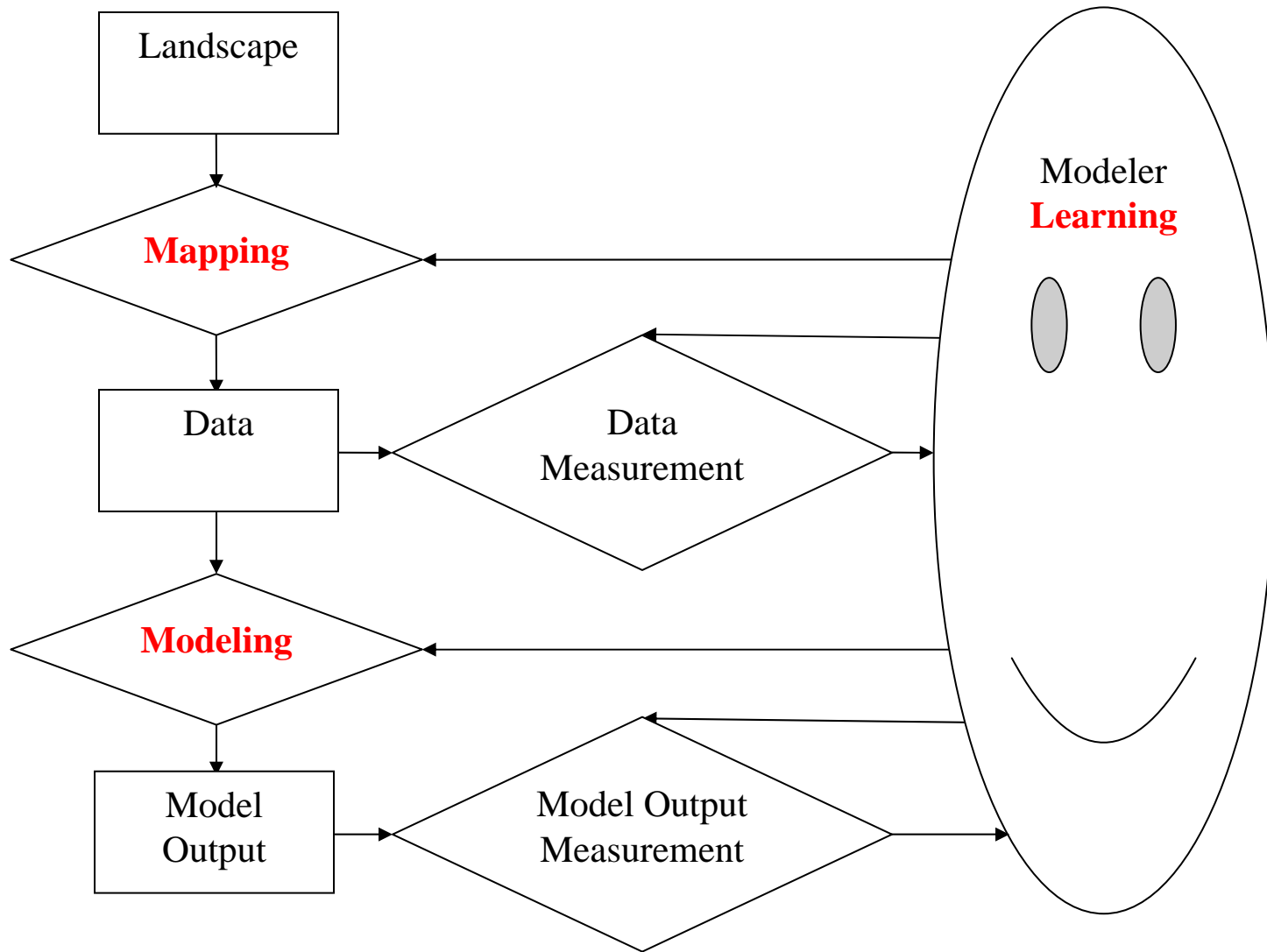
Exercise Guidelines

- We invited modelers to submit:
 - Reference Map of Time 1,
 - Reference Map of Time 2,
 - Prediction Map of Time 2,
 - Criterion to evaluate the maps.
- Seven laboratories participated.

Contributors' Twelve Sites

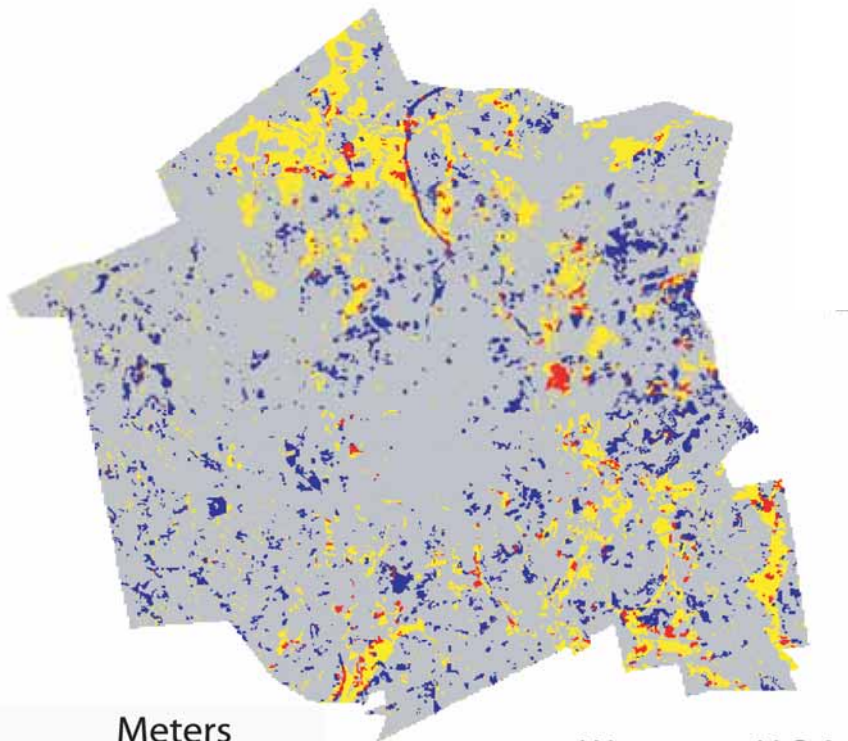


Flows of information in research

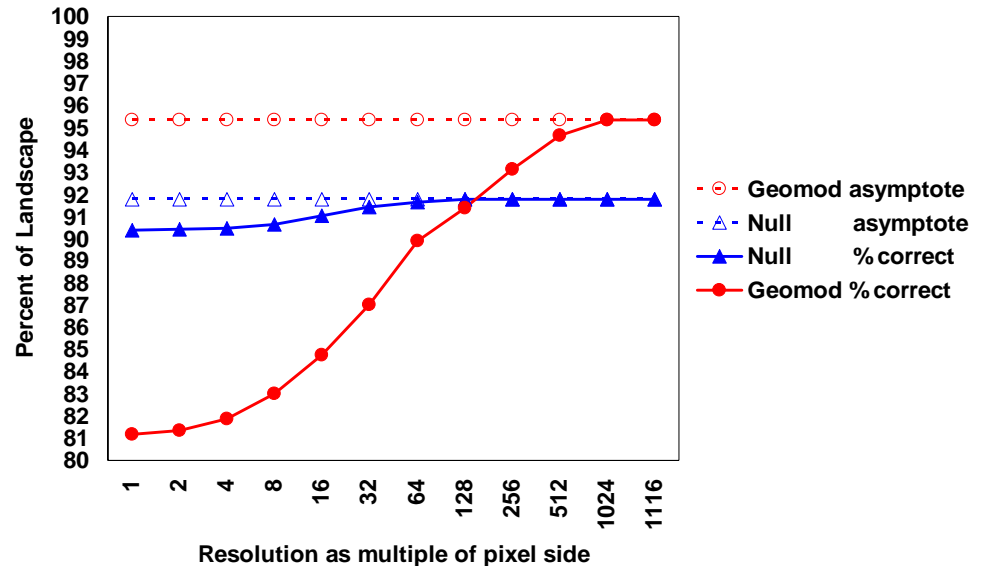


Mapping: to select relevant resolutions

Most of the error is due to predicting the wrong location by not more than 4 kilometers.

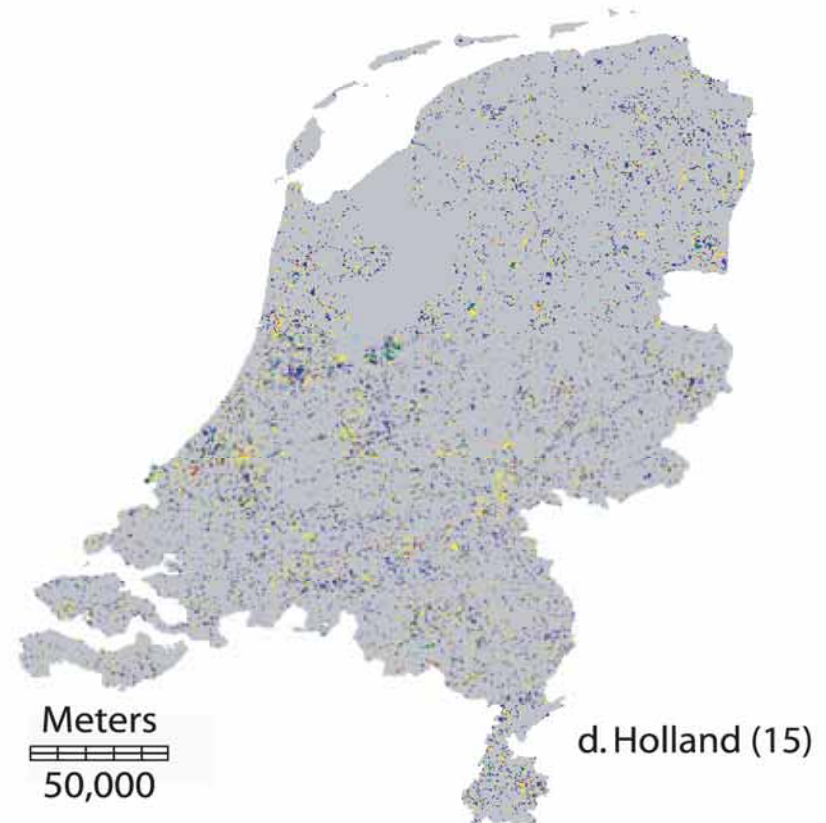
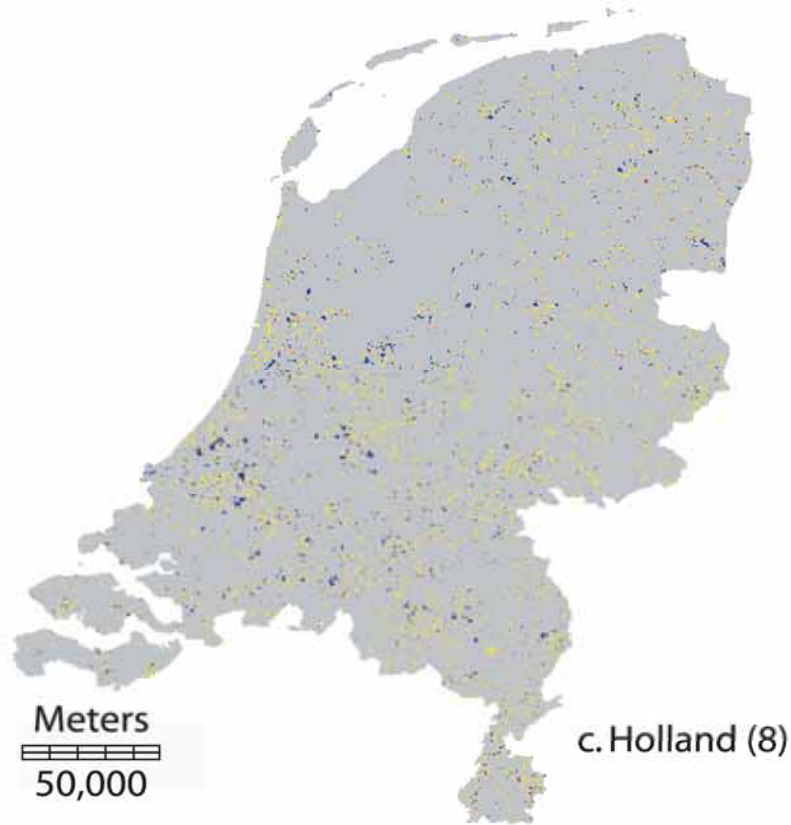


a. Worcester, U.S.A.

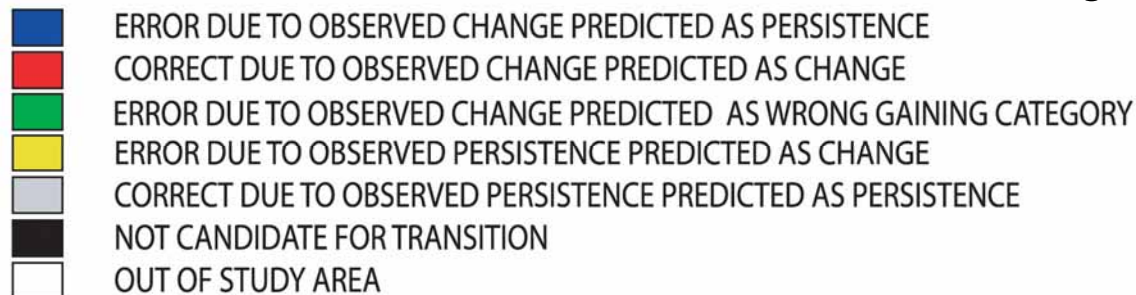


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- NOT CANDIDATE FOR TRANSITION
- OUT OF STUDY AREA

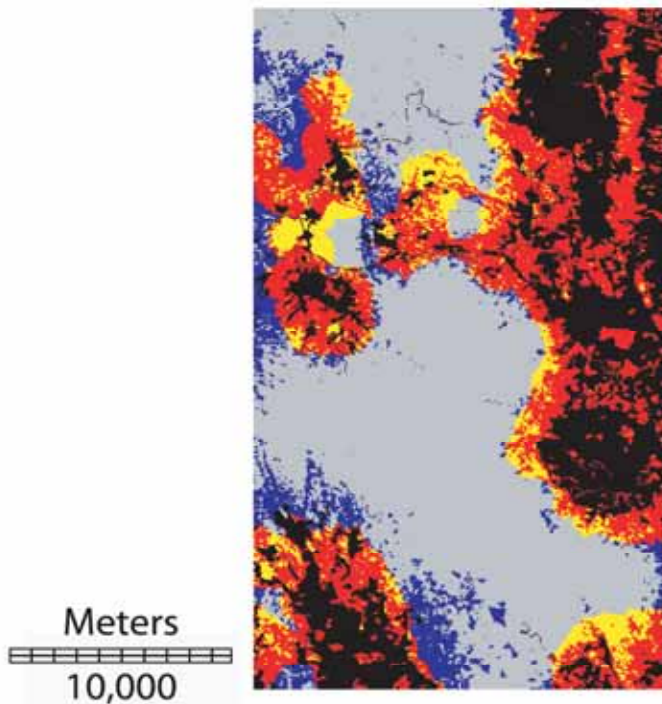
Mapping: to prepare data appropriately



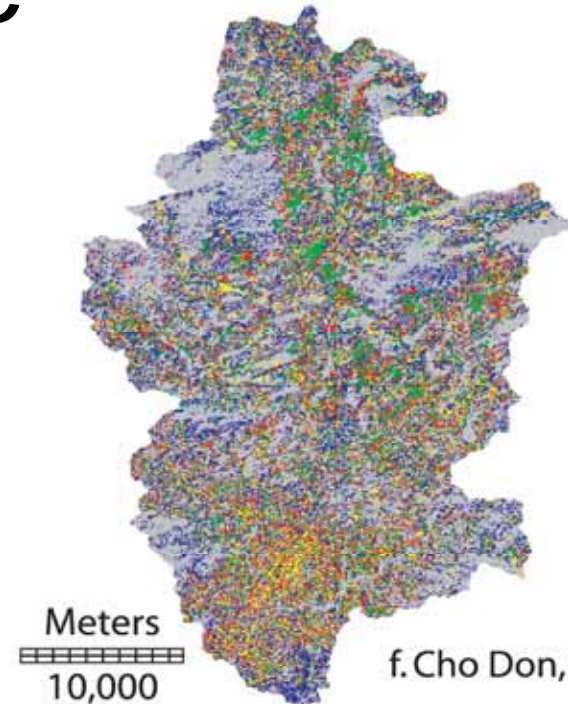
Artifacts due to data format account for the largest errors in Holland(8).



Mapping: to differentiate types of land change



e. Perinet, Madagascar

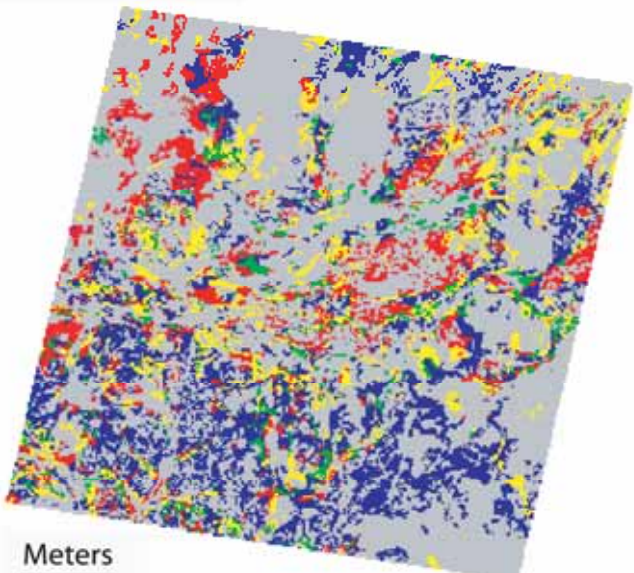


f. Cho Don, Vietnam

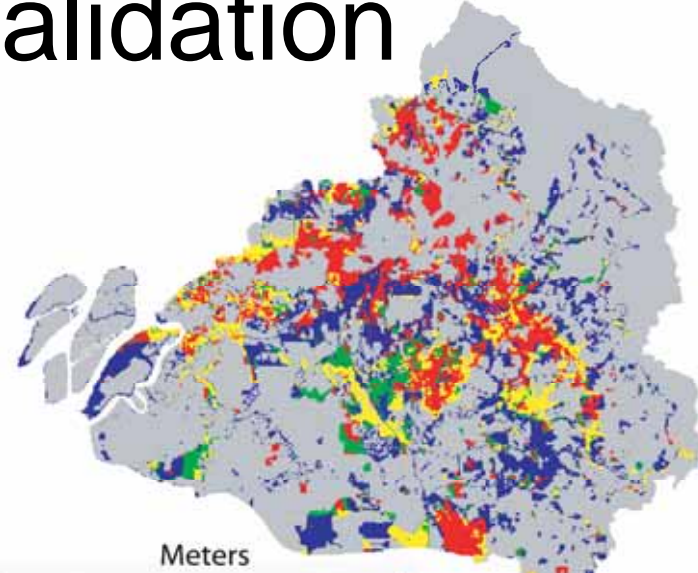
Perinet shows only forest loss, which is pure quantity change.
Cho Don shows simultaneous gains and losses of multiple categories, which is mostly location change.

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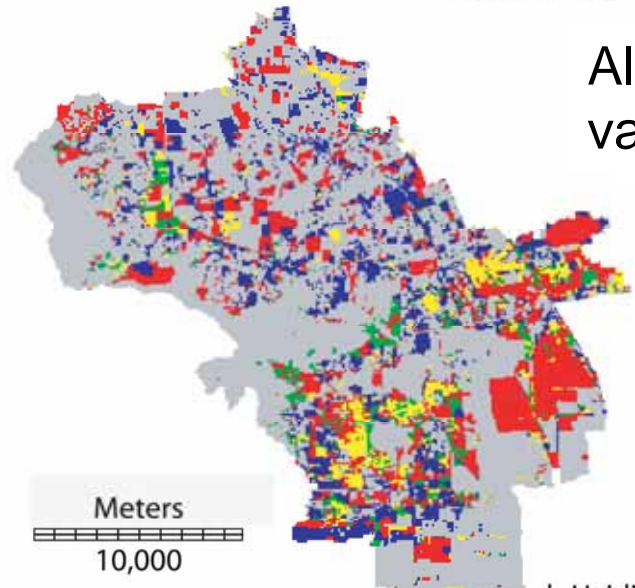
Modeling: to separate calibration from validation



i. Maroua, Cameroon



i. Kuala Lumpur, Malaysia

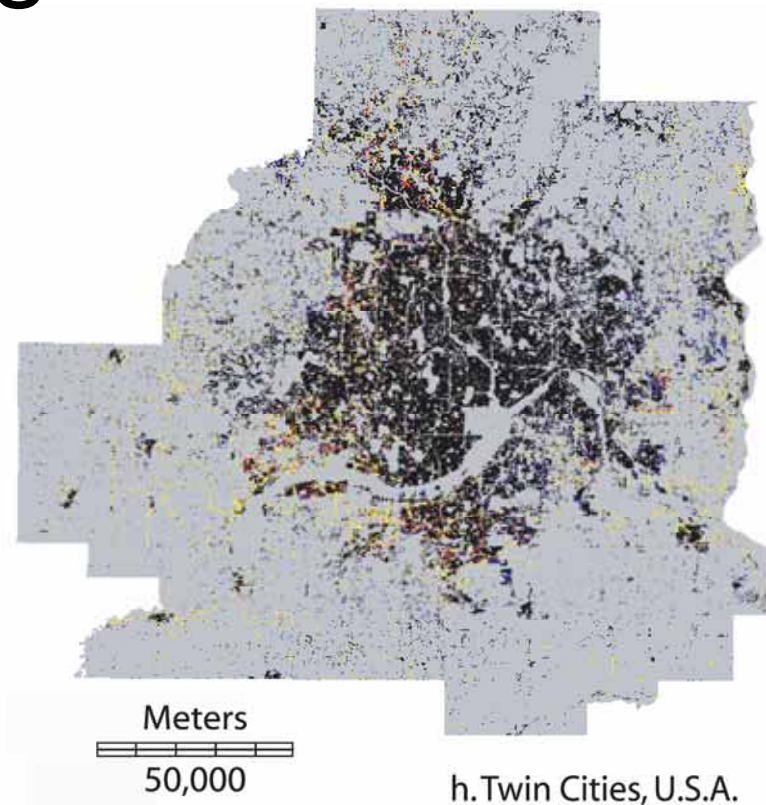
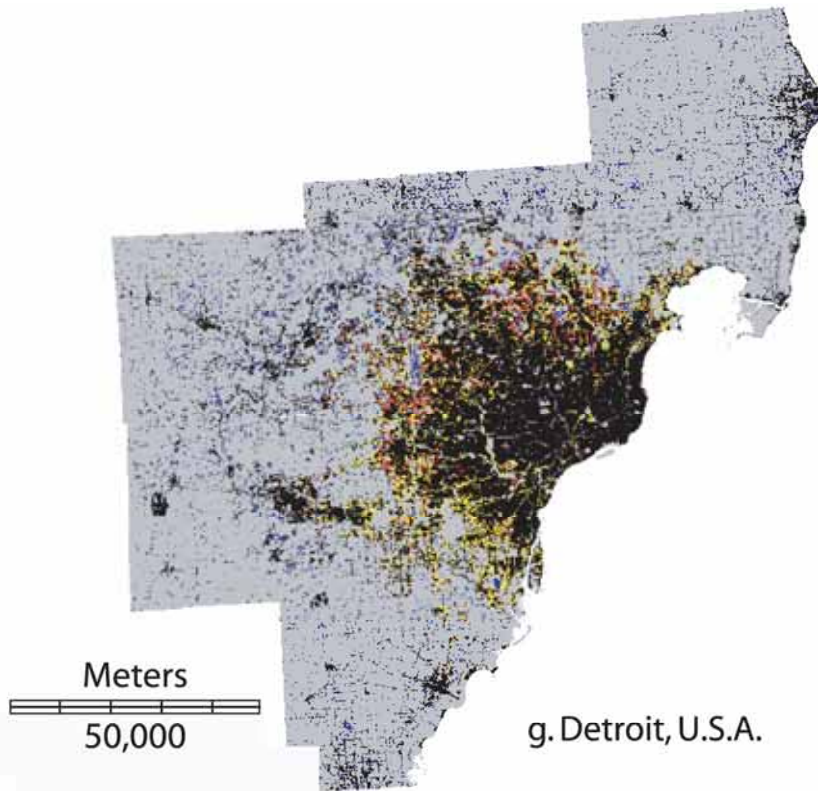


k. Haidian, China








All three use the correct quantities directly from the validation map.

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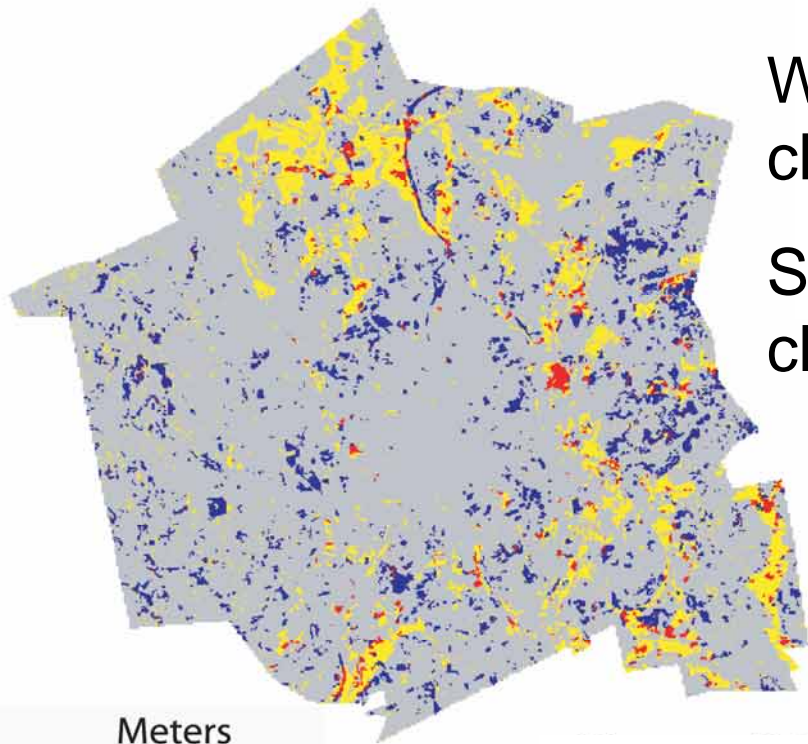
Mapping: to predict small amounts of change



Seven of the thirteen cases show less than 10% observed change.

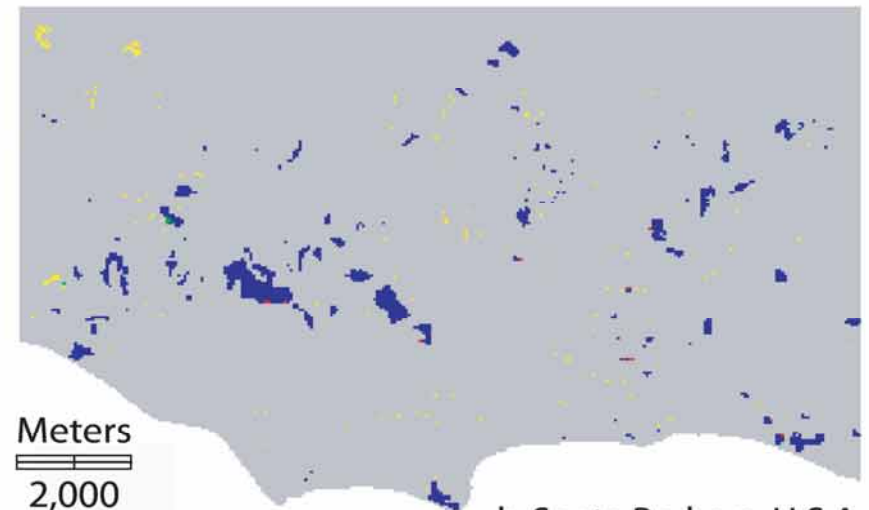
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Modeling: to interpret the influence of quantity error



Worcester case predicts too much change.

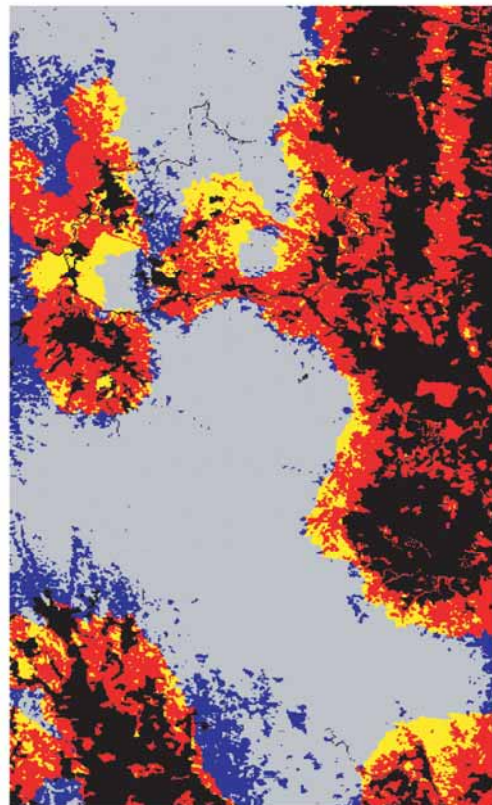
Santa Barbara case predicts too little change.



b. Santa Barbara, U.S.A.

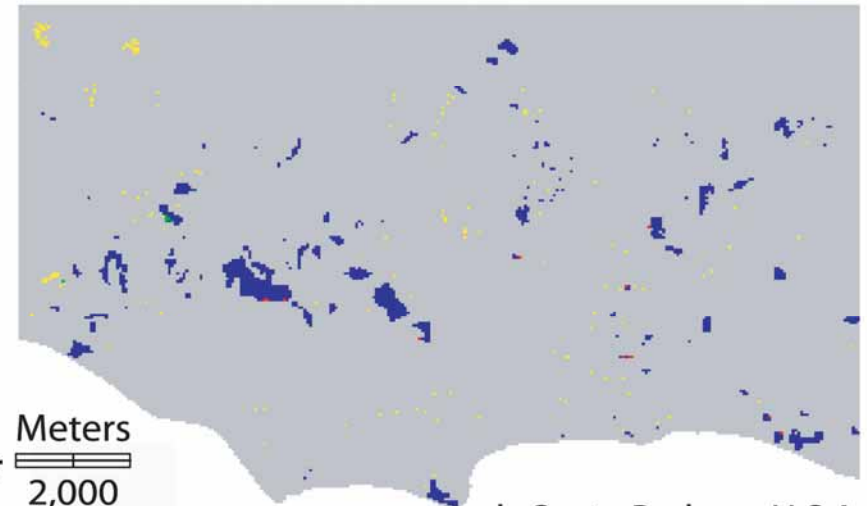
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Learning: to use appropriate map comparison measurements



Perinet ranks below median percent correct and highest figure of merit.

Santa Barbara ranks highest percent correct and lowest figure of merit.



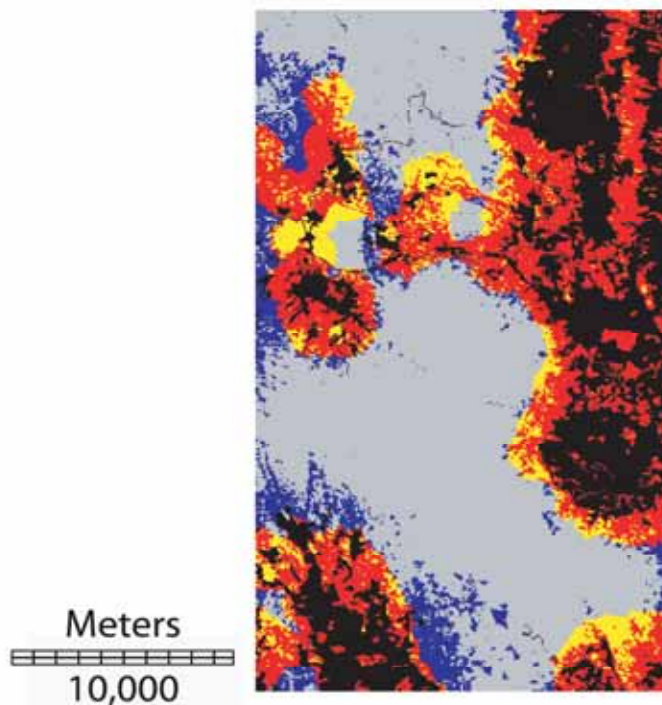
e. Perinet, Madagascar

b. Santa Barbara, U.S.A.

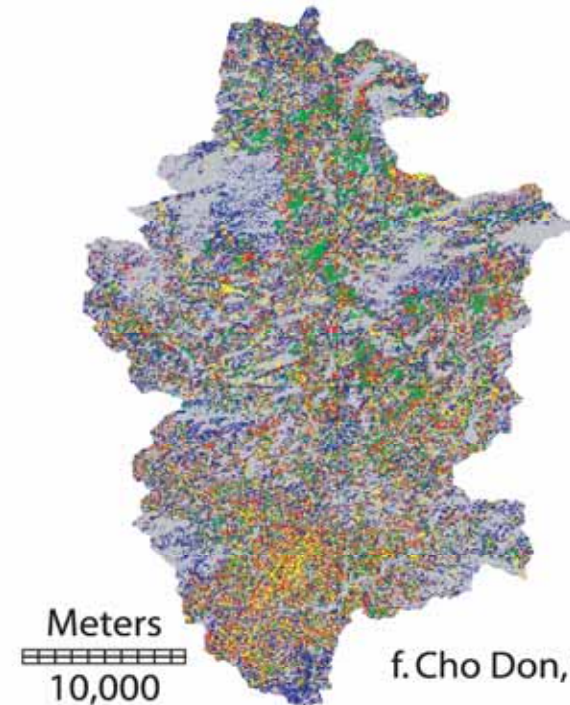
Meters
2,000

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Modeling: to learn about land change processes










e. Perinet, Madagascar



f. Cho Don, Vietnam

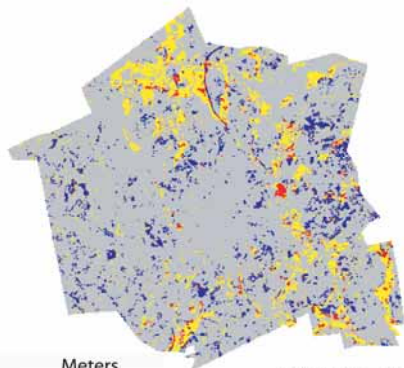
Perinet's logistic regression model measures association.
Cho Don's agent-based model examines processes.

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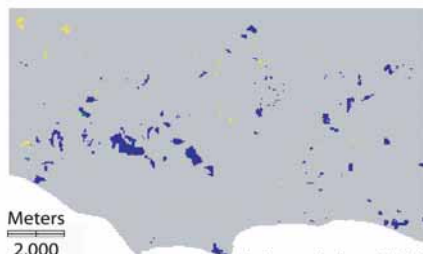
Learning: to collaborate openly

Legend for a-k

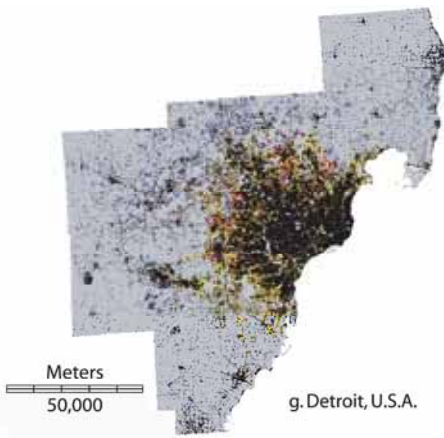
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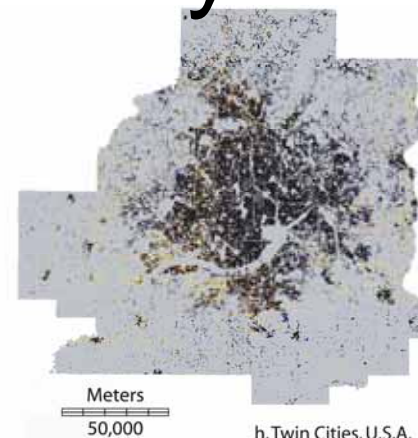
a. Worcester, U.S.A.



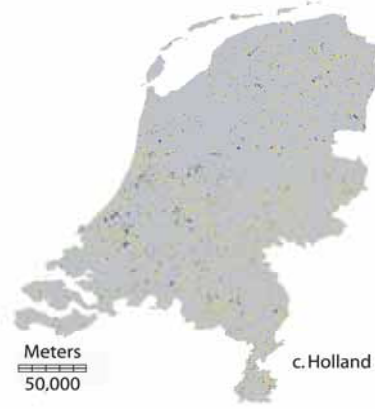
b. Santa Barbara, U.S.A.



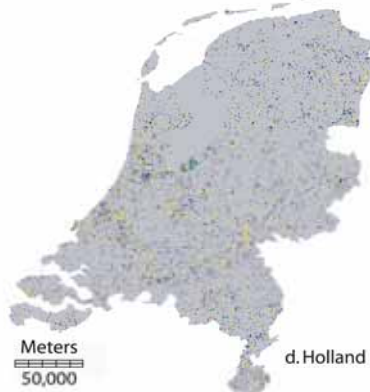
g. Detroit, U.S.A.



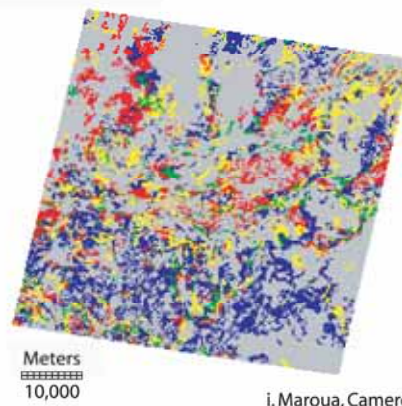
h. Twin Cities, U.S.A.



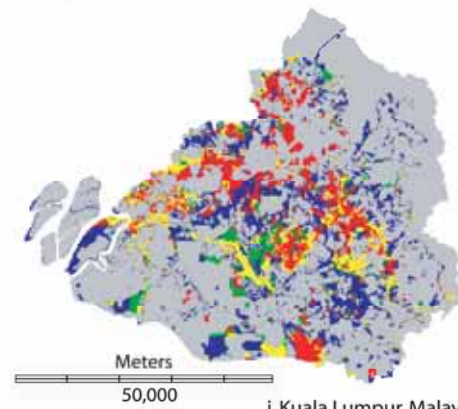
c. Holland (8)



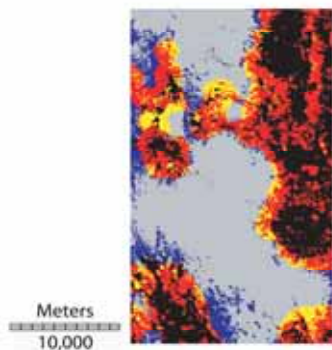
d. Holland (15)



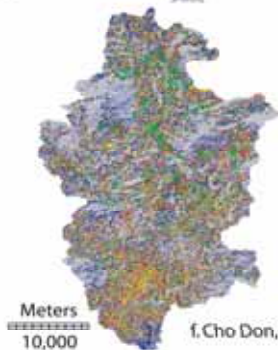
i. Maroua, Cameroon



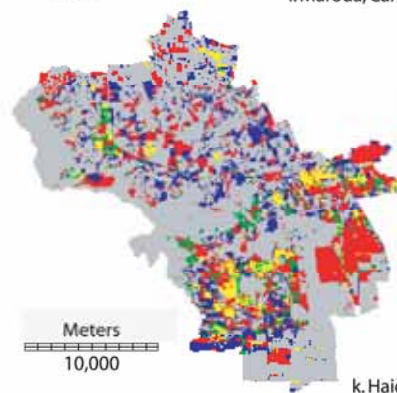
i. Kuala Lumpur, Malaysia



e. Perinet, Madagascar



f. Cho Don, Vietnam

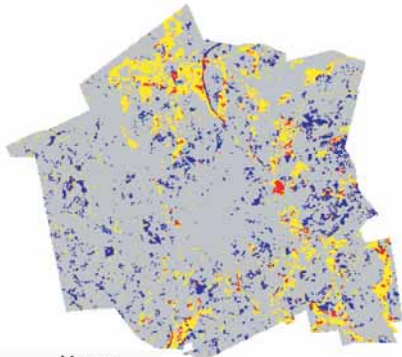


k. Haidian, China

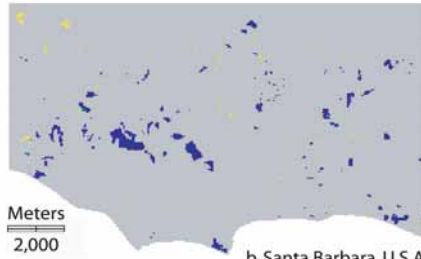
Learning: to collaborate openly

Legend for a-k

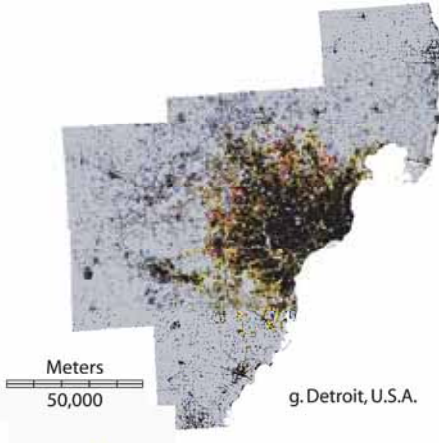
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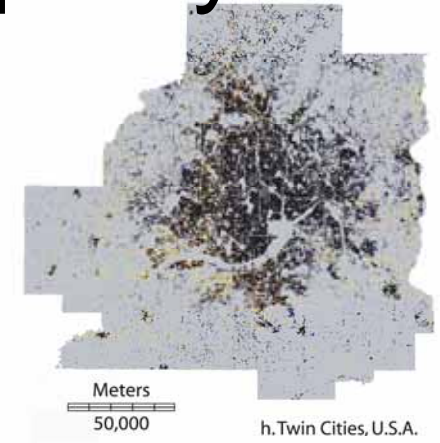
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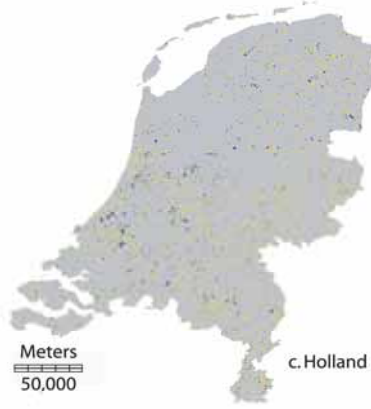
b. Santa Barbara, U.S.A.



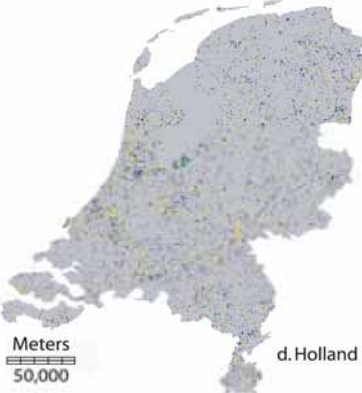
g. Detroit, U.S.A.



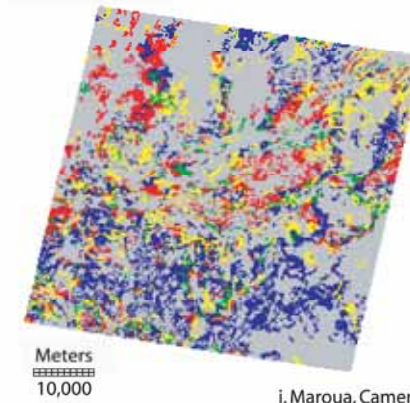
h. Twin Cities, U.S.A.



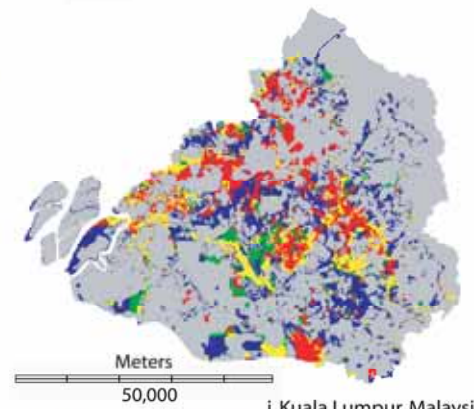
c. Holland (8)



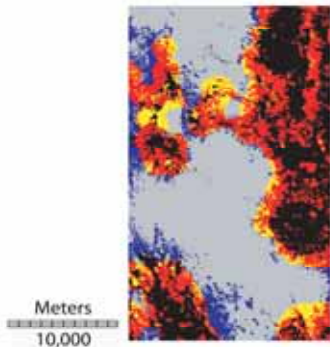
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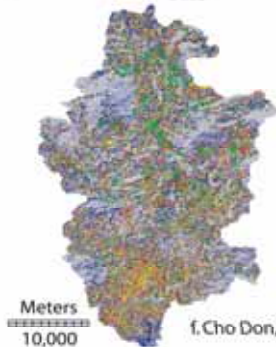
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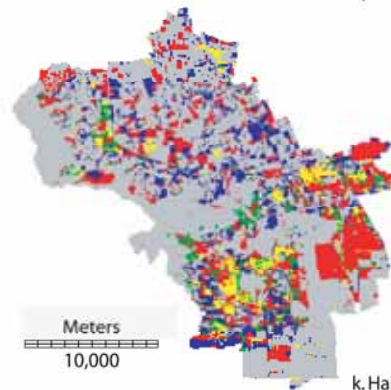
i. Kuala Lumpur, Malaysia



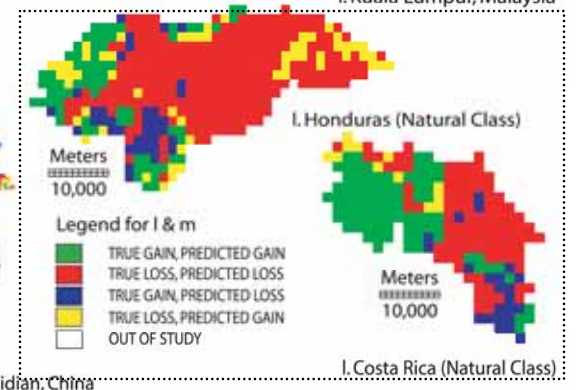
e. Perinet, Madagascar



f. Cho Don, Vietnam



k. Haidian, China



l. Honduras (Natural Class)

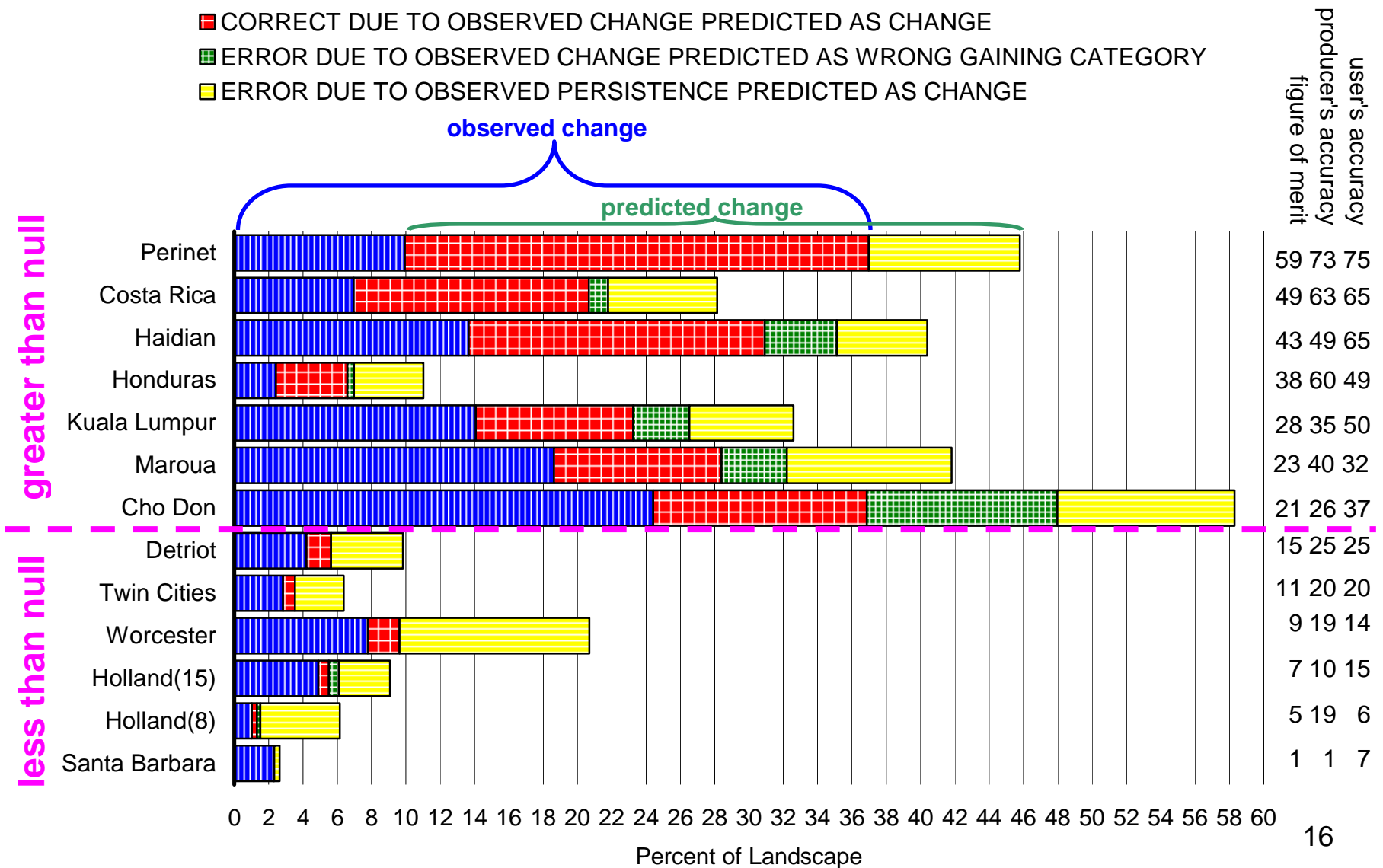
l. Costa Rica (Natural Class)

Legend for l & m

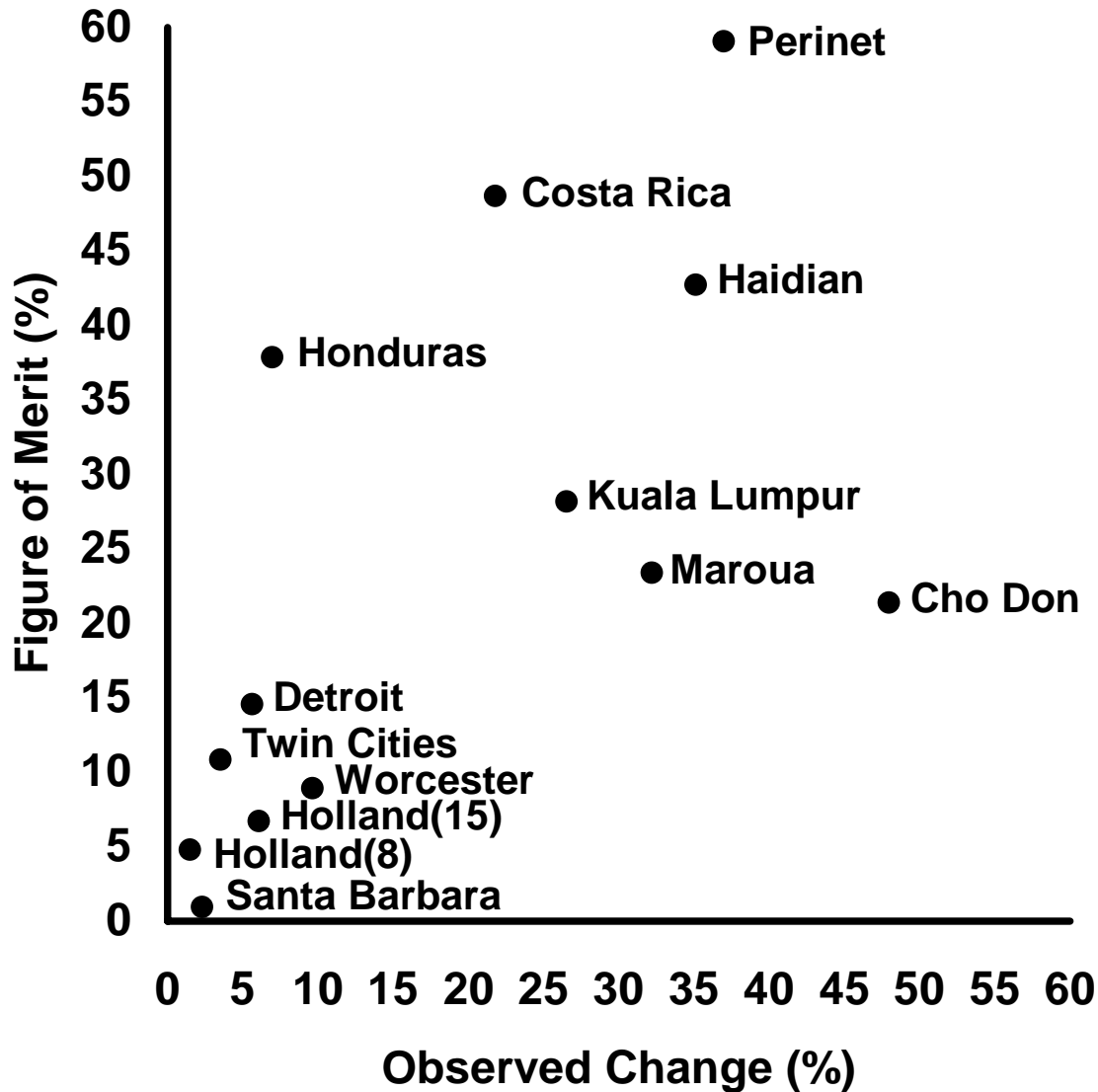
- TRUE GAIN, PREDICTED GAIN
- TRUE LOSS, PREDICTED LOSS
- TRUE GAIN, PREDICTED LOSS
- TRUE LOSS, PREDICTED GAIN
- OUT OF STUDY

Venn Diagrams for 13 cases

- ERROR DUE TO OBSERVED CHANGE PREDICTED AS PERSISTENCE
- CORRECT DUE TO OBSERVED CHANGE PREDICTED AS CHANGE
- ERROR DUE TO OBSERVED CHANGE PREDICTED AS WRONG GAINING CATEGORY
- ERROR DUE TO OBSERVED PERSISTENCE PREDICTED AS CHANGE



Low predictive accuracy occurs for cases with little observed change



Nine Challenges

1. Mapping

1. To select relevant resolutions
2. To prepare data appropriately
3. To differentiate types of land change

2. Modeling

1. To separate calibration from validation
2. To predict small amounts of change
3. To interpret the influence of quantity error

3. Learning

1. To use appropriate map comparison measurements
2. To learn about land change processes
3. To collaborate openly

Acknowledgements

- Literature is available from Gil Pontius
 - Click www.clarku.edu/~rpontius or Email rpontius@clarku.edu
 - Pontius et al. in press. Comparing the input, output, and validation maps for several models of land change. *Annals of Regional Science*.
 - Pontius et al. 2004. Useful techniques of validation for spatially-explicit land-change models. *Ecological Modelling*. **179**(4) p. 445-461.
- Methods are available in the software *Idrisi*.
 - Click www.clarklabs.org
- C. T. DeWit School for Production Ecology & Resource Conservation of Wageningen University funded this project.



Additional Results

1. It is not reasonable to rank the models because they have different purposes and sites.
2. Visual validation can be helpful if it is presented carefully to focus on the change.
3. Most models used information from the final time to predict the final time.
4. The LUCC models are more accurate than their respective null models in about half of the cases *at the fine resolution of the raw data*.
5. We did not find other clear conclusions concerning model performance.

Characteristics of 13 cases

Site Name	Spatial extent (sq. km.)	Spatial resolution (m)	# of pixels	# of classes	Year 1	Year 2	Year Interval	Uses year 2 quantity	Null resolution (km)	Model
Worcester, U.S.A.	586	30	651591	2	1971	1999	28	No	4	Geomod
Santa Barbara, U.S.A.	123	50	49210	7	1986	1998	12	No	3	SLEUTH
Holland(8)	37280	500	149119	8 ^[1]	1996	2000	4	No	Worse	Land Use Scanner
Holland(15)	37280	500	149119	15	1996	2000	4	No	16	Environment Explorer
Perinet, Madagascar	715	30	794955	2 ^[2]	1957	2000	43	No	Better	Logistic Regression
Cho Don, Vietnam	892	32	892136	6	1990	2001	11	No	Better	SAMBA
Detroit, U.S.A.	9175	26	13209072	2 [†]	1978	1998	20	Yes	27	LTM
Twin Cities, U.S.A.	6347	30	7052459	2 [†]	1991	1998	7	Yes	2	LTM
Maroua, Cameroon	3572	250	57144	6	1987	1999	12	Yes	Better	CLUE-S
Kuala Lumpur, Malaysia	3810	150	169333	6	1990	1999	9	Yes	Better	CLUE-S
Haidian, China	431	100	43077	8	1991	2001	9	Yes	Better	CLUE-S
Honduras	96975	15000	431	6 ^[3]	1974	1993	19	Yes	Better	CLUE
Costa Rica	48600	15000	216	6 [‡]	1973	1984	11	Yes	Better	CLUE

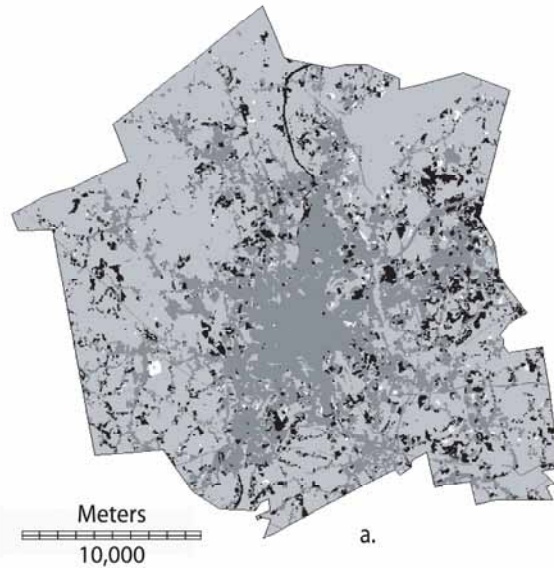
[1] The original pixels contain partial membership to 36 categories, which are then reassigned the dominant category after the prediction.

[2] The reference maps and the model are designed to show exclusively a one-way transition.

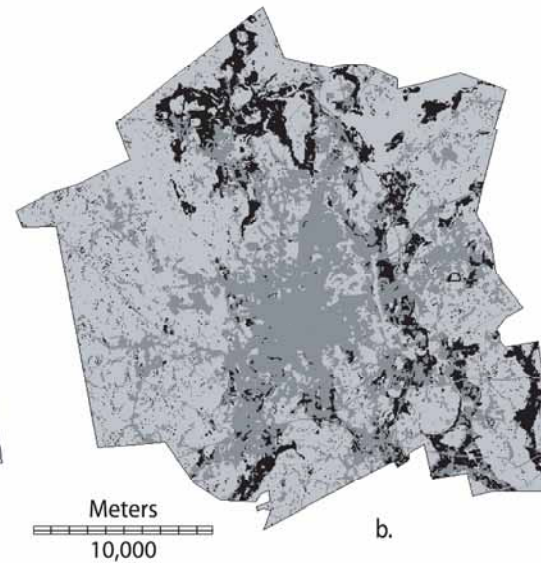
[3] The pixels contain simultaneous partial membership to multiple categories.

Three pair-wise comparisons

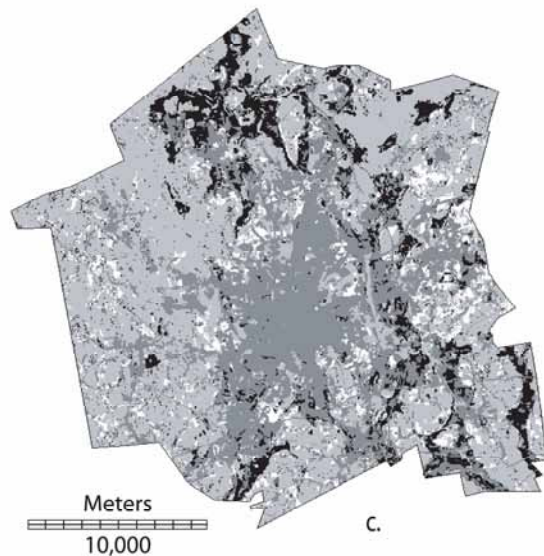
Observed
Change



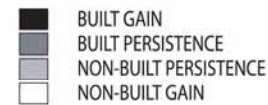
Predicted
Change



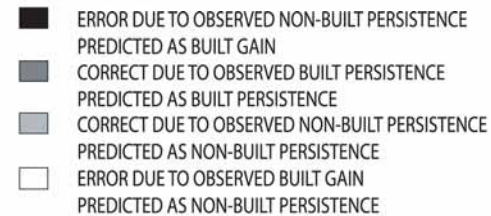
Error and
Accuracy



Legend for a and b

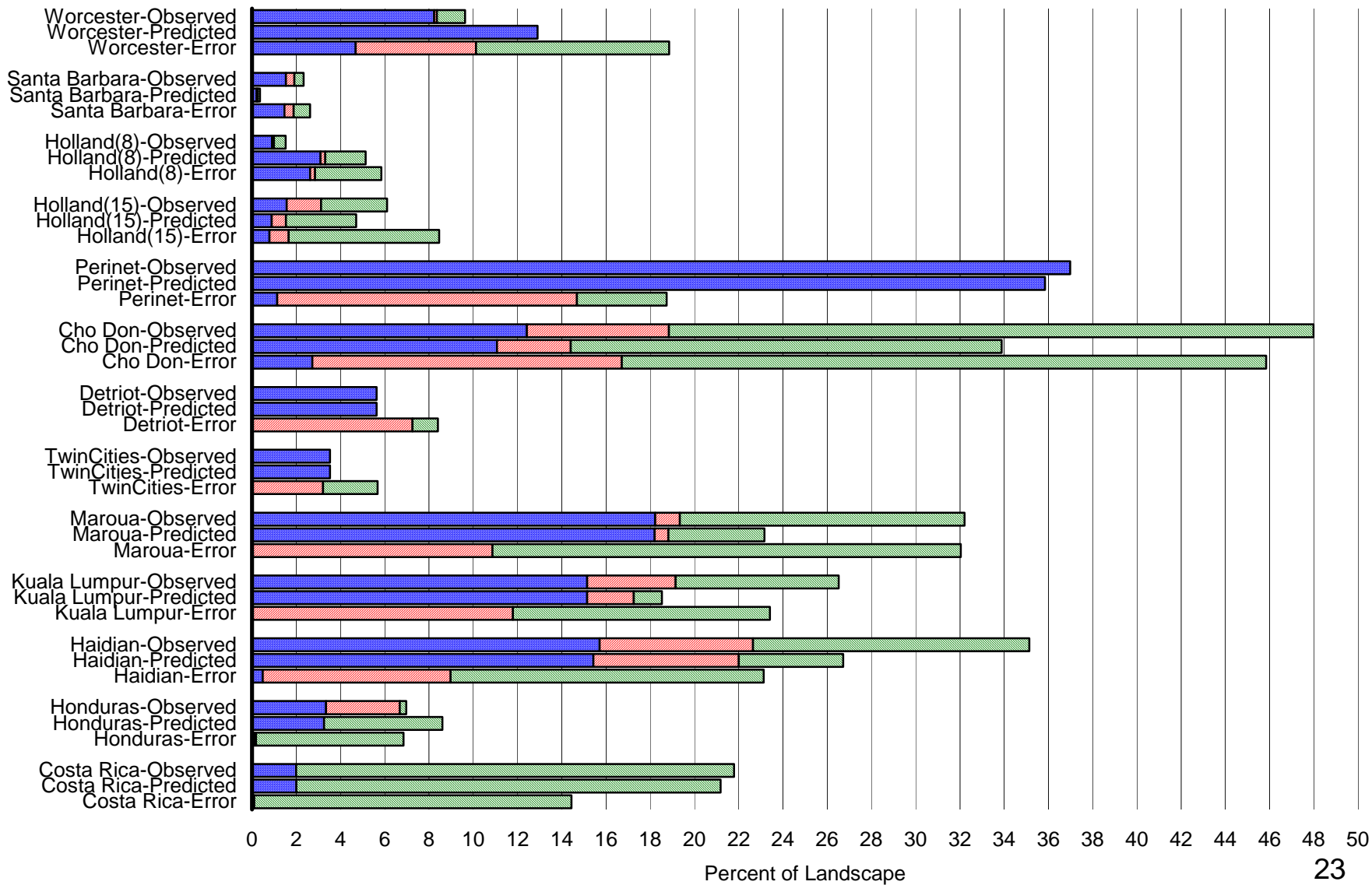


Legend for c

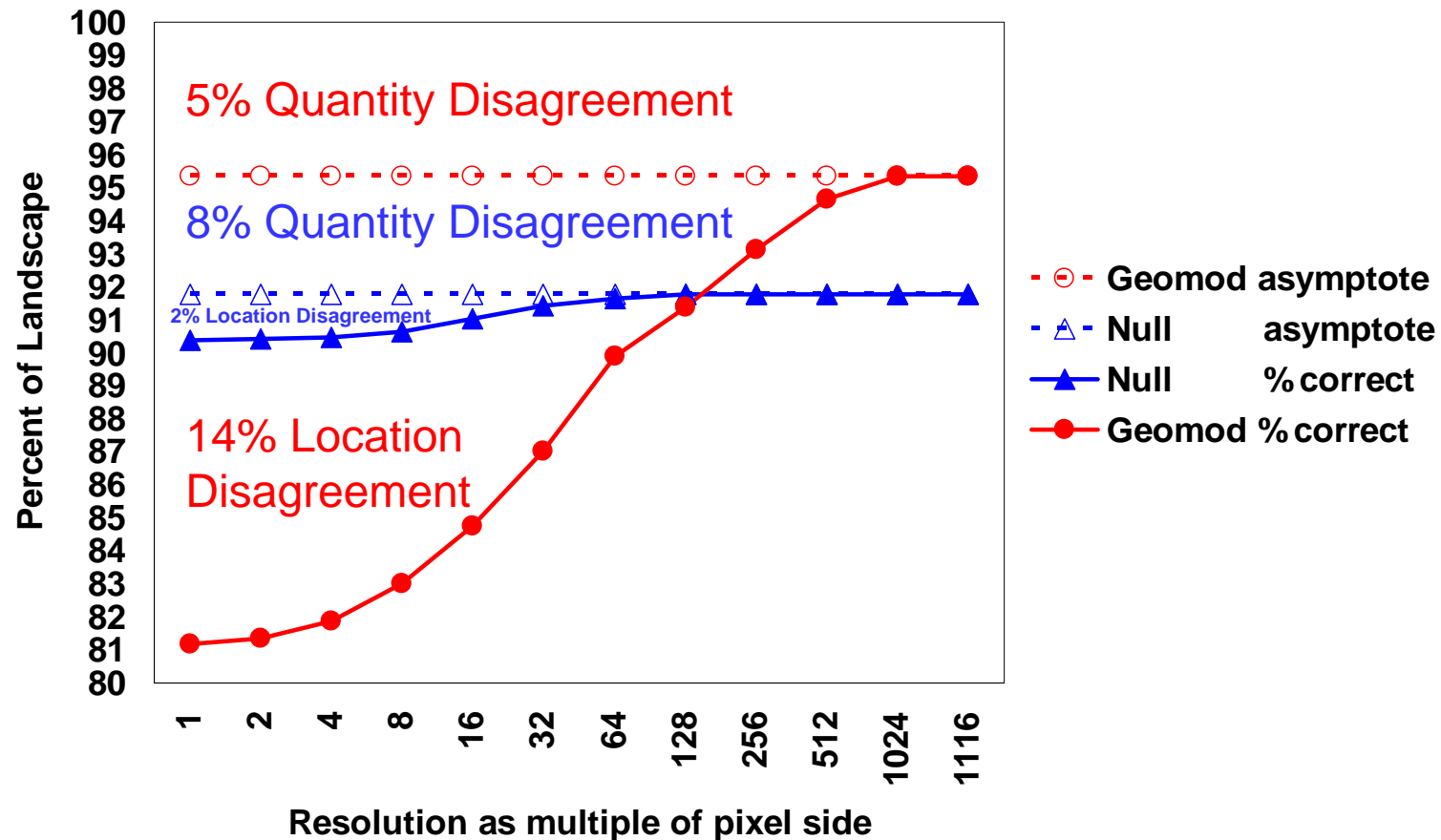


Three pair-wise comparisons for 13 cases

■ QUANTITY DISAGREEMENT, ■ COARSE-SCALE LOCATION DISAGREEMENT, ■ FINE-SCALE LOCATION DISAGREEMENT

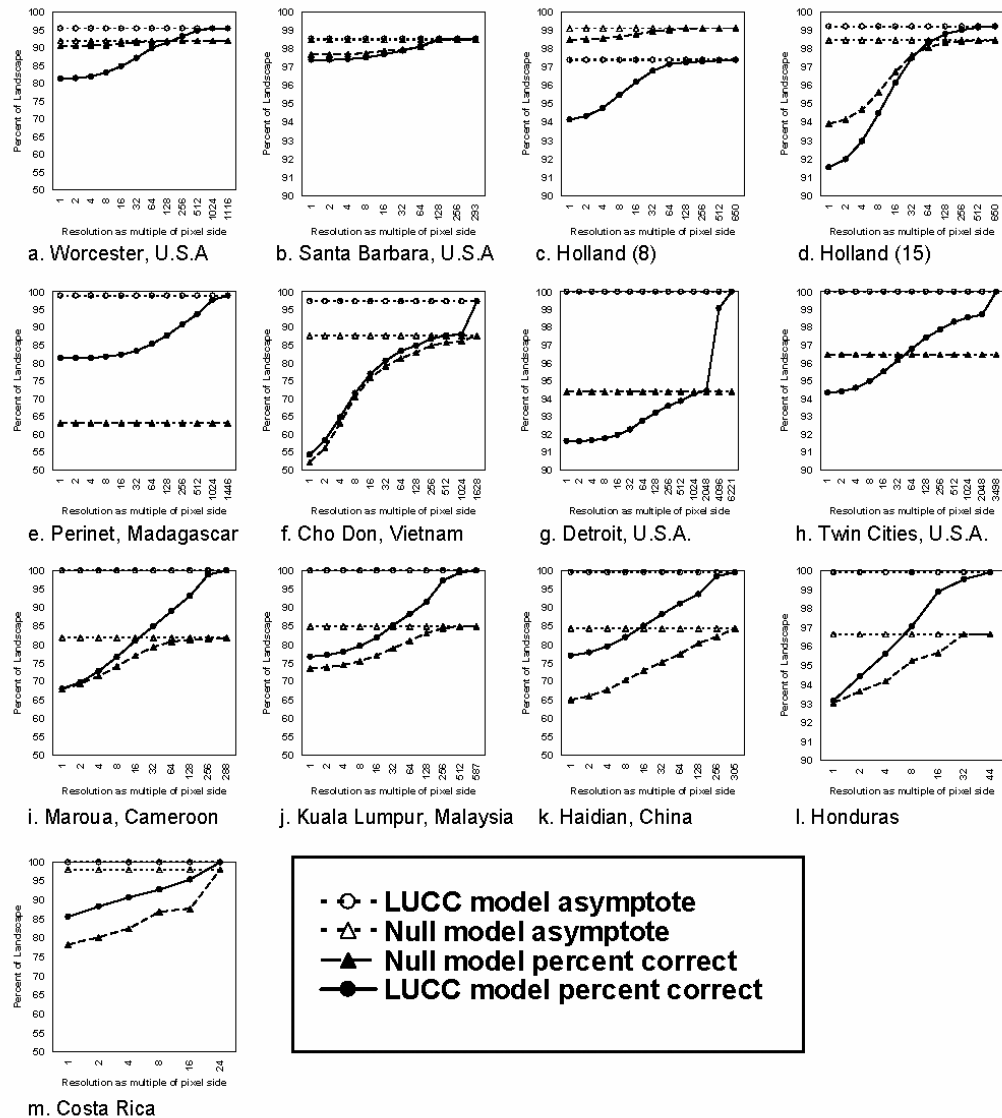


Worcester Multiple Resolution Comparison to Null model

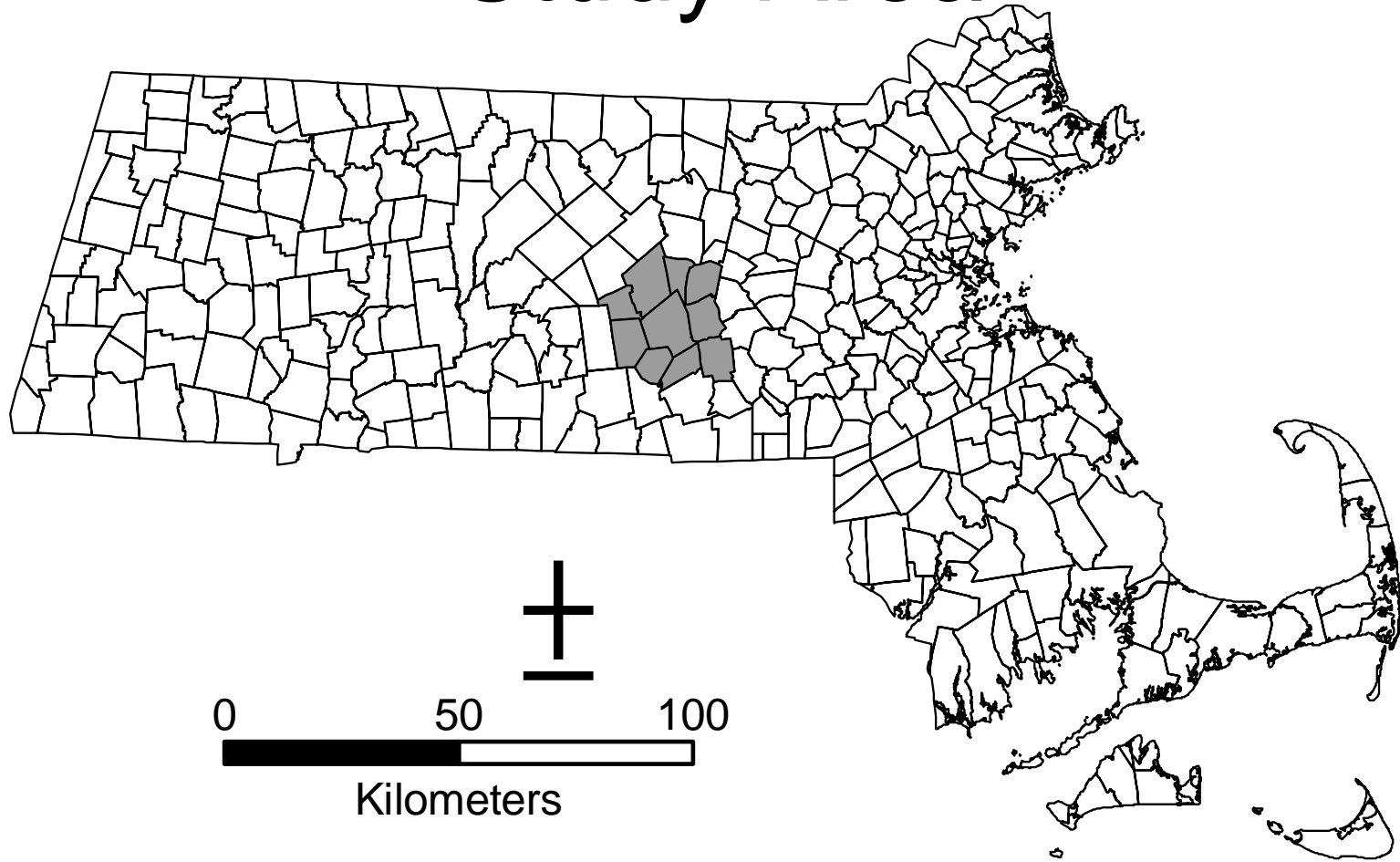


Null model of persistence is more accurate than Geomod at resolutions finer than 128 times 30 meters, which is 3.84 kilometers.

Multiple resolution comparison of LUCC model versus Null model



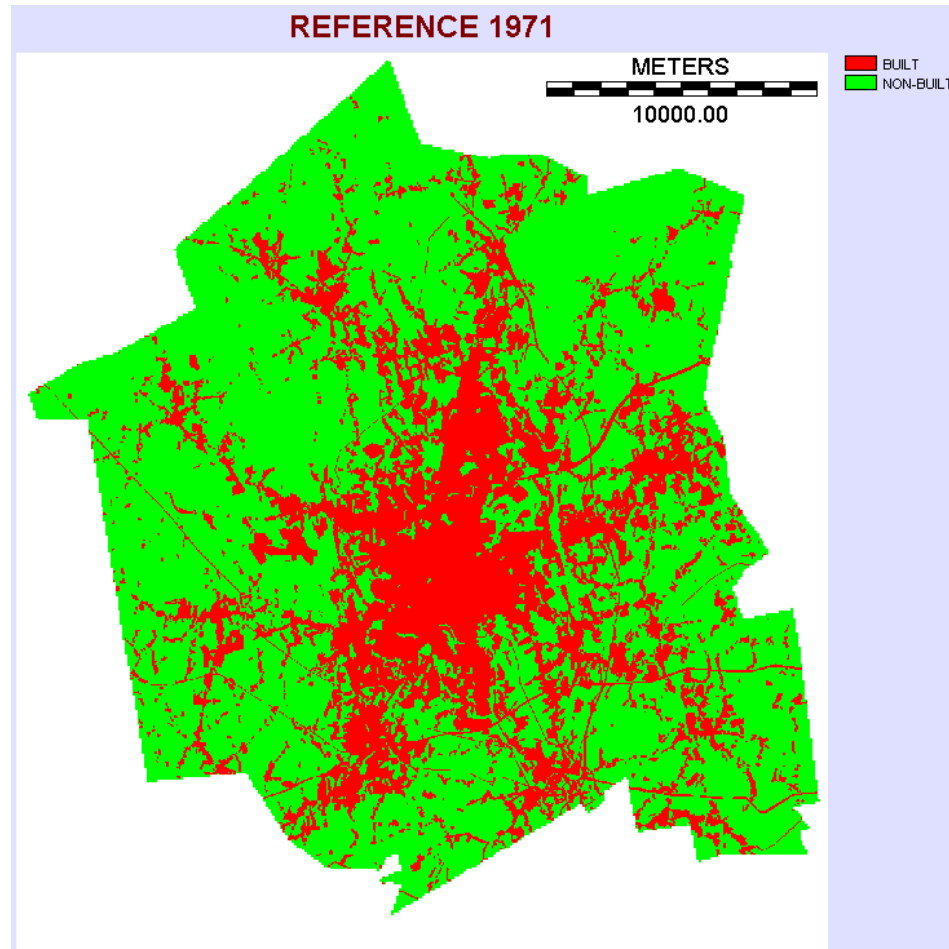
Study Area



Worcester and nine surrounding towns
in Central Massachusetts

Worcester Initial Time

There is 30% Built in 1971.



There are 2 categories.

Each pixel side is 30 meters.

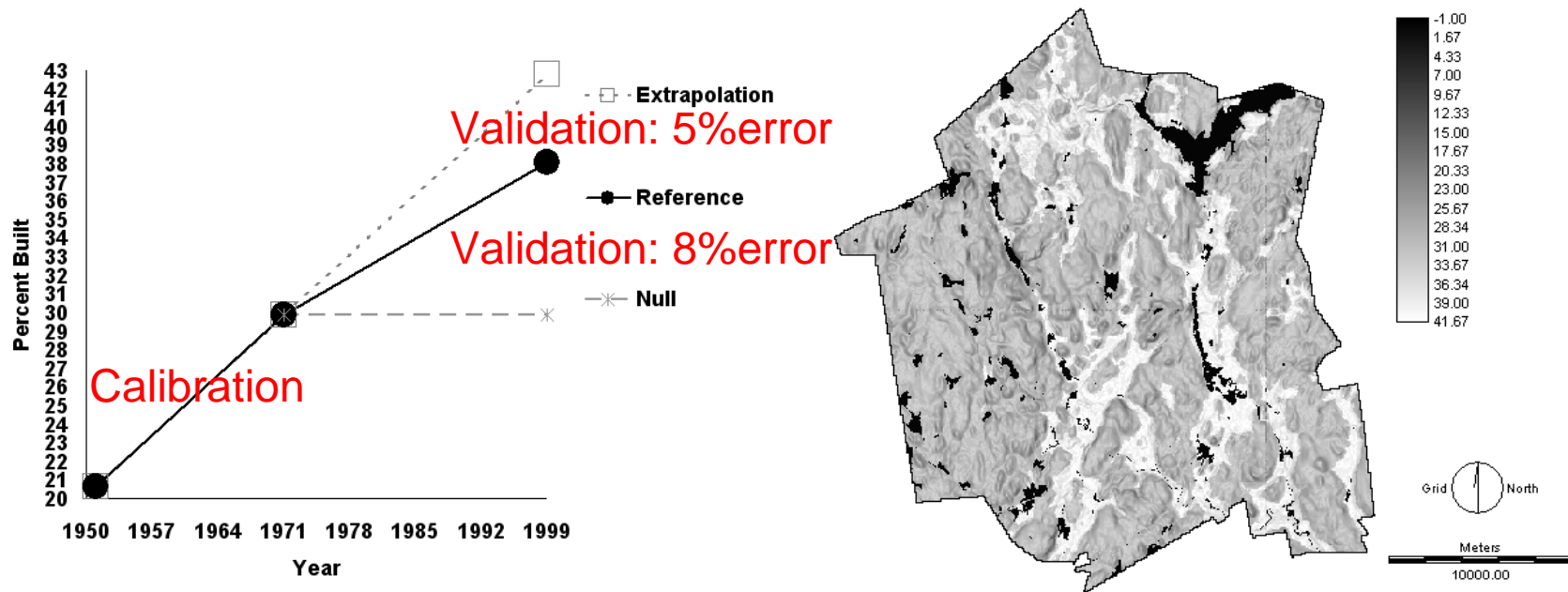
Validation Approach

Quantity Specification

based on linear extrapolation.

Location Specification

based on slope and geology.



Calibration information is from initial time or before.

Validation is for final time.

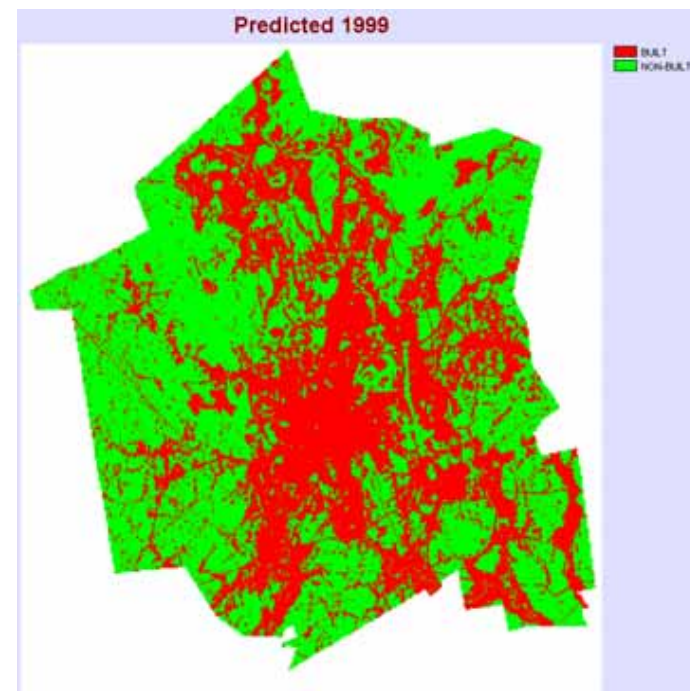
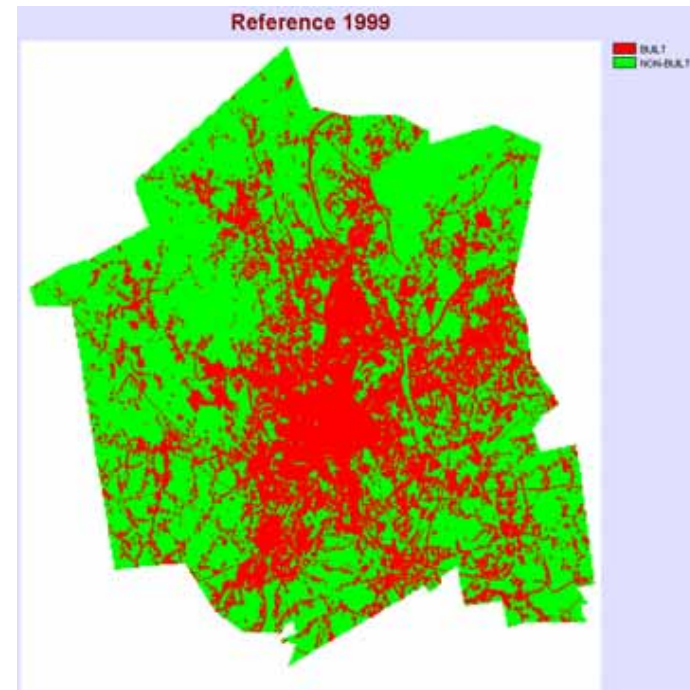
Null model predicts pure persistence between initial and final times.

2-map comparison

Time 2 Reference

LUCC model is 81% correct.

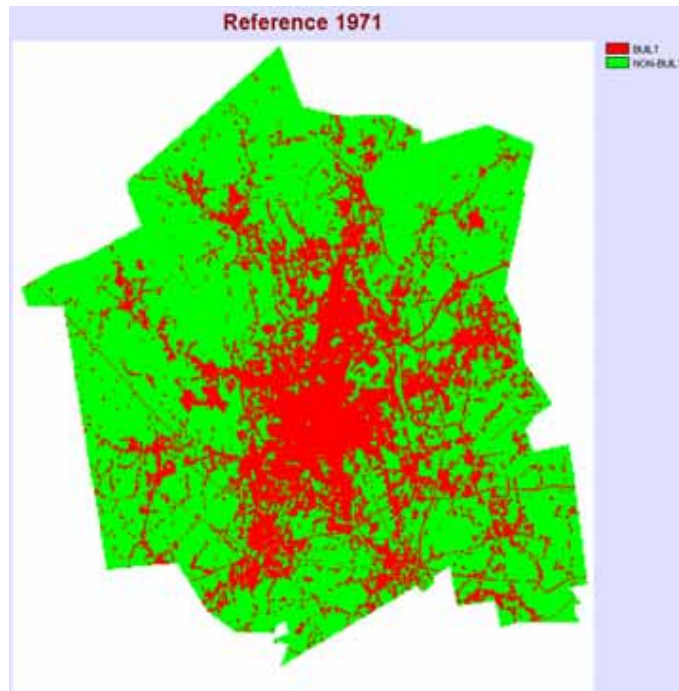
Time 2 Prediction



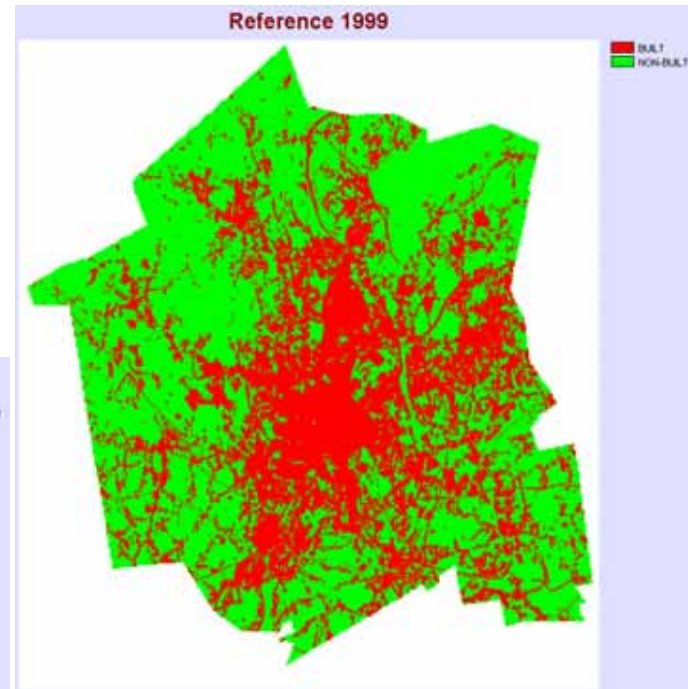
3-map comparison

Null
model is
90%
correct.

Time 1
Reference



Time 2 Reference



Time 2 Prediction

