Potentially useful impacts of spatio-temporal pattern on agriculture

Scott Mitchell - Research Program
GEOG5803 Seminar, Winter 2019

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GEOMATICS AND LANDSCAPE ECOLOGY RESEARCH LABORATORY

(When, Where and How Much)

Does Pattern Matter ?

Spatio-temporal modelling strategies to predict grassland productivity dynamics, Grasslands National Park, Saskatchewan

Scott W. Mitchell

Ph.D. Defence (2003)

Agricultural Production Heterogeneity - Biodiversity

- NSERC Strategic Project 2010-2013
- Co-PI with Lenore Fahrig, Doug King, Kathryn Lindsay, Post-docs Jon Pasher, Adam Smith, Jude Girard, Dennis Duro
- Actually, "Landscape indicators and agri-environmental policies for biodiversity enhancement on agricultural lands"

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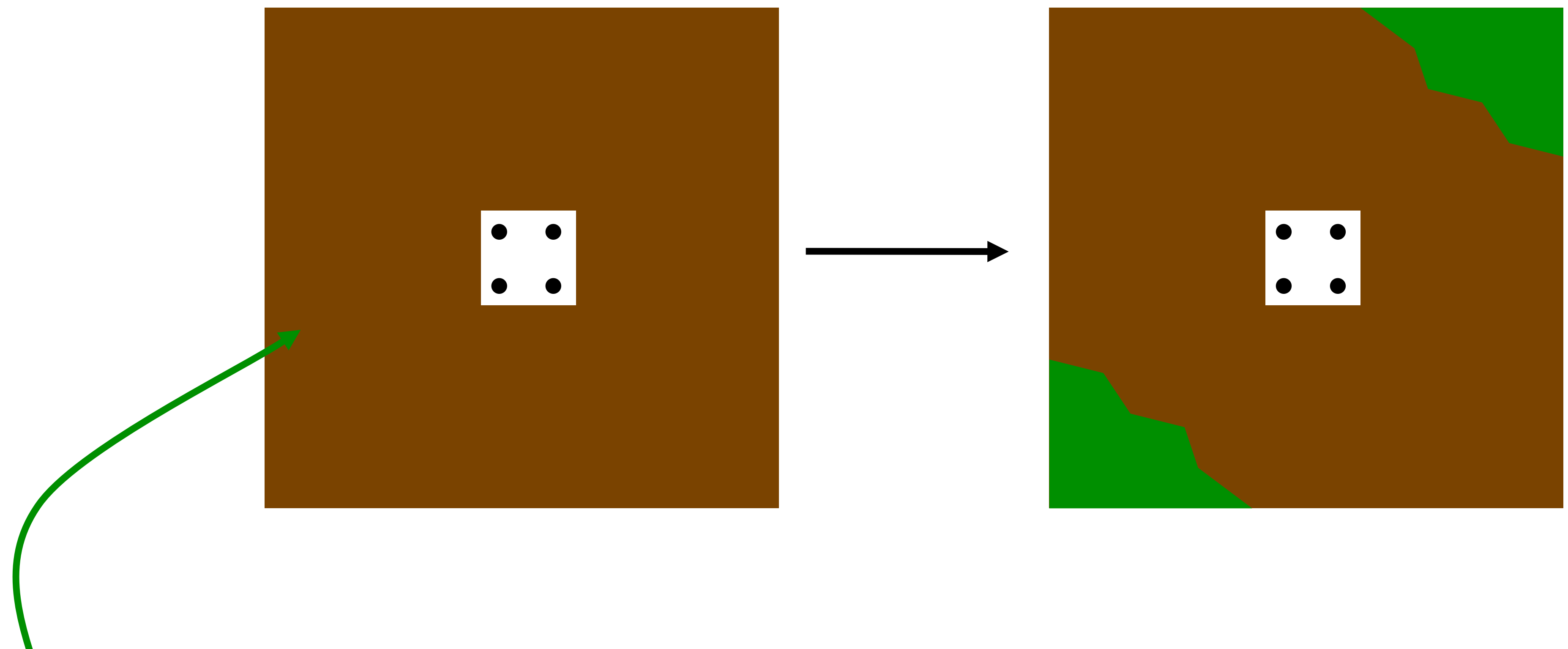
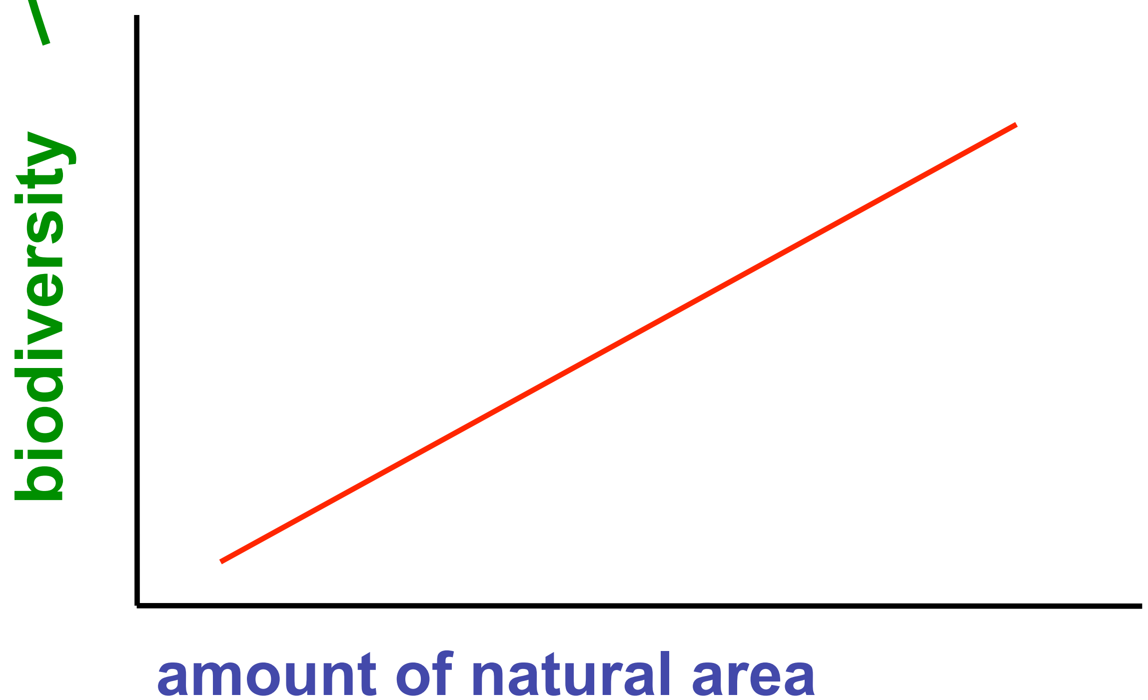
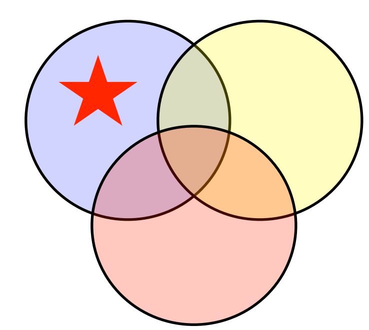
Research Objectives

1. to determine which measure(s) of landscape heterogeneity are the best indicators (i.e., best predictors) of biodiversity in agricultural landscapes;
    - heterogeneity of natural area
    - diversity of production area
    - pattern of production area

Amount of Natural Area is NOT in our Study



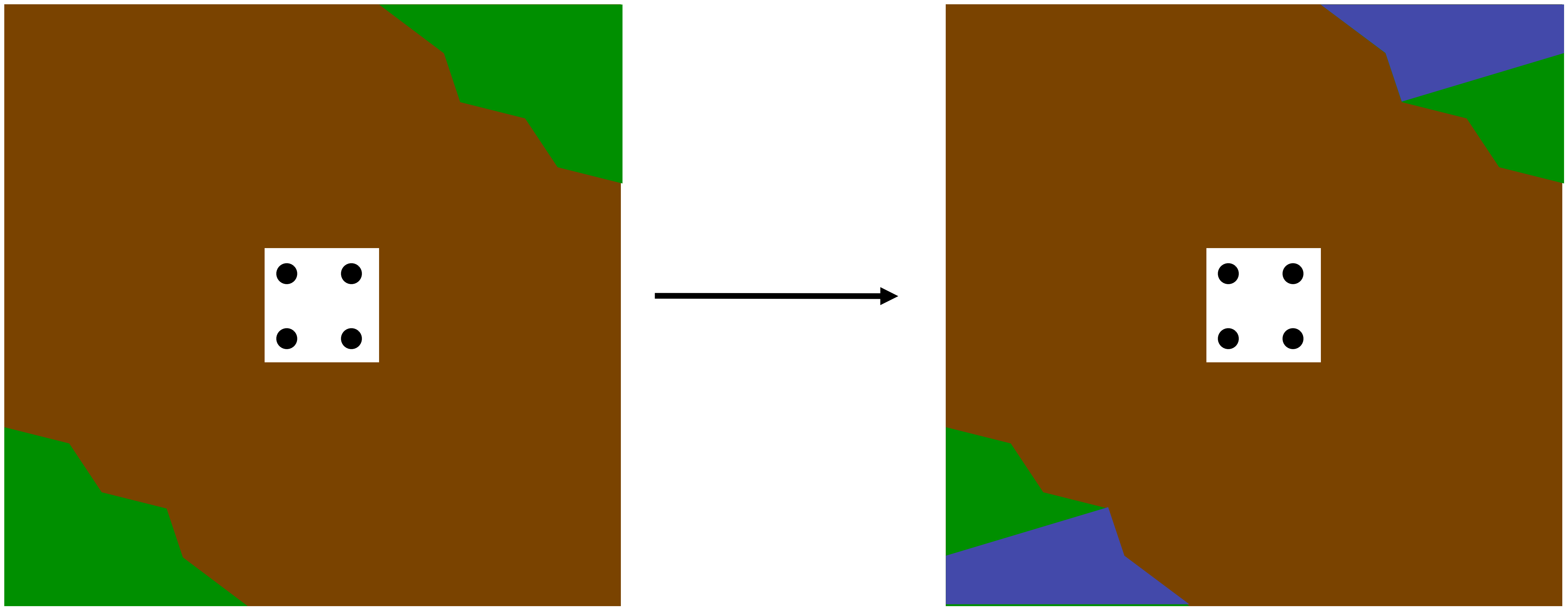


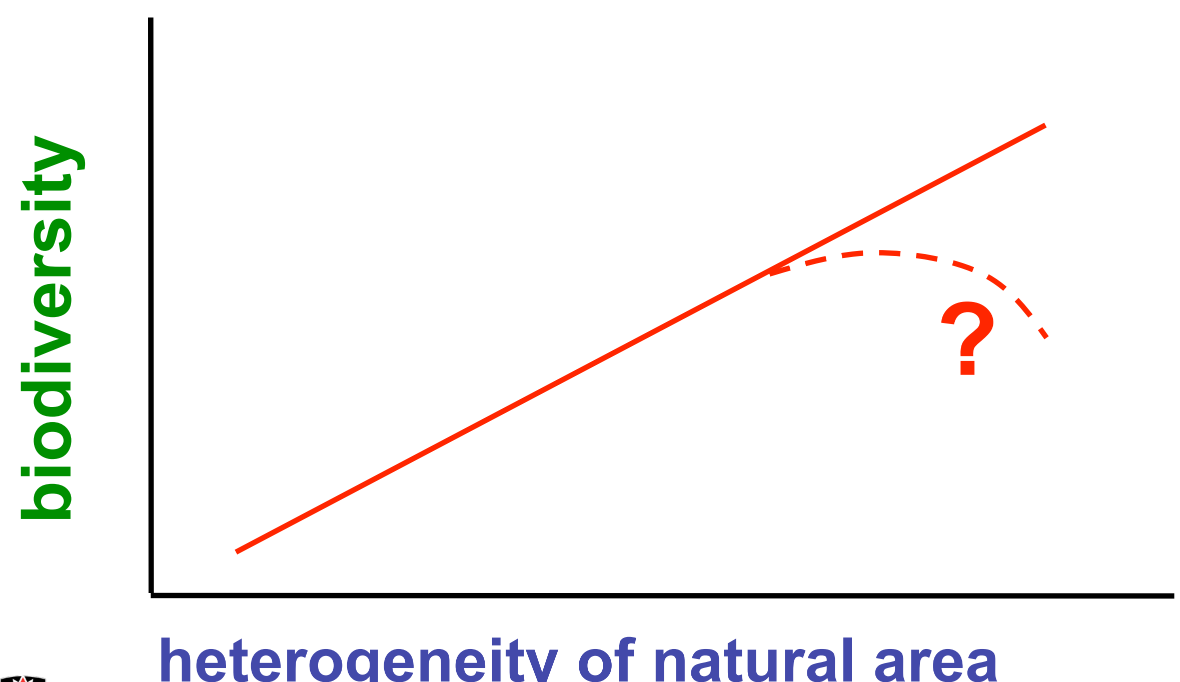


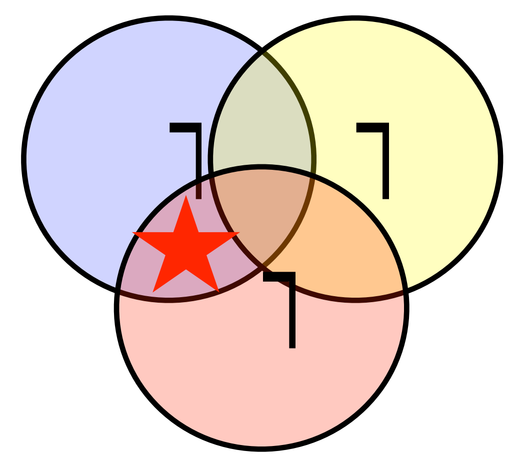
research is feasible,
results are known, policy is limited

→ **low research priority**

Heterogeneity of Natural Area







research is feasible,
results are partly known, policy is feasible?

→ **moderate research priority**

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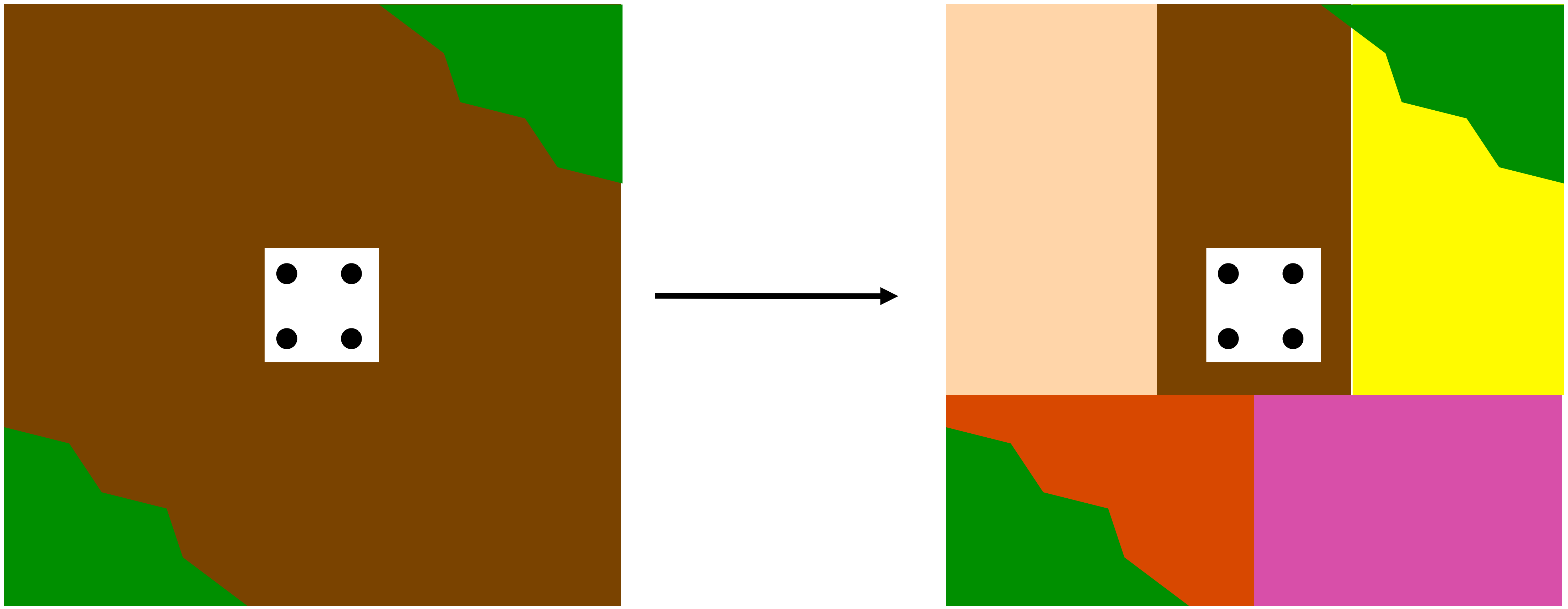
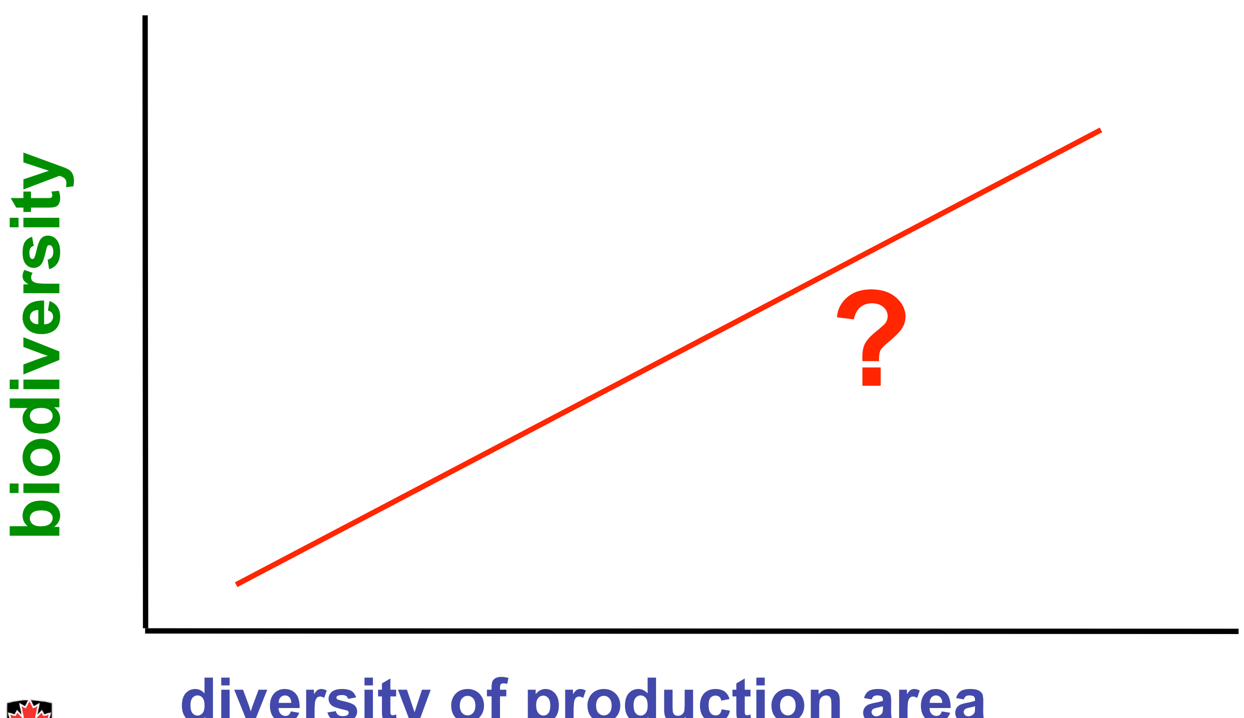
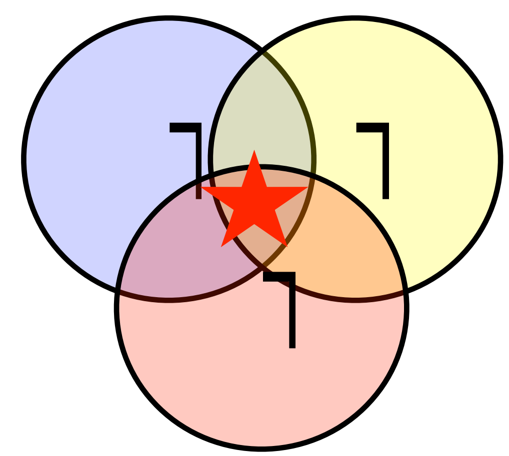
Diversity of Production Area



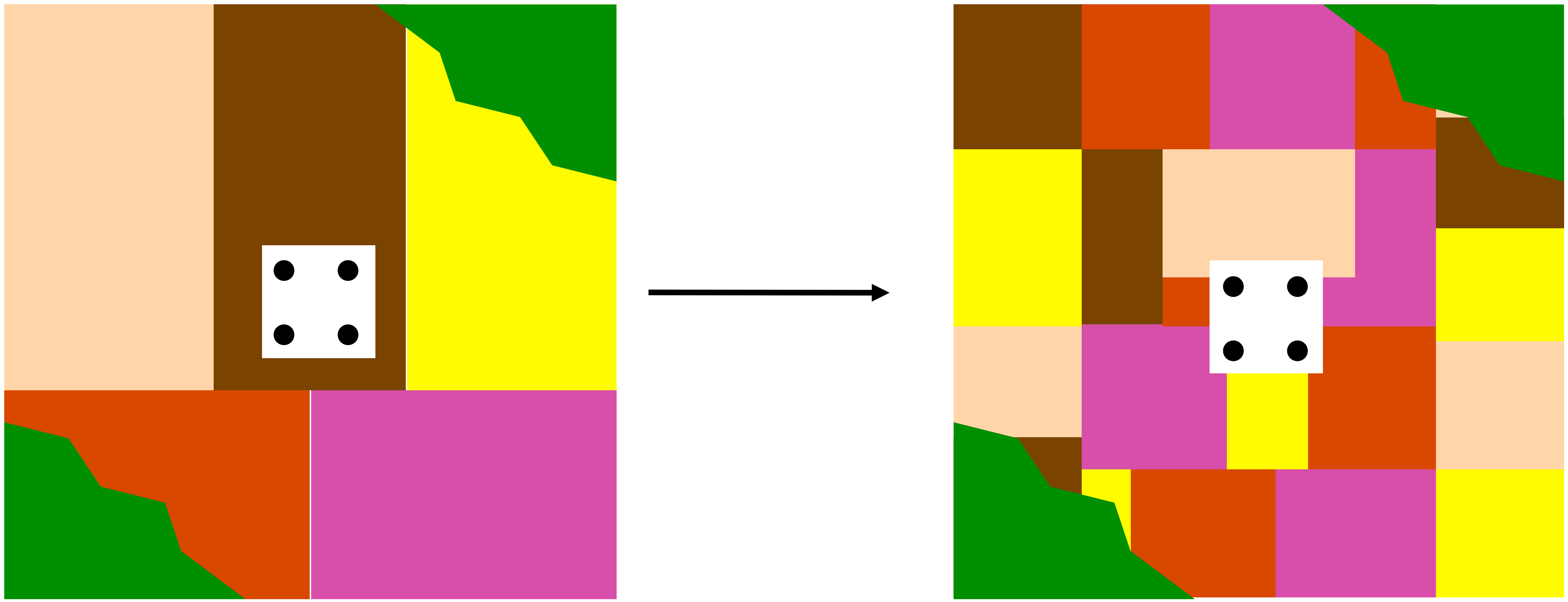


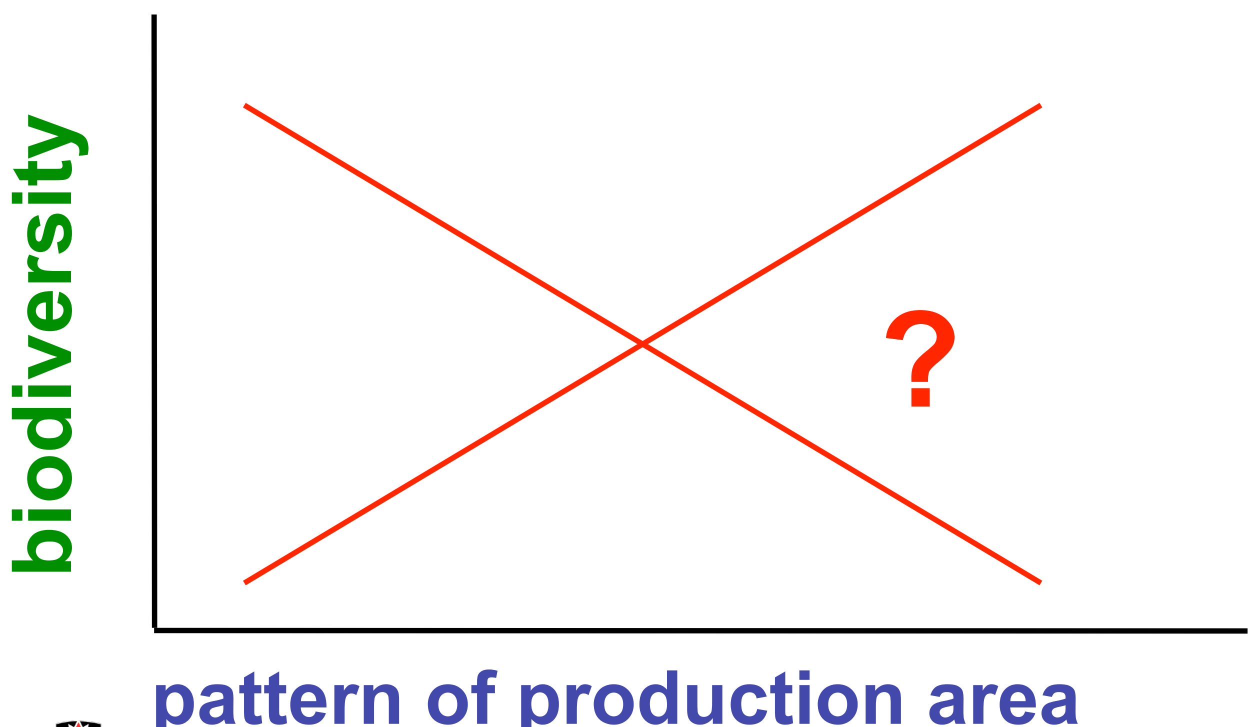


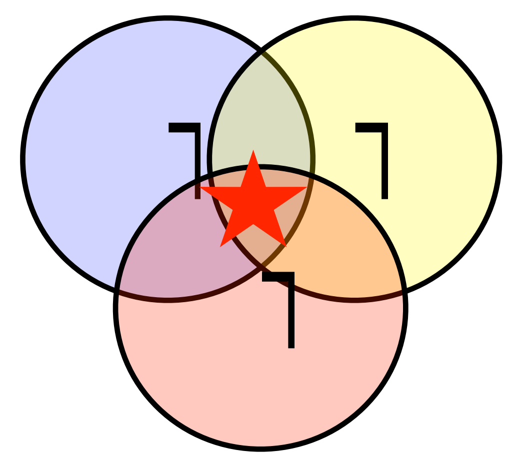
research is feasible,
results are unknown, policy is feasible

→ **high research priority**

Pattern of Production Area







research is feasible,
results are unknown, policy is feasible

→ **high research priority**

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Research Objectives

1. to determine which measure(s) of landscape heterogeneity are the best indicators (i.e., best predictors) of biodiversity in agricultural landscapes;
2. to determine the appropriate spatial extent(s) at which the indicators best predict biodiversity and therefore the spatial extent(s) at which farmland policies should be implemented;

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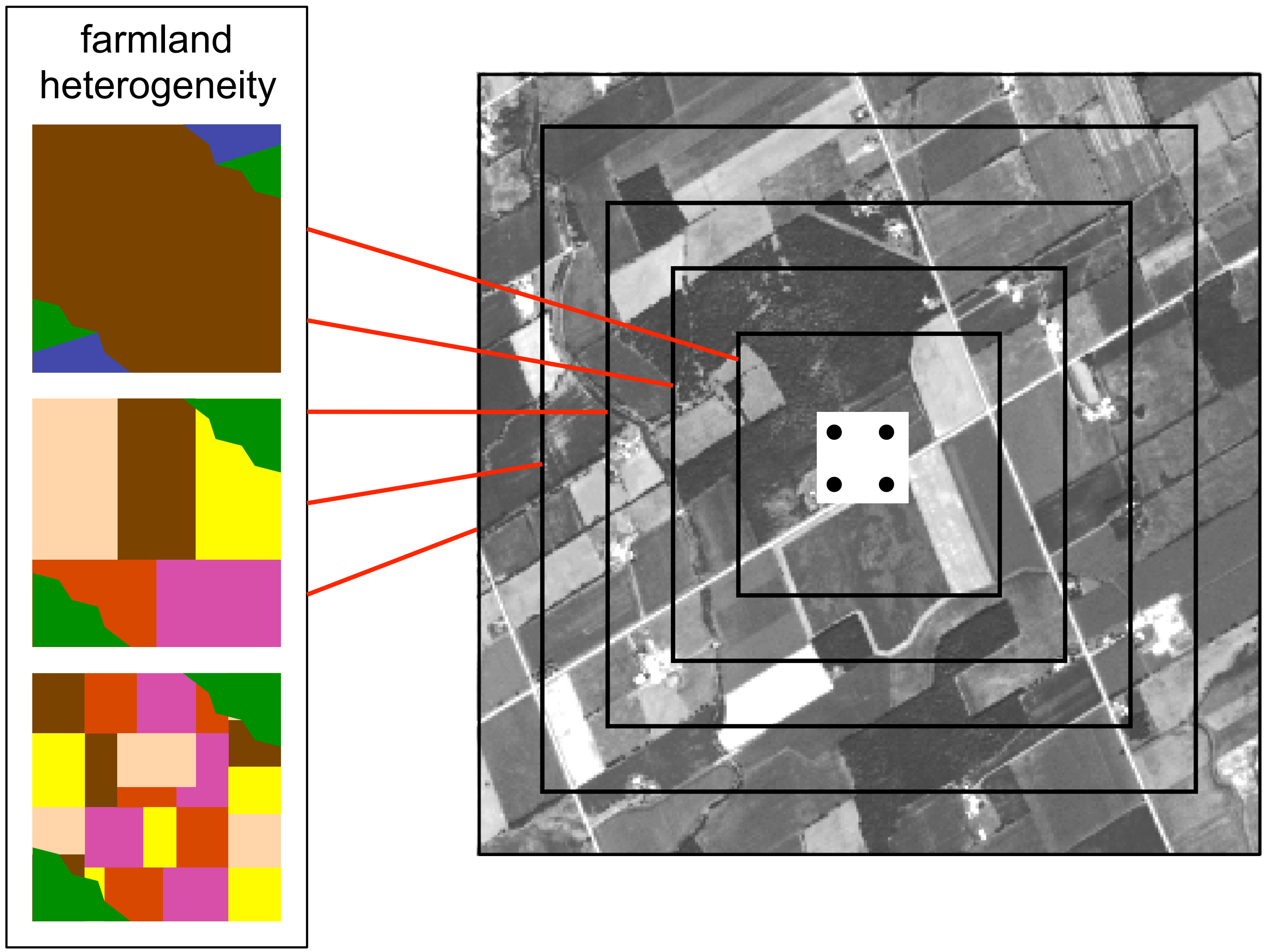

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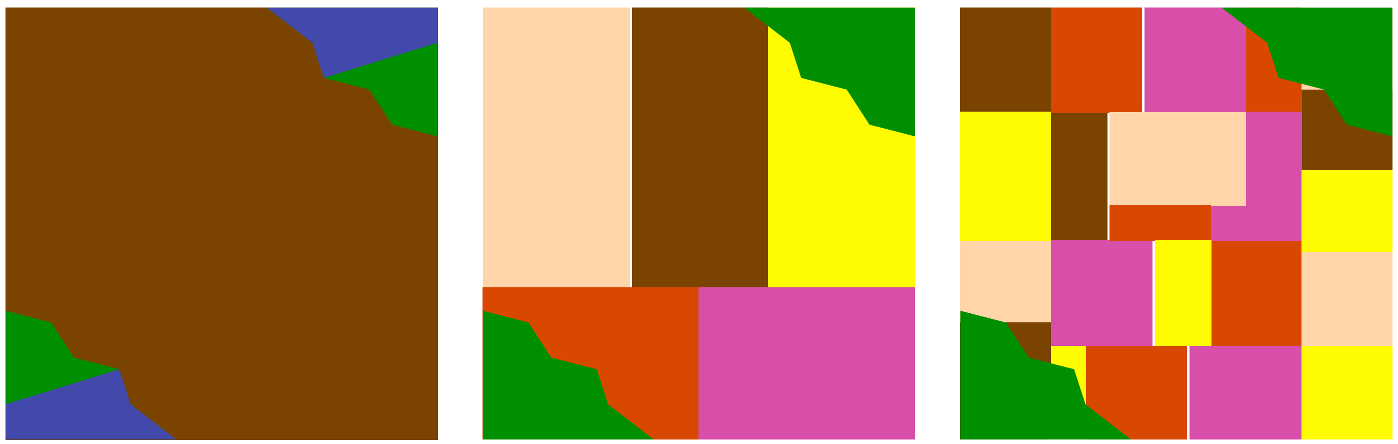
3. to determine the relative importance of landscape heterogeneity and farming practices on farmland biodiversity;

farmland heterogeneity



biodiversity

farming practices

Research Objectives

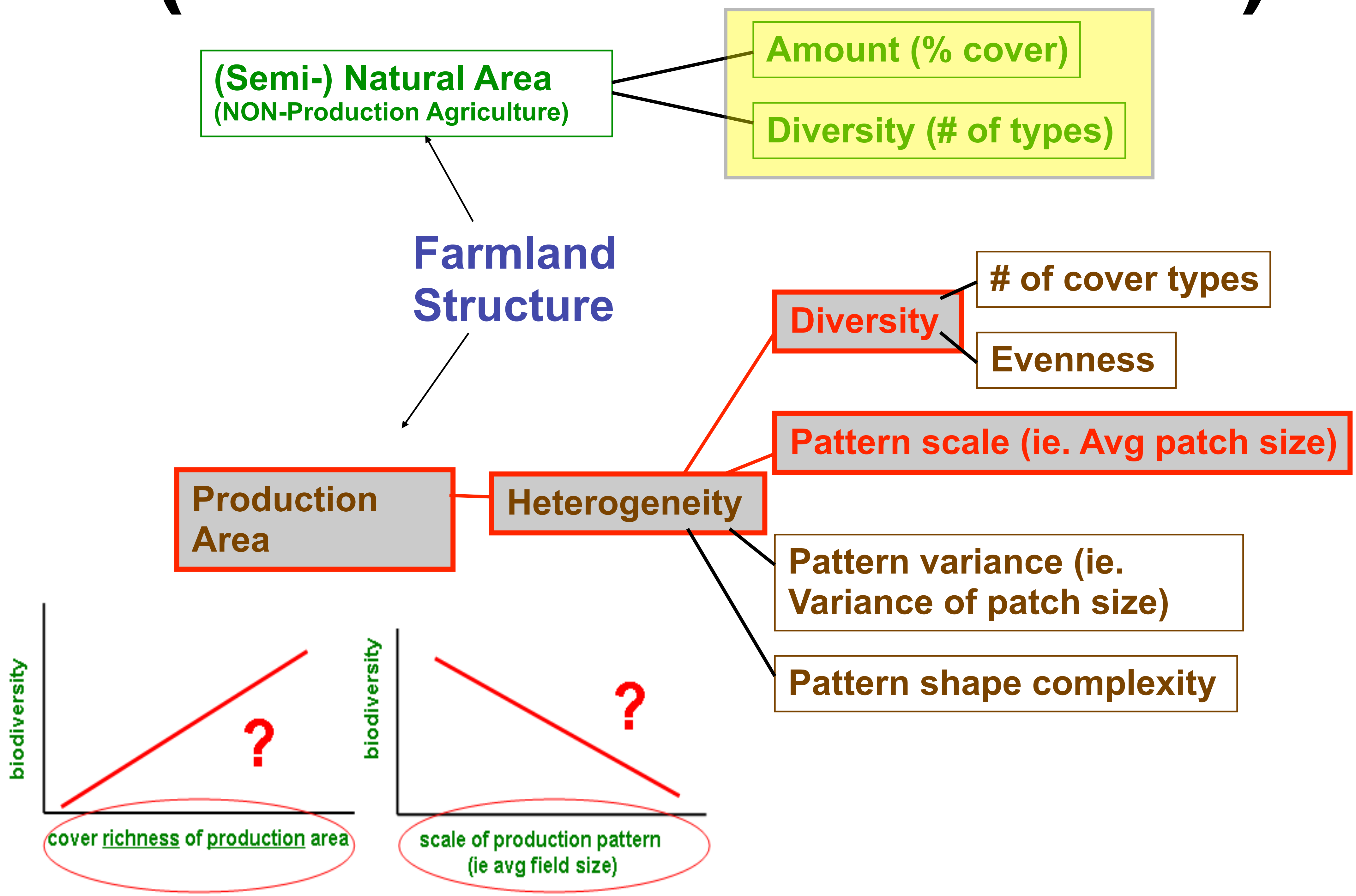
1. to determine which measure(s) of landscape heterogeneity are the best indicators (i.e., best predictors) of biodiversity in agricultural landscapes;

2. to determine the appropriate spatial extent(s) at which the indicators best predict biodiversity and therefore the spatial extent(s) at which farmland policies should be implemented;

3. to determine the relative importance of landscape heterogeneity and farming practices on farmland biodiversity; &

4. to determine which agri-environmental policies are most effective at increasing the 'best' farmland biodiversity indicators (as identified in objective 1).

Site Selection
(“Pasher Protocol”)



Pasher et al. (2013)

Selection Criteria

- N = 100 (final set)
  - > N → Temporal changes / permissions / errors / other…
- Multiple Extents (i.e. 1x1 km, 2x2 km…)
  - All criteria satisfied at each extent (!)
- > 60% Production Agriculture (row crops, hay, pasture)
- Variety of Heterogeneity Levels
  - Diversity - # of cover types
  - Distribution of average field sizes

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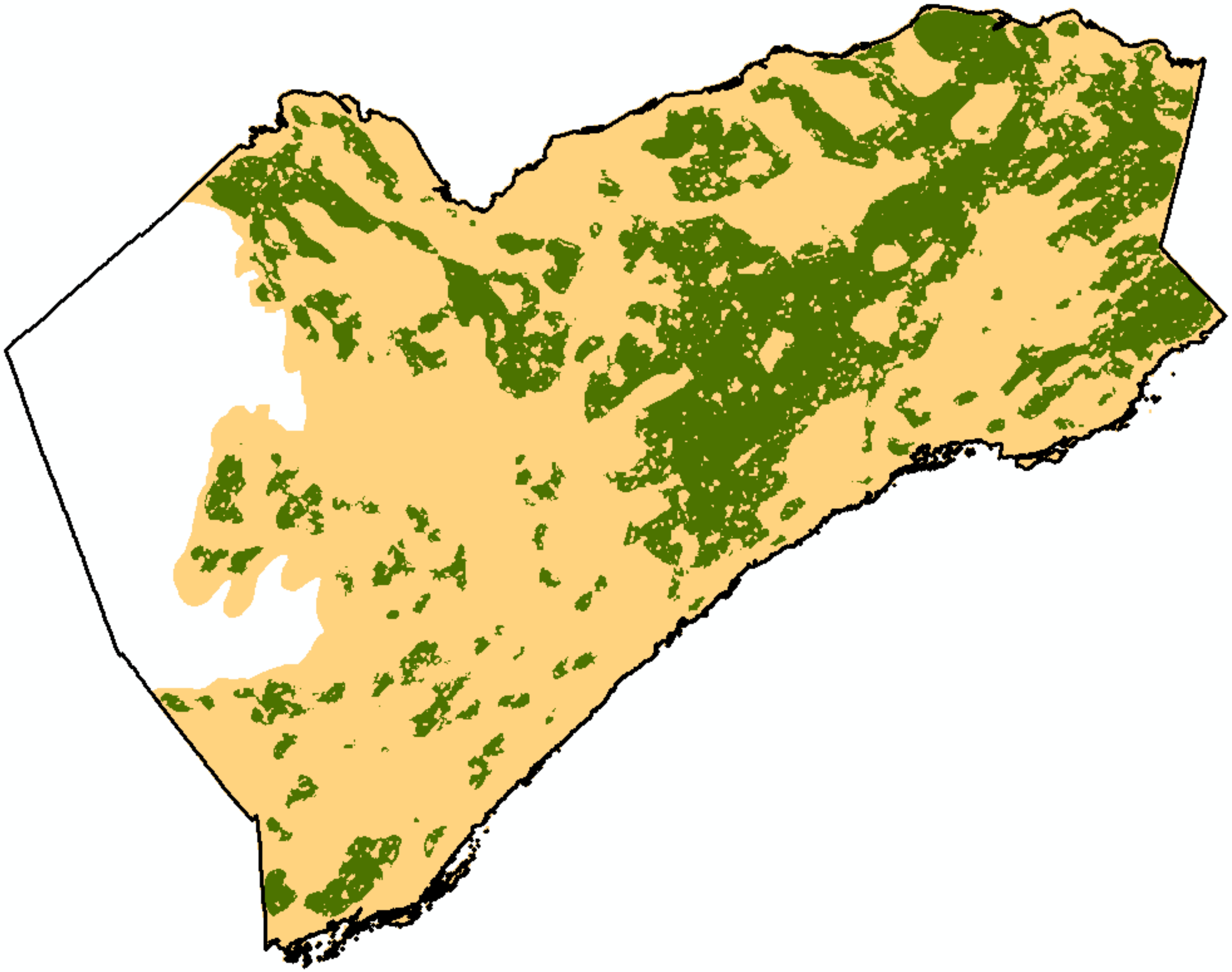
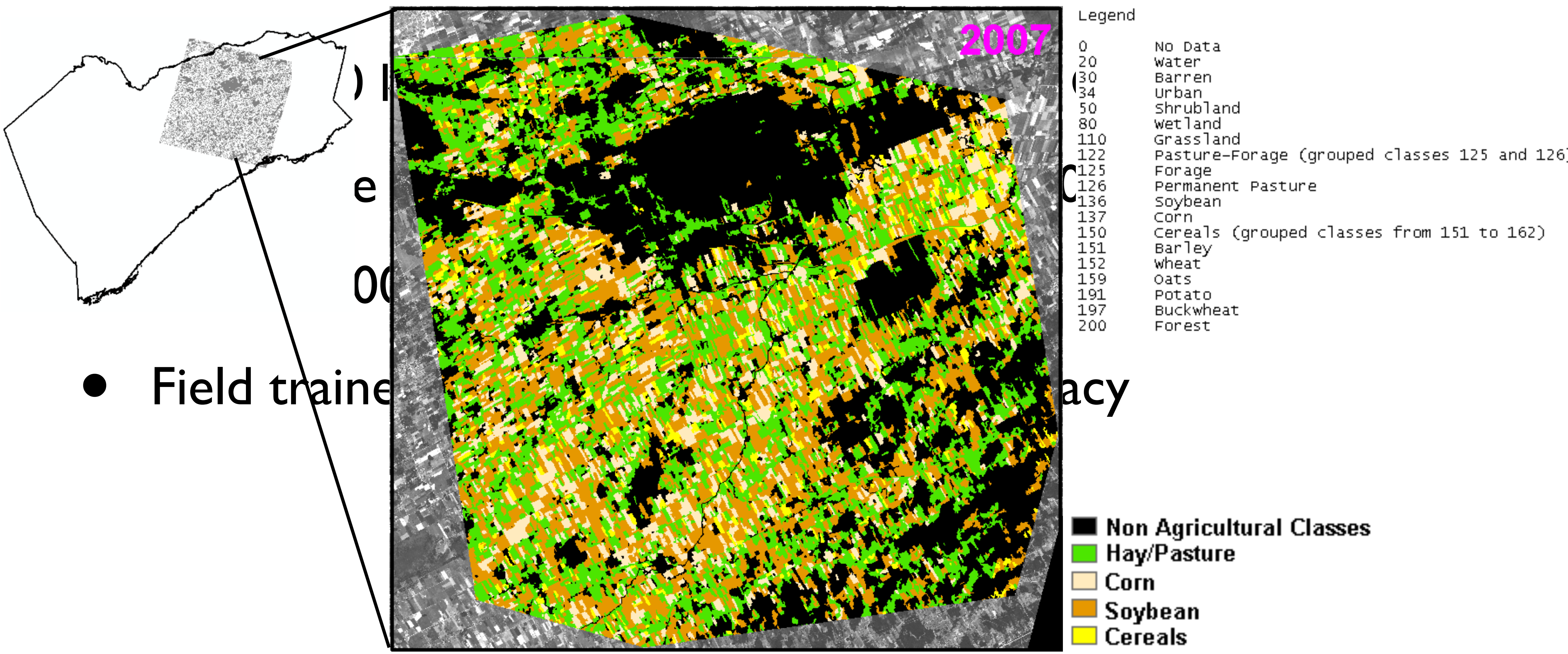
Areas With > 60% Active Agriculture?



AAFC Crop Classification Data



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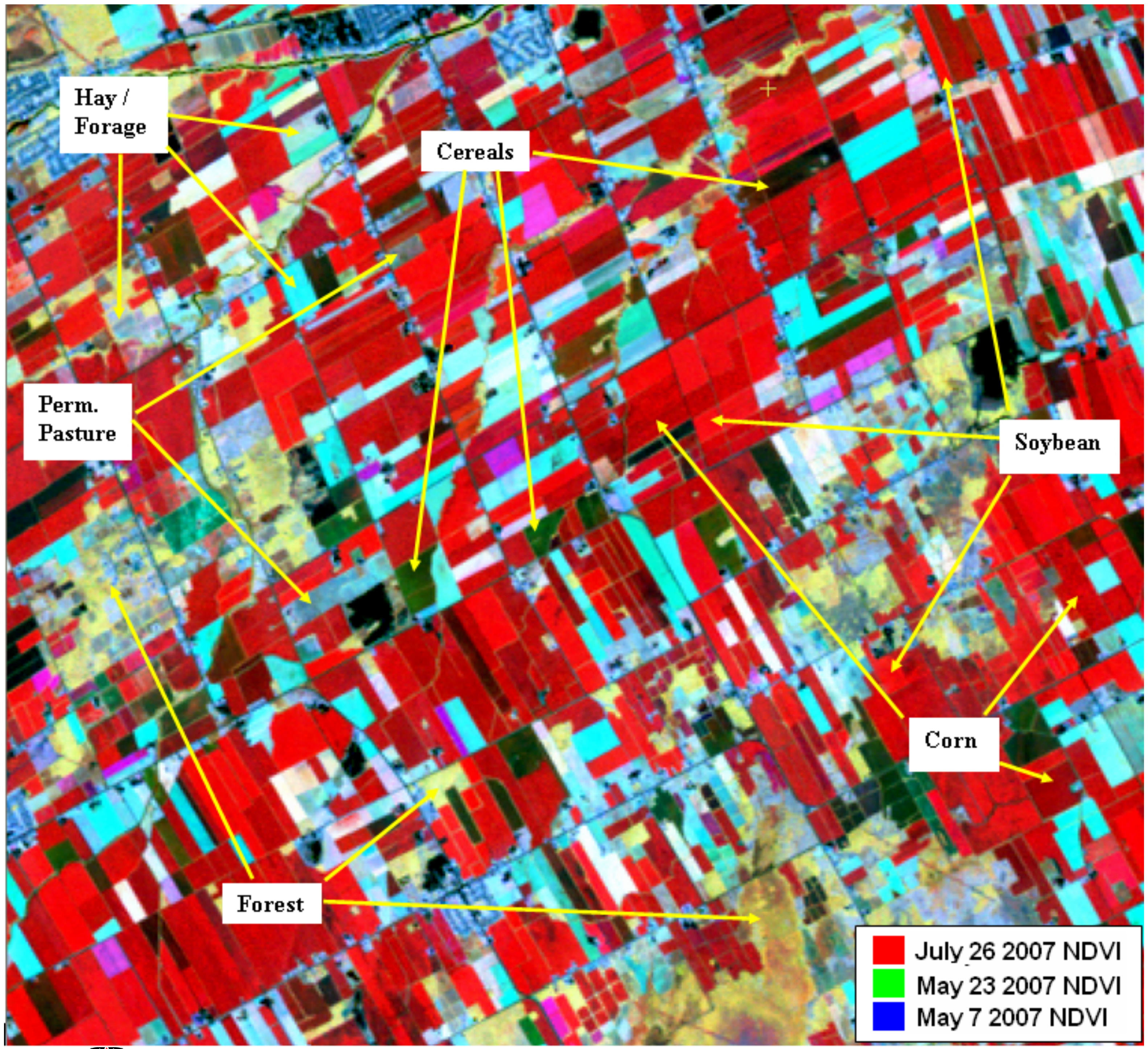
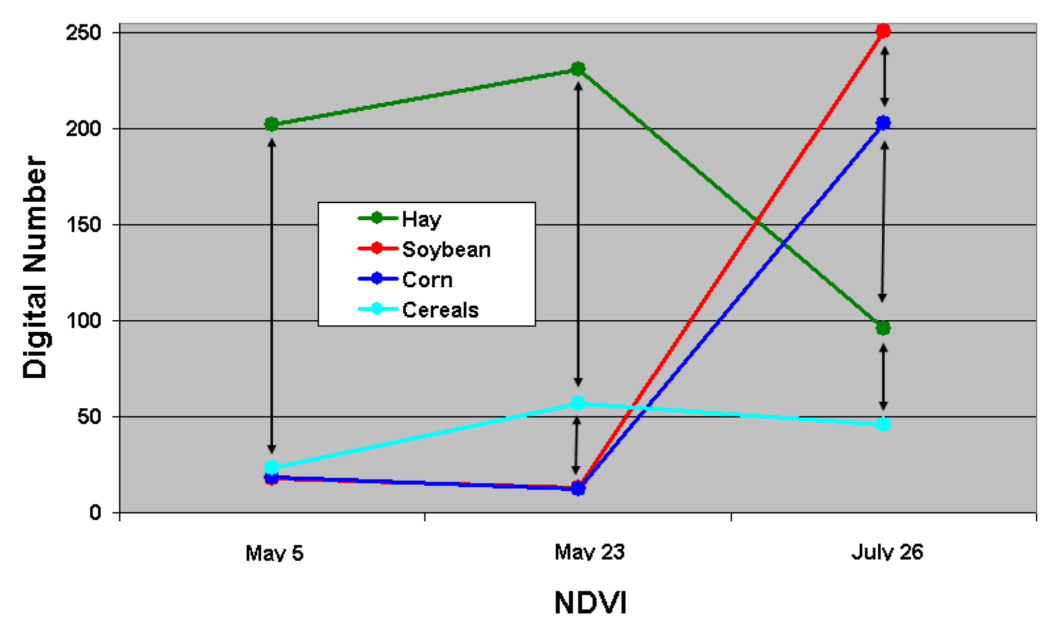
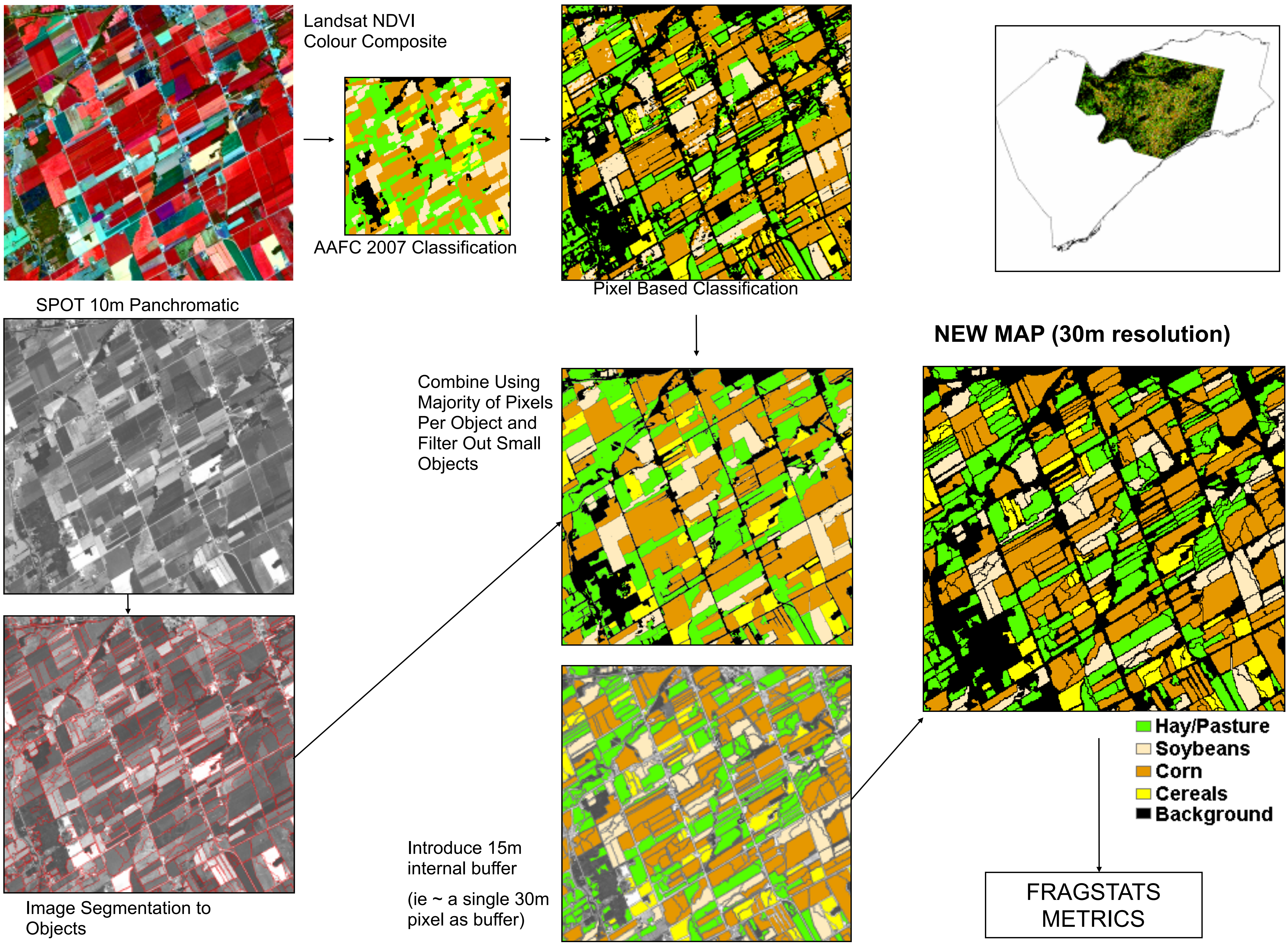
Landsat Multispectral Imagery

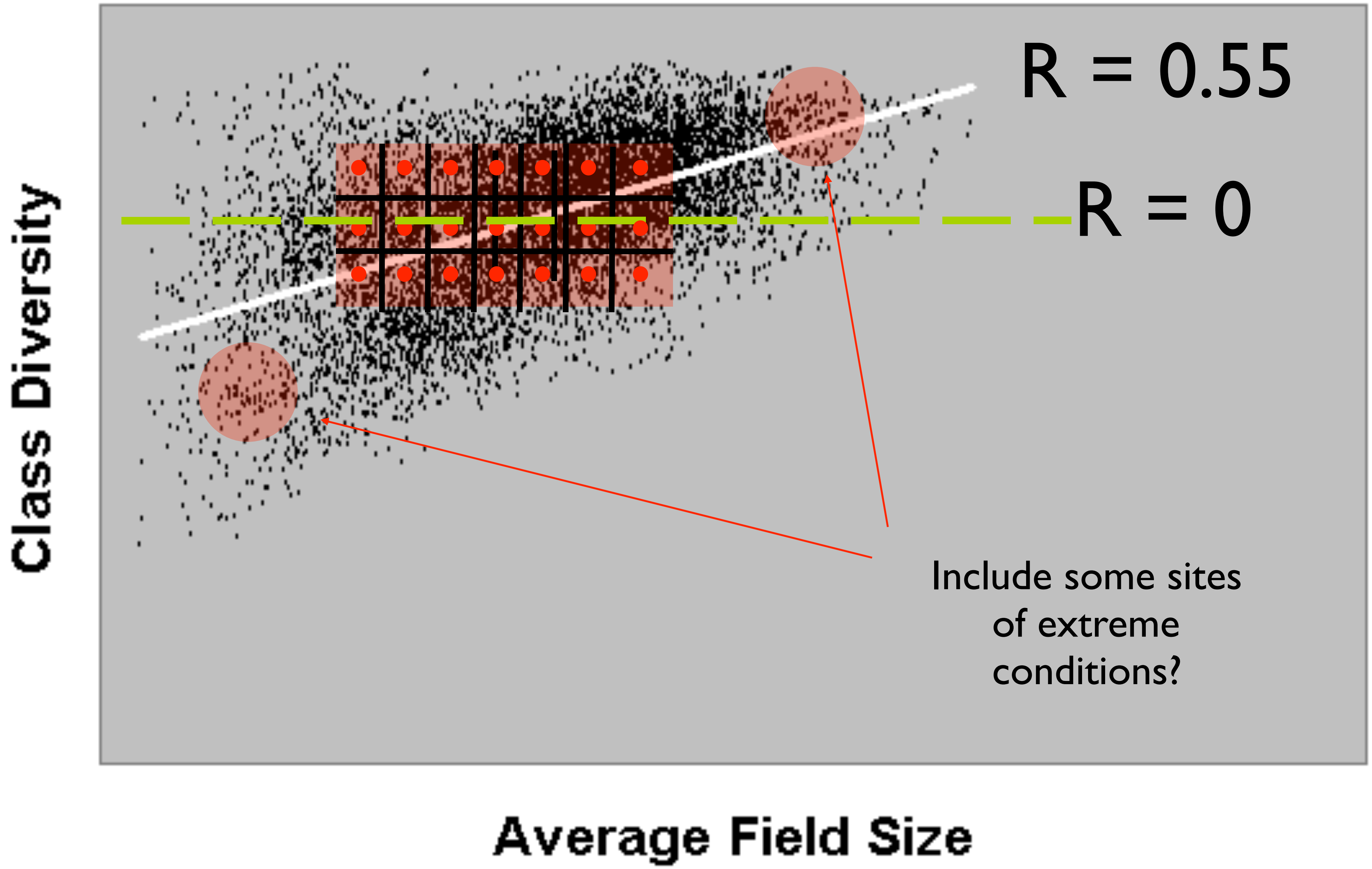


- 3 x Normalized Difference Vegetation Index (NDVI)
- Best combination for differentiating between classes of interest




Landsat NDVI
Colour Composite
AAFC 2007 Classification
Pixel Based Classification
SPOT 10m Panchromatic
NEW MAP (30m resolution)
Combine Using
Majority of Pixels
Per Object and
Filter Out Small
Objects
Hay/Pasture
Soybeans
Corn
Cereals
Background
Introduce 15m
internal buffer
(ie ~ a single 30m
pixel as buffer)
Image Segmentation to
Objects
FRAGSTATS
METRICS

Scatterplot Between Metrics (1km x 1km window)



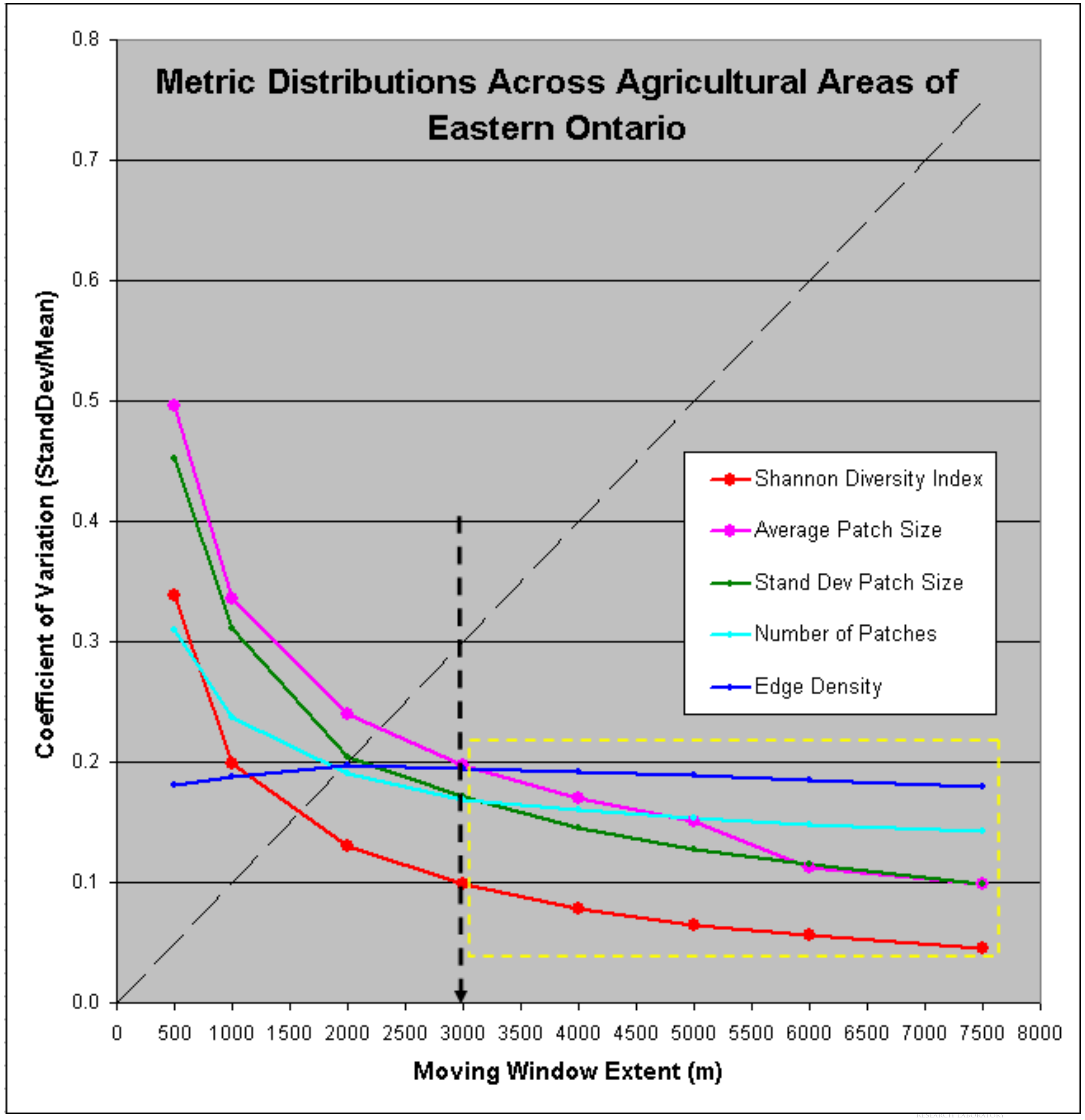
Maximum Extent for Landscapes

- $c_v = \frac{\sigma}{\mu}$

- Beyond a maximum extent (of interest) landscapes would not have enough variation to provide variability in field sites

- Approximately 3km x 3km extent

- Insignificant differences once > 3km
  - Also want landscapes as small as possible since they cannot overlap!



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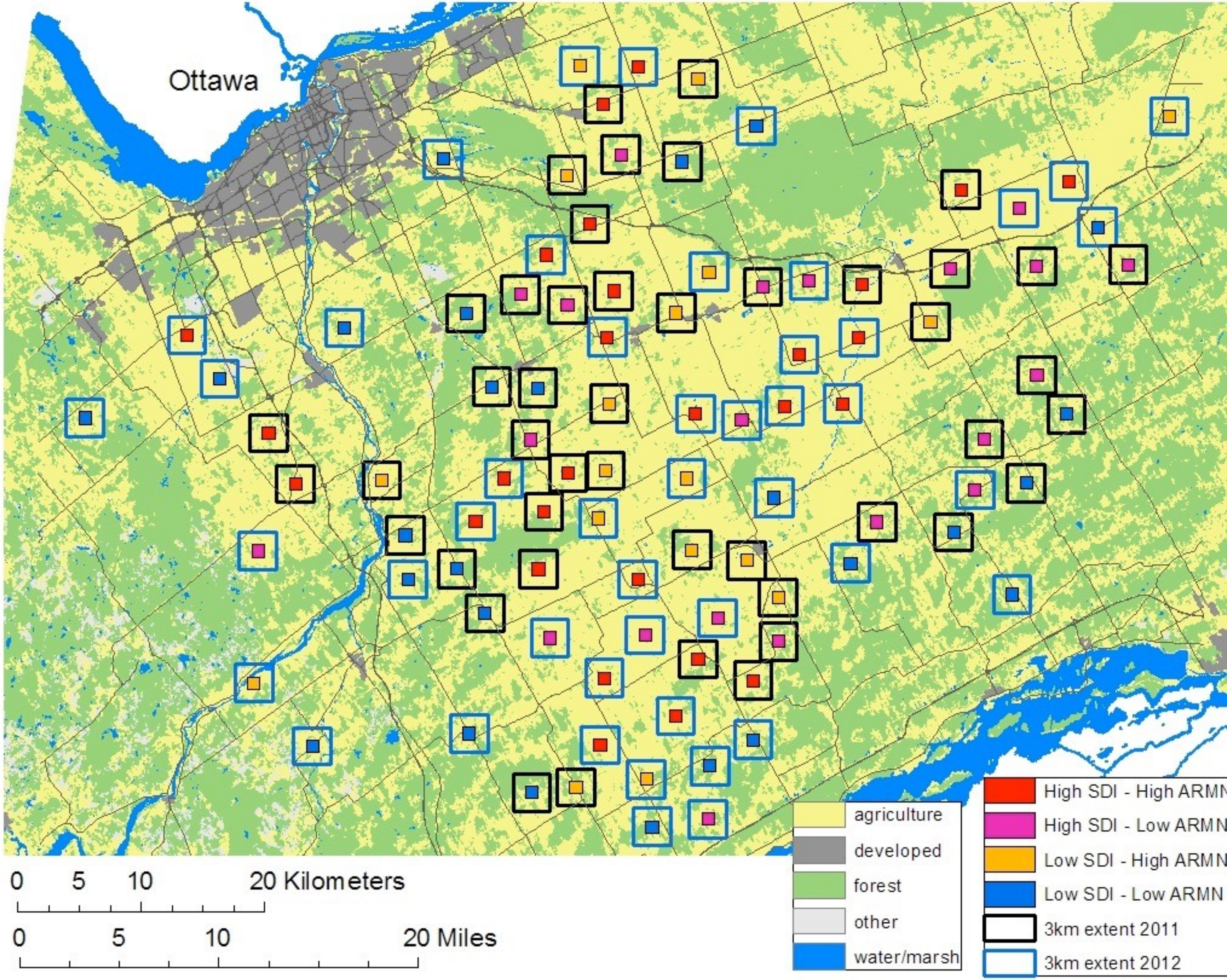
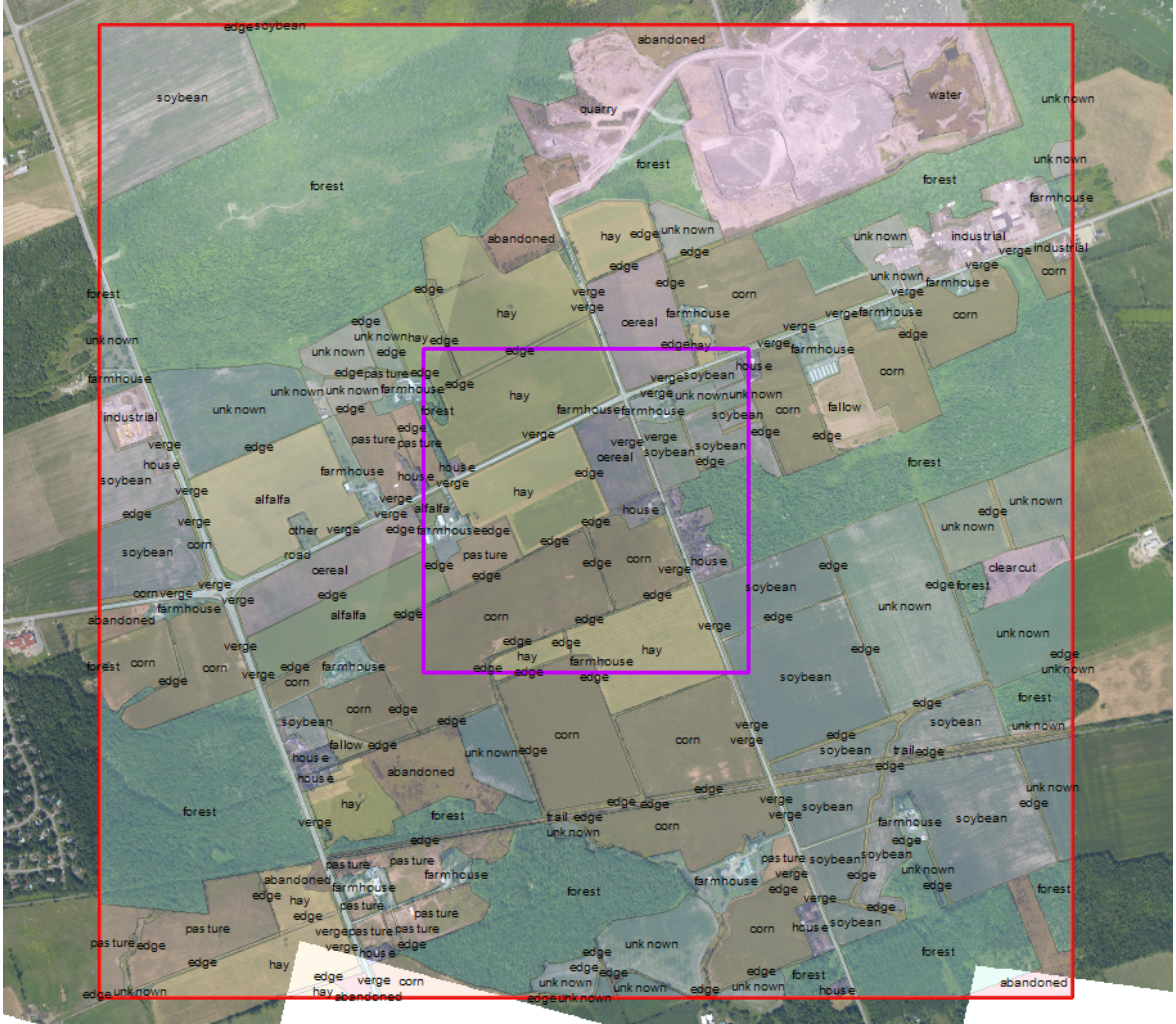

Ottawa
agriculture
developed
forest
other
water/marsh
High SDI - High ARMN
High SDI - Low ARMN
Low SDI - High ARMN
Low SDI - Low ARMN
3km extent 2011
3km extent 2012
0 5 10 20 Kilometers
0 5 10 20 Miles

Biodiversity Surveys

Experiments

Land use ground-mapping


0
125
250
500 Meters
H_H_27



edge soybean
abandoned
water
quarry
unk nown
soybean
forest
unk nown
forest
forest
farmhouse
forest
abandoned
hay edge unk nown
unk nown
industrial
edge
verge industrial
edge
unk nown farmhouse
corn
edge
verge
edge
hay
verge
verge
cereal
farmhouse
corn
verge farmhouse
corn
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verge farmhouse
edge
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verge soybean
hous e
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hay
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unk nown
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forest
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corn
fallow
industrial
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verge
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soybean
edge
verge
cereal
soybean
forest
hous e
edge
farmhouse
hous e
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clear cut
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edge forest
soybean
corn verge
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farmhouse
abandoned
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farmhouse
farmhouse
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fallow
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corn
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pas ture
pas ture soybean soybean
farmhouse
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edge
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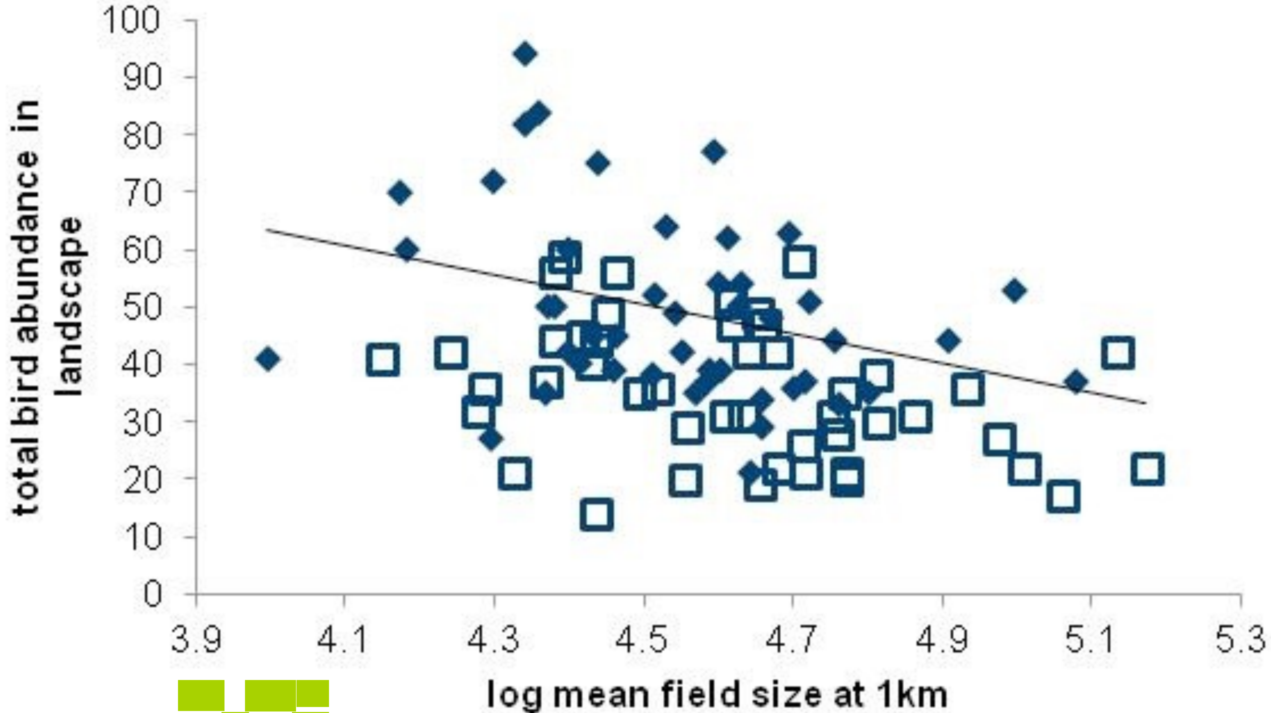
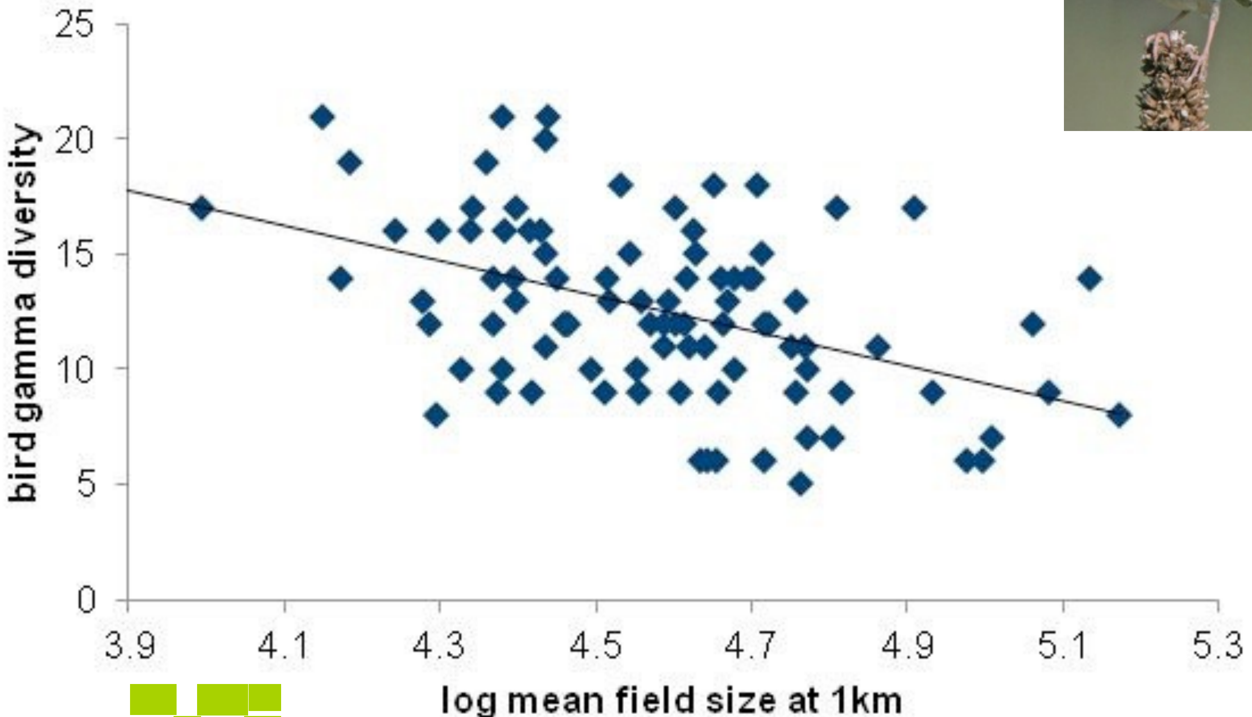
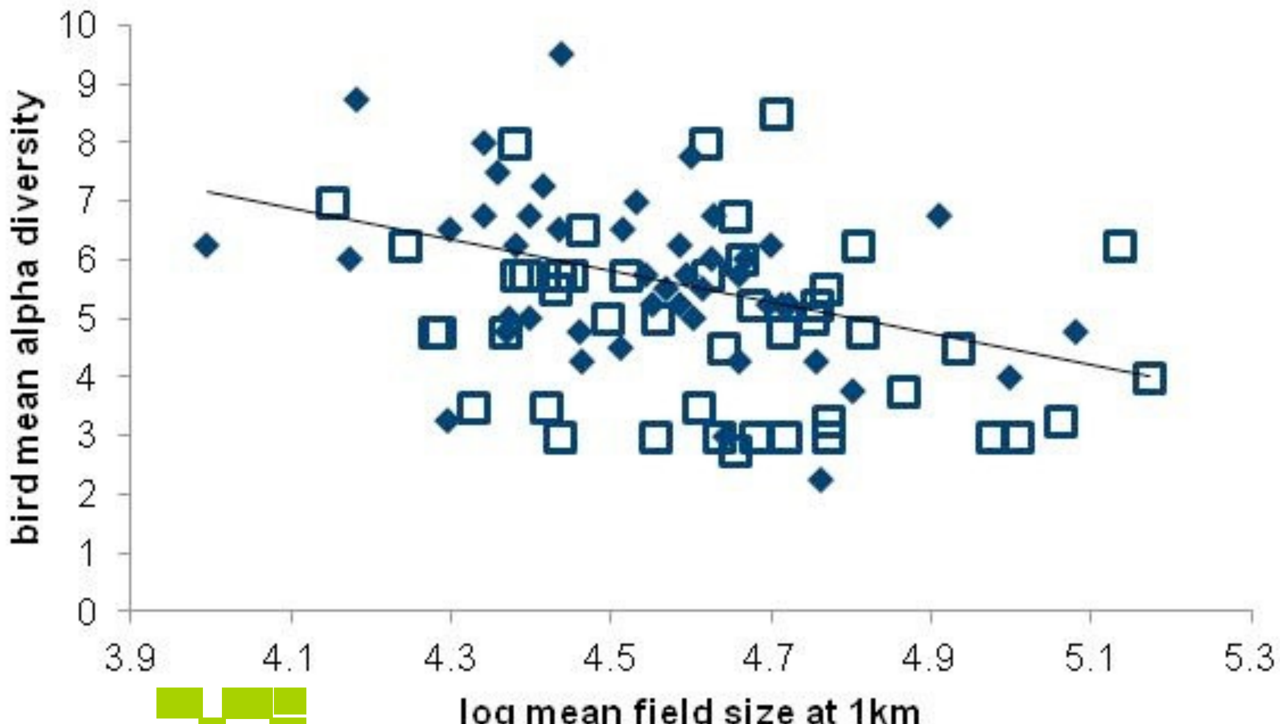
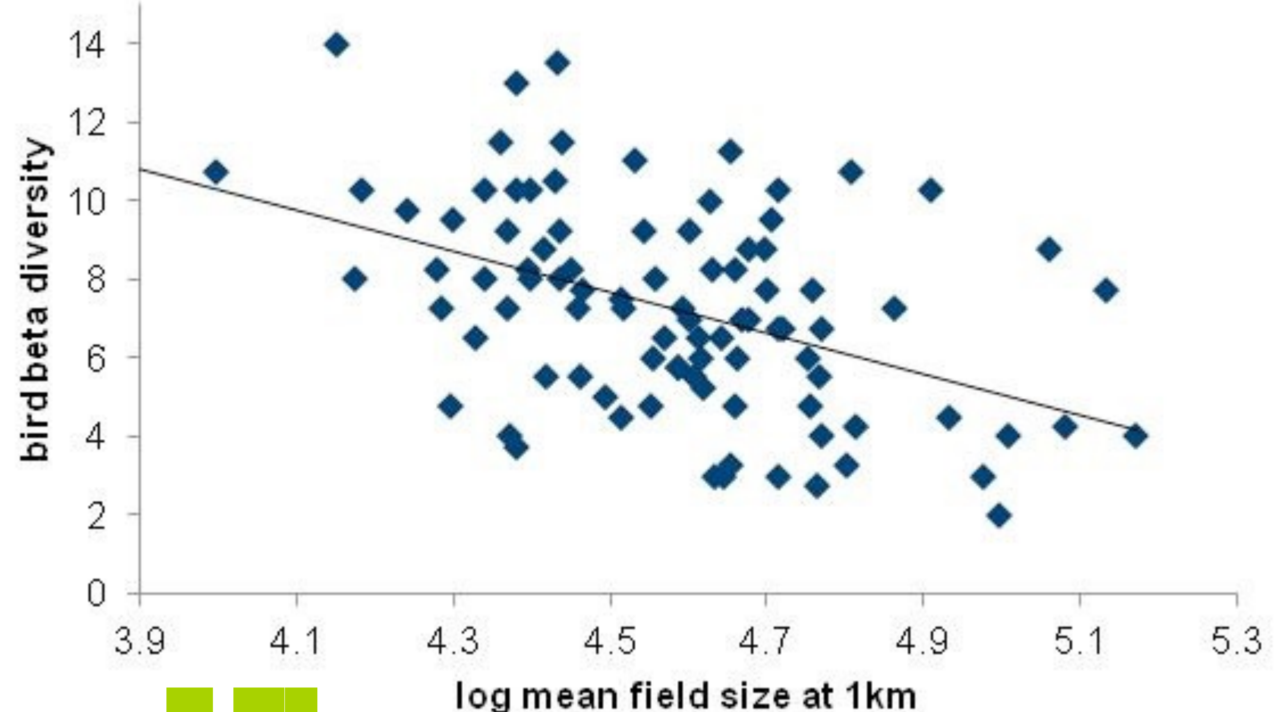
abandoned

Some results

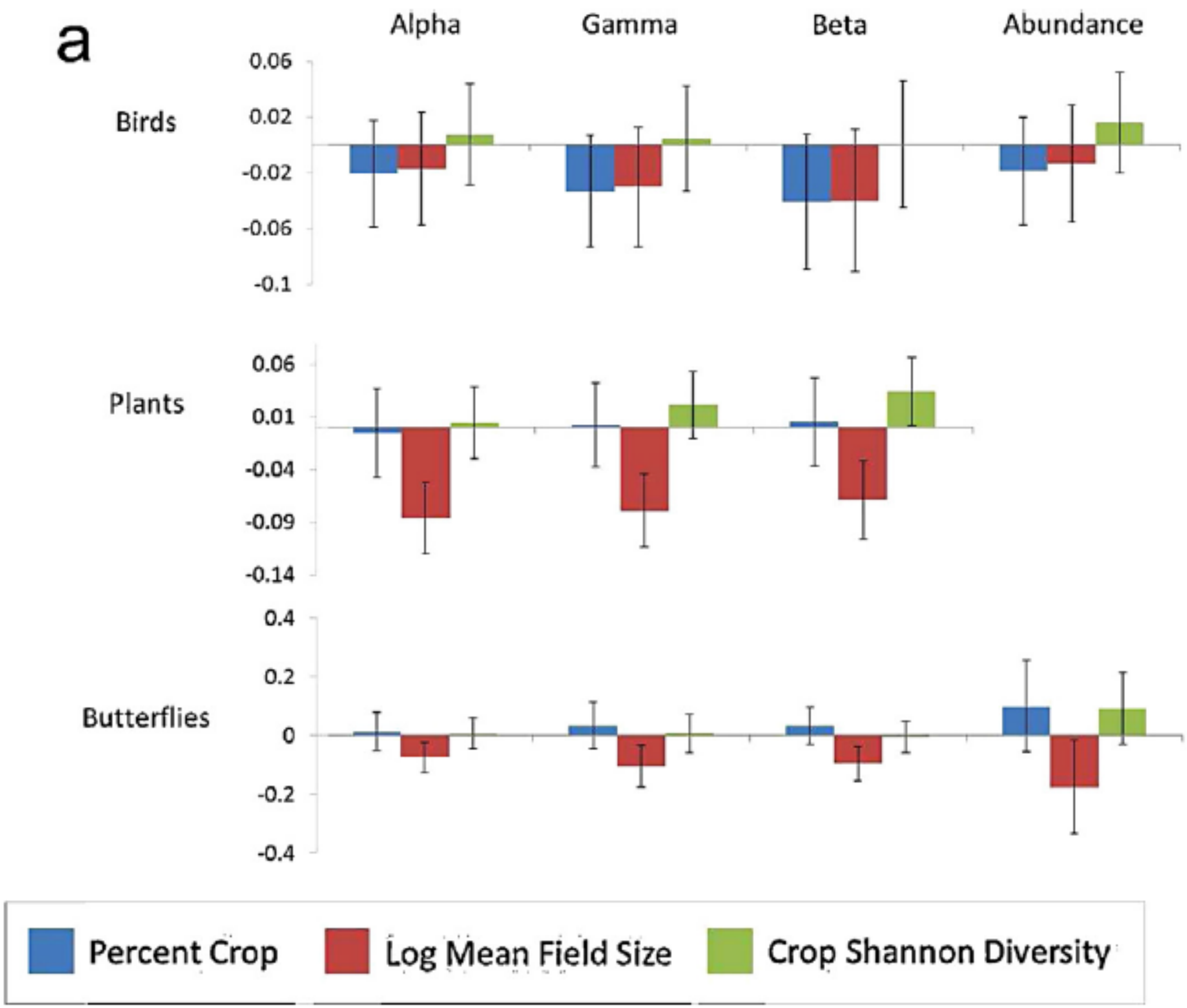








L. Fahrig et al. / Agriculture, Ecosystems and Environment 200 (2015) 219–234



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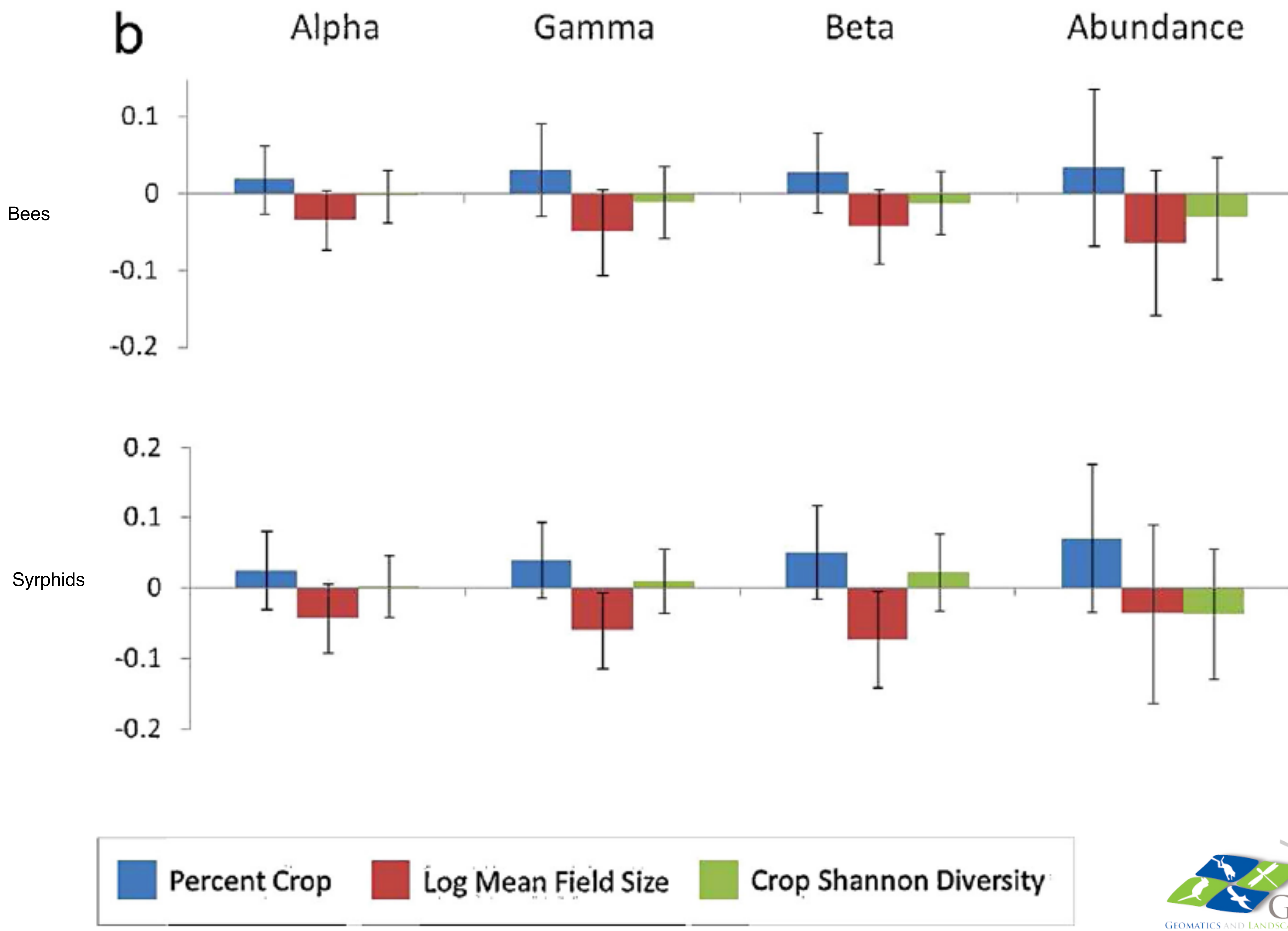
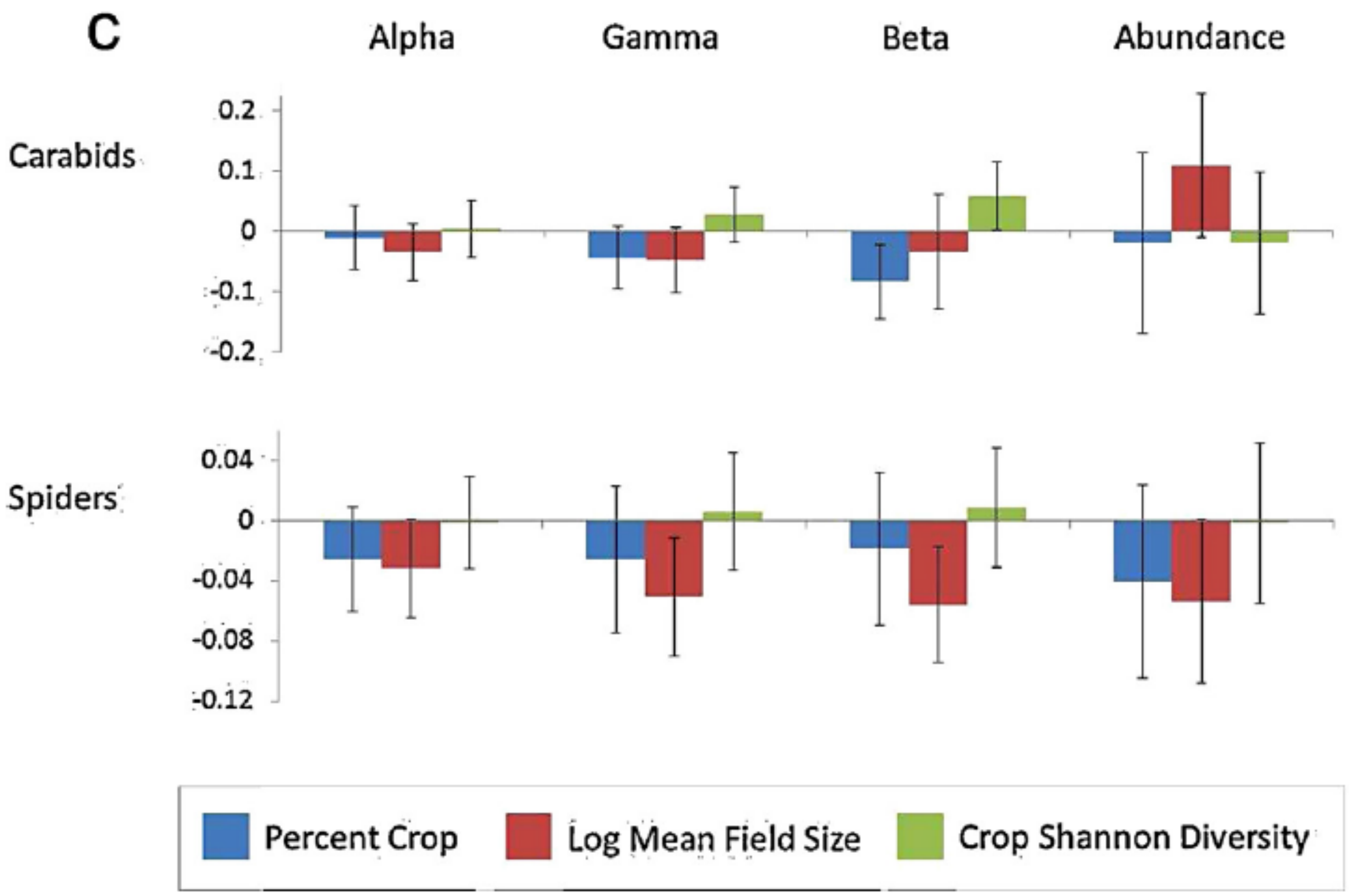
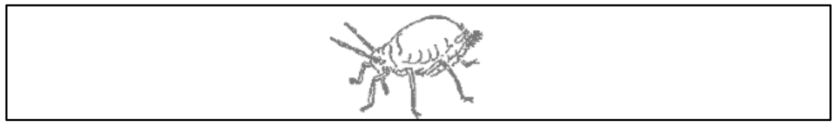
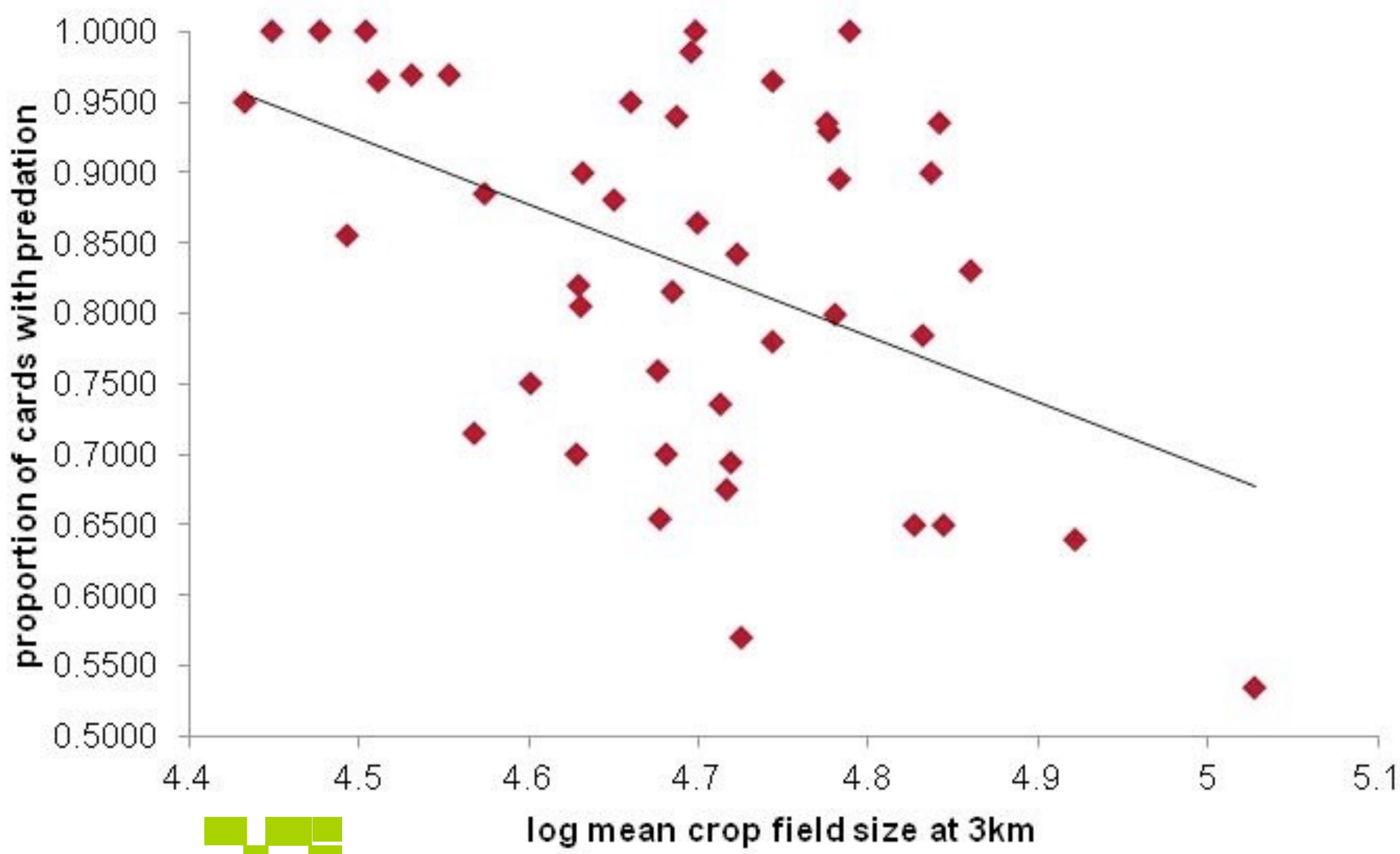
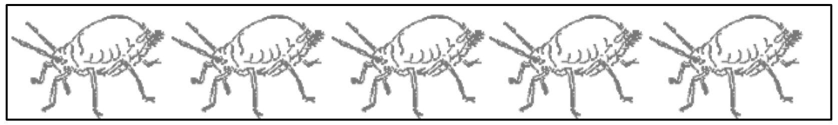

b
Alpha
Gamma
Beta
Abundance
Bees
Syrphids
0.2
0.1
0
-0.1
-0.2
Percent Crop
Log Mean Field Size
Crop Shannon Diversity

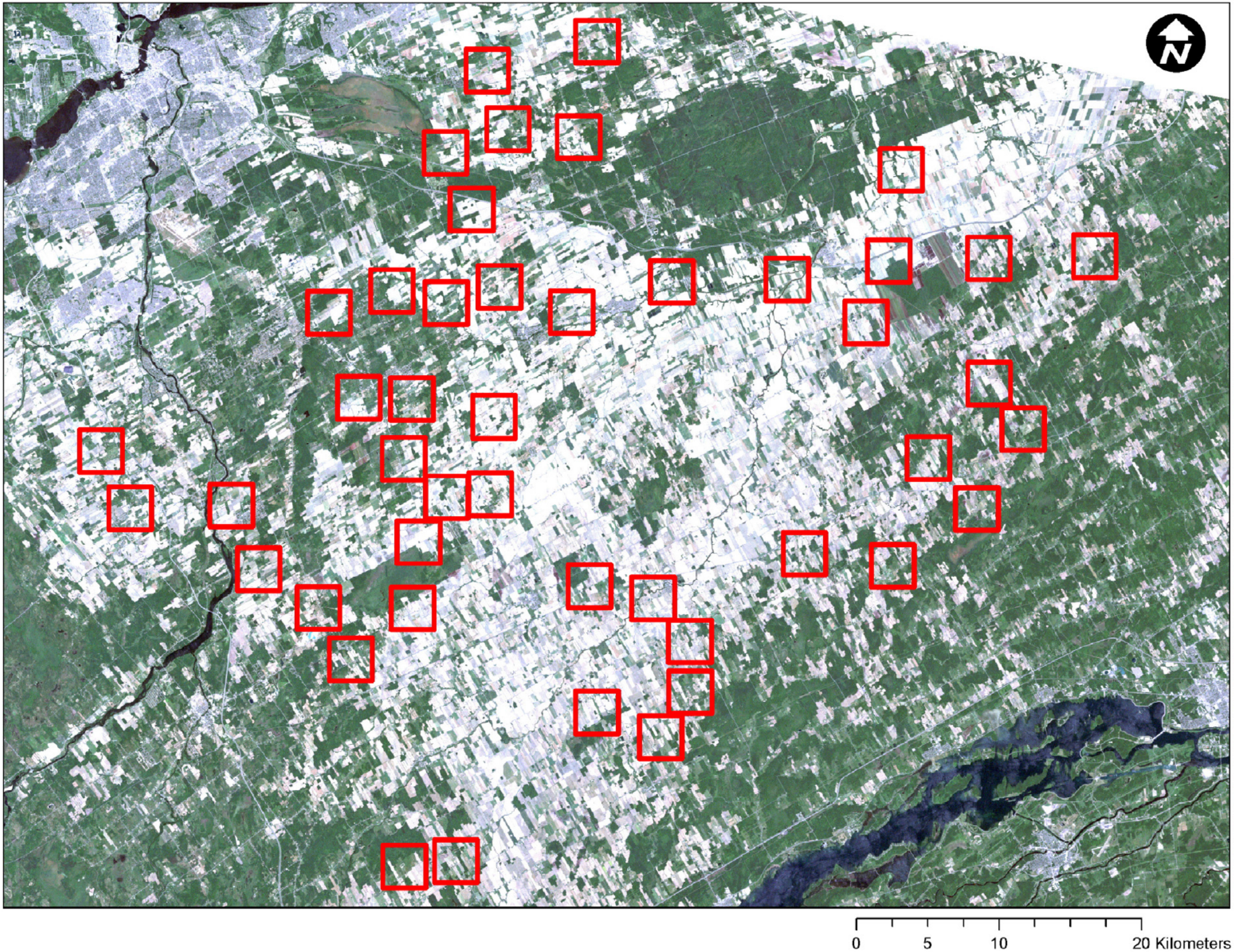

C
Alpha
Gamma
Beta
Abundance
Carabids
0.2
0.1
0
-0.1
-0.2
Spiders
0.04
0
-0.04
-0.08
-0.12
Percent Crop
Log Mean Field Size
Crop Shannon Diversity

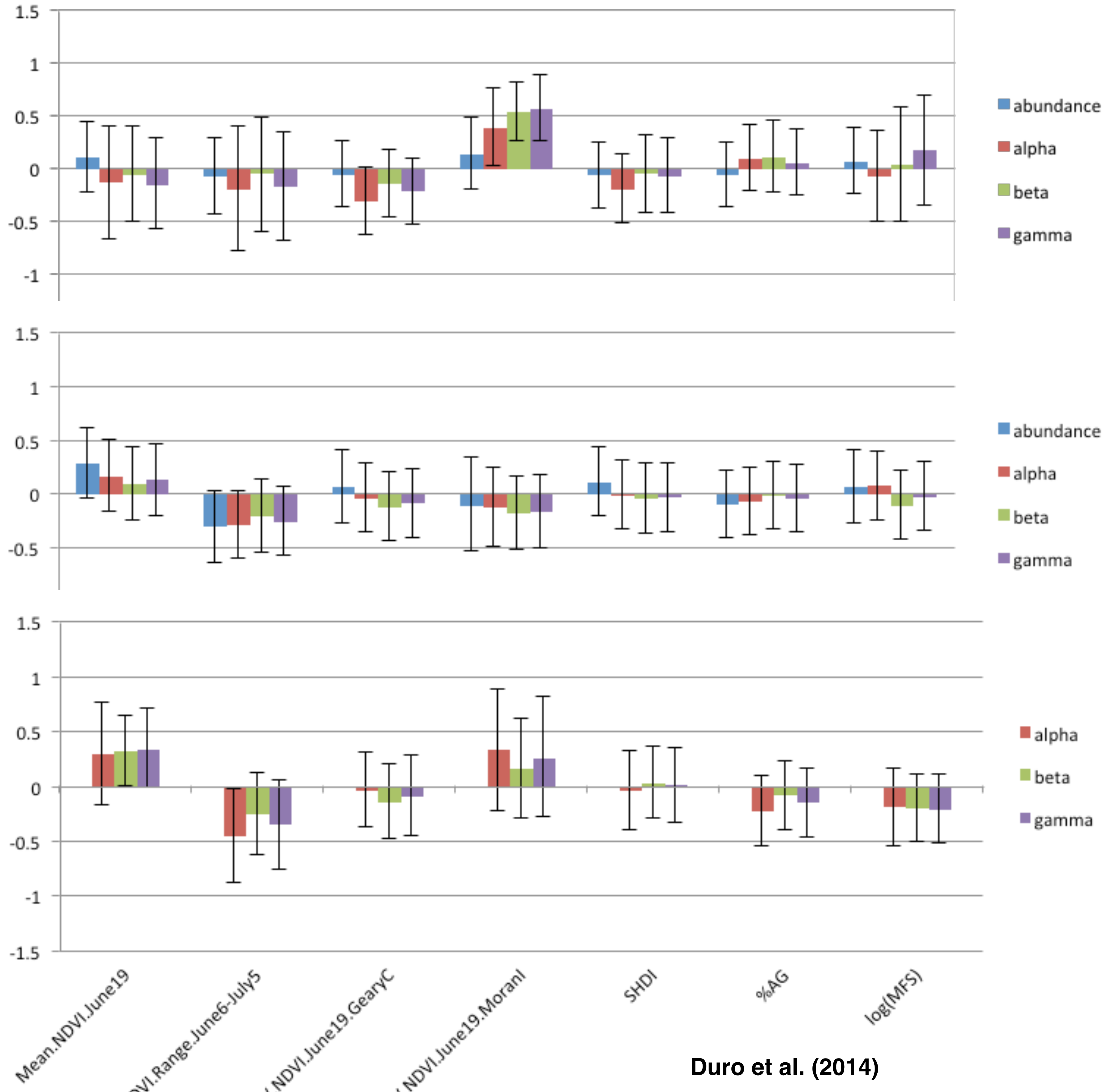
Ecosystem services results – biological control








N
0
5
10
20 Kilometers



Duro et al. (2014)

5. Conclusion

Our findings indicate that when modeling species diversity of birds and plants in agricultural environments, predictors derived from continuous information of crop productivity (NDVI) were consistently ranked higher than predictors derived from information based on a discrete classification of Landsat imagery. Furthermore, local measures of spatial autocorrelation, specifically the local Moran's I, are useful indicators of spectral heterogeneity, at least on par with existing measures such as simple image-based texture (CV). From a practical standpoint, the use of continuous information is preferable, as discrete land cover classifications involve an inherent level of error and generalization, and can be costly to produce and validate. While the overall amounts of variability explained by our taxon-specific models were low, they were generally commensurate with similar studies that relied on Landsat imagery.

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Further work in E.On.

- Jesse van den Berg: fuzzy logic to express heterogeneity
- Patrick Kirby: uncertainty from spatial data
- Niloofar Alavi: further investigation of getting more info from imagery
- Michelle Fairbrother: evaluating other measures of landscape heterogeneity
- Tonia Tanner: "porting" results from this project to landscape scenario exploration tool/project
- Amanda Martin: practices

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Monte Carlo-based analysis of the effect of spatial and thematic uncertainty on biodiversity models

Carleton UNIVERSITY

Department of Geography & Environmental Studies

Patrick Kirby & Dr. Scott Mitchell
Geomatics & Landscape Ecology Laboratory, Dept. of Geography and Environmental Studies, Carleton University, Ottawa, Canada - (Patrick.Kirby, Scott.Mitchell)@carleton.ca

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Abstract

Monte Carlo (MC) simulation is a common approach to quantifying uncertainty. We used MC simulation to generate multiple alternate landscape maps, based on estimates of spatial and thematic uncertainty. From these maps, alternate sets of landscape metrics were calculated and used to refit biodiversity models. Results indicate that the uncertainty estimates from model averaging outweigh the effects of spatial and thematic uncertainty in the landscape metrics. Some shifts between reference and simulated model averaged coefficients indicate the need for further research into simulation approaches that consider spatial autocorrelation.

Introduction

- There is a recognized need for approaches to accounting for spatial and thematic uncertainties in remote sensing and Geographic Information Systems products (Shi *et. al.* 1999)
- MC simulation is a common, black-box approach to quantifying uncertainty, that involves generating multiple error-sensitized inputs (or realizations), performing an analysis, and analysing the output distribution

Objectives:

1. Demonstrate an approach to generating realizations of alternate landscape structure and composition in an agricultural landscape
2. For a set of biodiversity models, compare the influence of spatial and thematic uncertainties in landscape maps to modelling uncertainty estimates that do not consider these uncertainties

Background

- Models are from the GLEL Farmland Biodiversity project, based on work by Fahrig *et. al.* (2011), Pasher *et. al.* (2013), Duro *et. al.* (2014), and Fahrig *et. al.* (Submitted).

Predictors (landscape metrics):

1. Proportion of land in agricultural production (**prop.ag**)
2. Mean field size, logged (**log.mfs**)
3. Shannon crop diversity (**crop.div**)

- Year 2012 indicator variable included, as data was collected at plots from two separate years

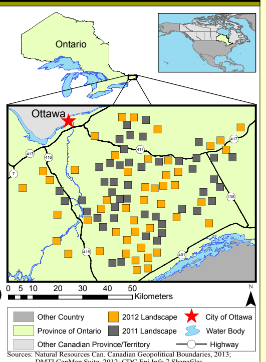

Figure 1. Study area map.

Response Variables: 3 to 4 diversity types for 6 taxonomic groups (23 total; 1 used for each biodiversity model)

- Diversity types: alpha, beta, gamma, abundance
- Taxonomic groups: beetles, birds, butterflies, plants, spiders, syrphids
- For each biodiversity model, the parameters of seven linear candidate models (different combinations of predictors) were averaged based on fit and simplicity (AICc weights)

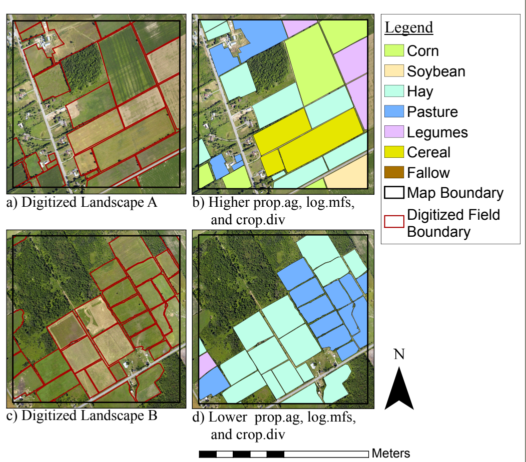

Figure 2. (a,c) Digitized landscapes with (b,d) corresponding ground referenced landscape maps

Methods: Spatial Uncertainty

- Spatial uncertainty considered for fields that had been digitized from high resolution air photos (0.5 m resolution)
- Spatial uncertainty estimates consider uncertainty in vertex position and uncertainty in boundary interpretation (Fig. 3).

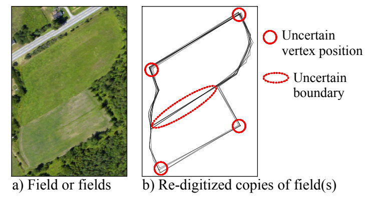

Figure 3. Spatial uncertainty considered in digitized fields.

Uncertainty in Vertex Position

- Modelled by normal distributions in horizontal and vertical directions with a global variance estimate
- Variance estimated by vertex matching across 24 re-digitized subsets of 100 fields

Uncertainty in Boundary Interpretation

- Reference fields with uncertain boundaries were duplicated
- Duplicates split or merged to represent alternate boundaries
- Alternates assigned probability estimates based on air photo interpretation and Canny edge detection (Fig. 4)

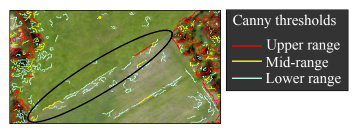

Figure 4. Potential field boundary with detections from three Canny edge detection runs of varying thresholds.

- Alternates weighted 25% in favour of reference boundary, with 75% determined by proportion of edge detected by Canny detector (up to 25% for each threshold range)
- Up to +/- 25% leeway based on photo interpretation
- Some alternates involved boundaries being taken out of consideration for fields that may be abandoned or lawns

Methods: Thematic Uncertainty

- We adopted a scenario where reference **crop.div** metrics for 2011 were based on a supervised random forest classification of four Landsat 5 Thematic Mapper scenes throughout the growing season
- Pixel-specific estimates of class membership probability were based on class assignments across 500 decision trees, re-scaled on 0 to 1
- Class membership probabilities aggregated to the field level by averaging pixels within field boundaries (shrunken boundaries used, where possible, to avoid mixed pixels along edges)

Table 1. Areal (km^2) error matrix of the crop classification.

		Reference							User's Accuracy
		Corn	Soybean	Hay	Pasture	Legumes	Cereal	Fallow	
Classification	Corn	8650.1	415.2	109.1	38.8	0	26.0	64.0	93.0%
	Soybean	710.2	9517.3	75.5	16.2	0	21.5	0.0	92.0%
	Hay	0	0	3462.2	333.5	861.6	0	109.7	72.6%
	Pasture	9.2	5.7	442.8	1600.8	101.0	0	30.8	73.1%
	Legumes	0	40.9	761.8	16.0	909.1	0	0	52.6%
	Cereal	0	57.3	247.0	0	0	735.0	126.0	63.1%
	Fallow	0	7.3	90.3	104.7	142.7	0	143.4	29.4%
Producer's Accuracy		92.3%	94.8%	66.7%	75.9%	45.1%	93.9%	30.3%	Overall: 83.4%

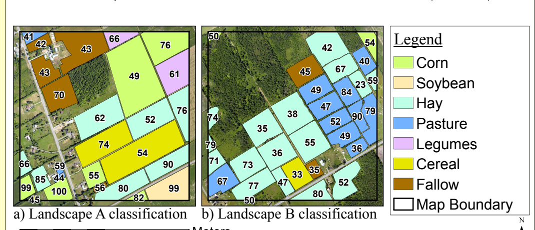

Figure 5. Classifications of (a) Landscape A and (b) Landscape B, showing the most-likely class with probability of belonging to that class.

Methods: Simulation

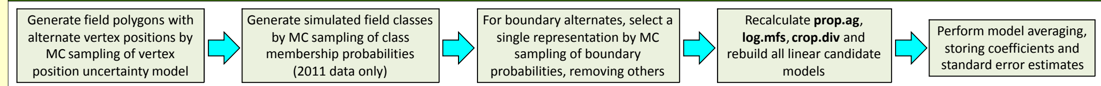

Figure 6. Flow chart for full realization generation. Repeated 2000 times.

Results: Realizations and Simulated Landscape Metrics

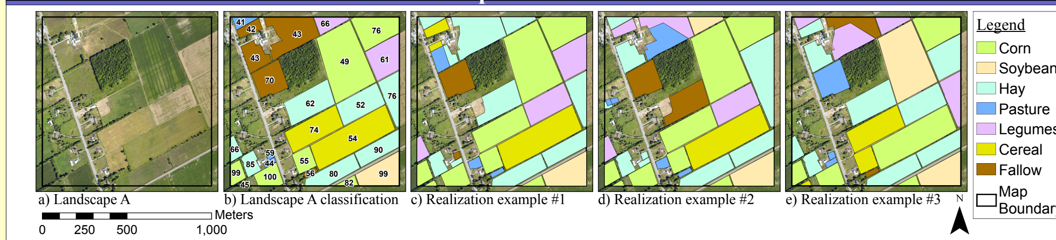

Figure 7. Example of (a) a landscape with (b) a classification and (c,d,e) realizations of alternate crop type and boundary interpretation. Vertex realizations not shown.

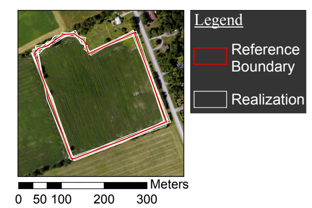

Figure 8. Reference field boundary with ten realizations of vertex positions.

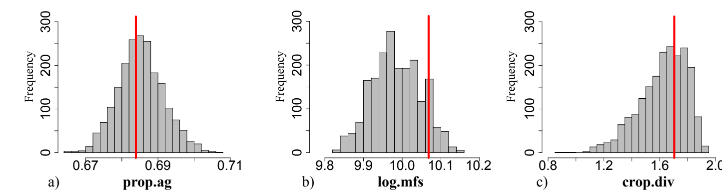

Figure 9. Distribution of simulated landscape metrics for Landscape A, across 2000 realizations. Red line represents the reference value. (a) Proportion of land in agricultural production. (b) Mean field size, logged. (c) Shannon crop diversity.

Results: Uncertainty in Model Averaged Coefficients

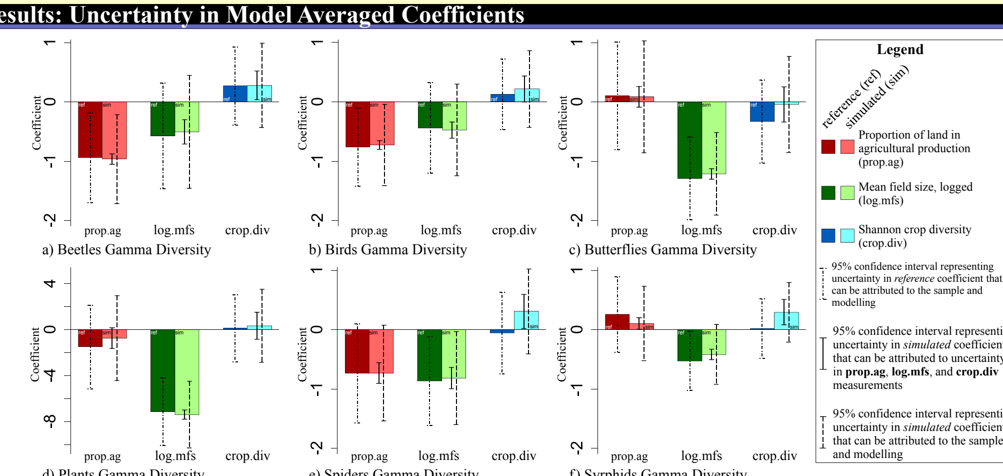

Figure 10. Model averaged biodiversity coefficients for the reference and simulated data. Comparison of error bars on the simulated coefficients shows the influence of spatial and thematic uncertainties in the landscape metrics, relative to the model averaging uncertainty estimates (consider sample and modelling uncertainties).

- Effects of uncertainty in the landscape metrics ($s^2_{metrics}$) on the coefficients was less was less than the effects of the uncertainty associated with the sample and modelling ($s^2_{mod.avg.}$) (Fig. 10 and Table 2)
- See Anderson (2008) for model averaging details
- Some shifts between reference and simulated coefficients were observed, particularly for **crop.div** (Fig. 10)
- Shifts indicate a need for further research into simulation approaches that consider spatial autocorrelation in landscapes of this nature

Table 2. Uncertainty in coefficients due to uncertainty in landscape metrics, relative to uncertainty due to the sample and modelling.

Coefficient	Average $s^2_{metrics}$ to $s^2_{mod.avg.}$ proportion
$\beta_{prop.ag}$	0.029
$\beta_{log.mfs}$	0.033
$\beta_{crop.div}$	0.144

Conclusions

For these landscapes, Monte Carlo simulation can be used to quantify and compare the effects of spatial and thematic uncertainties on model coefficients, without the need for likely more-complex analytical approaches. The influence of these uncertainties on the coefficients was considerably less than the influence of uncertainties associated with the sample and modelling (which were considered by the model averaging uncertainty estimates). The landscape metrics, particularly **prop.ag** and **log.mfs**, were reliable.

Shifts between reference and simulated coefficients, mainly for **crop.div**, were an issue. These likely arose due, in part, to fields being simulated independently, without consideration of spatial autocorrelation of crop types in nearby fields. More research into simulation approaches that consider spatial autocorrelation, without reliance on high-accuracy reference data, could be useful for simulations in landscapes of a similar nature.

Acknowledgements

We appreciate assistance and guidance from Andrew Davidson, Dennis Duro, Lenore Fahrig, Jude Girard, Doug King, Kathryn Lindsay, Jon Pasher, Murray Richardson, Adam Smith, Lutz Tischendorf, Jessica van den Berg as well as others involved in the GLEL Farmland Biodiversity project. Ground reference data from Agriculture Canada were used to supplement training samples. Funding provided through Environment Canada.

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Fahrig, L., Baudry, J., Brotons, L., Burel, F.G., Crist, T.O., Fuller, R.J., Sirami, C., Siriwardena, G.M., Martin, J.L. (2011). Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. *Ecology Letters*, 14(2): 101–112.

Fahrig, L., Girard, J., Duro, D., Pasher, J., Smith, A., King, D., Lindsay, K., Mitchell, S., Tischendorf, L. Farmlands with smaller crop fields have higher biodiversity. Submitted 24 Feb 2014 to *Ecological Applications*.

Pasher, J., Mitchell, S.W., King, D.J., Fahrig, L., Smith, A.C., & Lindsay, K.E. (2013). Optimizing landscape selection for estimating relative effects of landscape variables on ecological responses. *Landscape Ecology*, 28(3), 371–383.

Shi, W.Z., Ehlers, M., Tempfli, K. (1999). Analytical Modelling of Positional and Thematic Uncertainties in the Integration of Remote Sensing and Geographical Information Systems. *Transactions in GIS*, 3(2): 119–136.

Martin et al. (in prep)

- We found important effects of both farming practices and farmland heterogeneity on multidiversity. In particular, we found greater diversity in untilled, perennial crop fields than tilled, annual row crop fields, and greater diversity in agricultural landscapes with smaller crop fields and less diverse crops. The negative effect of crop diversity on multidiversity indicates that this aspect of farmland heterogeneity does not necessarily benefit wildlife species. Nevertheless, a compelling implication of this study is that it suggests that policies/guidelines aimed at reducing crop field sizes would be at least as effective for conservation of biodiversity within working agricultural landscapes as those designed to promote wildlife-friendly farming practices.

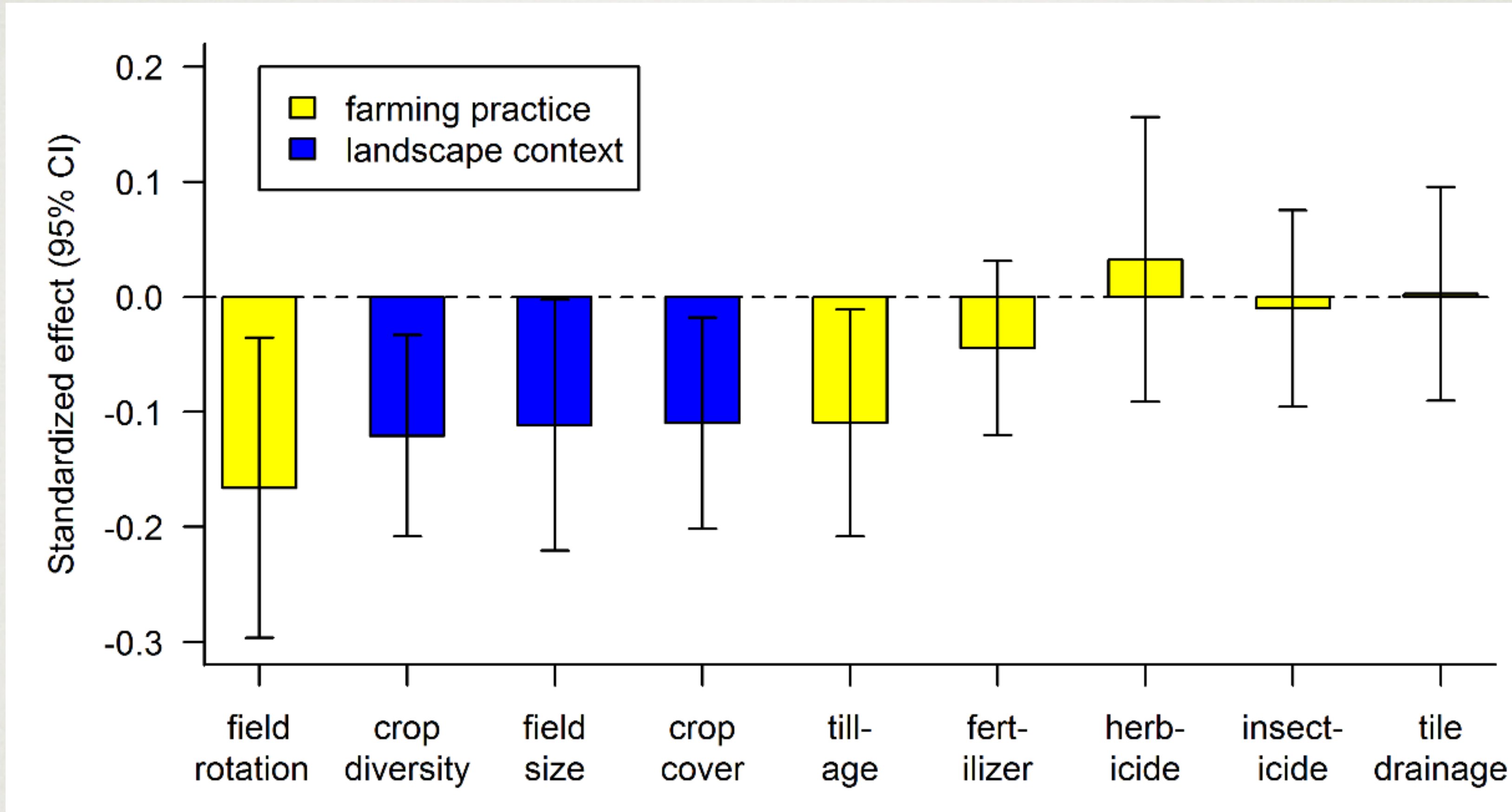


Fig. 5. Standardized effects (95% confidence interval; CI) of six farming practices (field rotation, fertilizer use, herbicide use, insecticide use, tiling, tillage), two measures of farmland heterogeneity (field size, crop diversity), and crop cover on farmland multidiversity. We modeled multidiversity as a function of the nine standardized predictor variables, plus a fixed effect of sampling location (field edge or field interior) and a random effect of sampling area, using a linear mixed effects model. Effects are ordered from the strongest (left) to weakest (right) effect.

biodiversa

FarmLand

European network on farmland heterogeneity, biodiversity and ecosystem services

About Objectives Partners Funding

About the project FarmLand

Agricultural landscapes occupy 40% of the available land area in Europe. They play an important role in providing habitat for wild plants and animals that contribute significantly to agricultural production through services such as crop pollination and control of crop pests. In many regions farm fields are becoming ever larger, and many agricultural regions are now dedicated to a small number of crop types. How did these changes in farmland pattern affect farmland wildlife and the services they provide for agriculture? FarmLand addresses this question by bringing together teams from France, Germany, Great Britain, Spain and Canada.

Agricultural landscapes which contain significant areas of semi-natural lands have higher wildlife diversity and better ecosystem services. However, policies encouraging seminatural field margins or semi-natural strips within crop fields require taking crop area out of production, which is often not feasible. It has been suggested that, in addition to the area of seminatural habitats, the spatial heterogeneity of the cropped lands may be positively related to wild plant and animal diversity and to their provision of ecosystem services.

The aim of FarmLand is to test the role of both compositional and configurational heterogeneity for biodiversity and ecosystem services in agricultural landscapes. This has not been attempted so far at such a scale and through such an integrated approach.

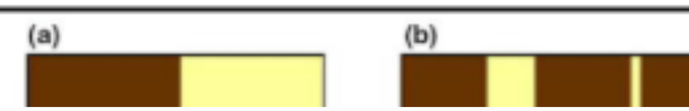
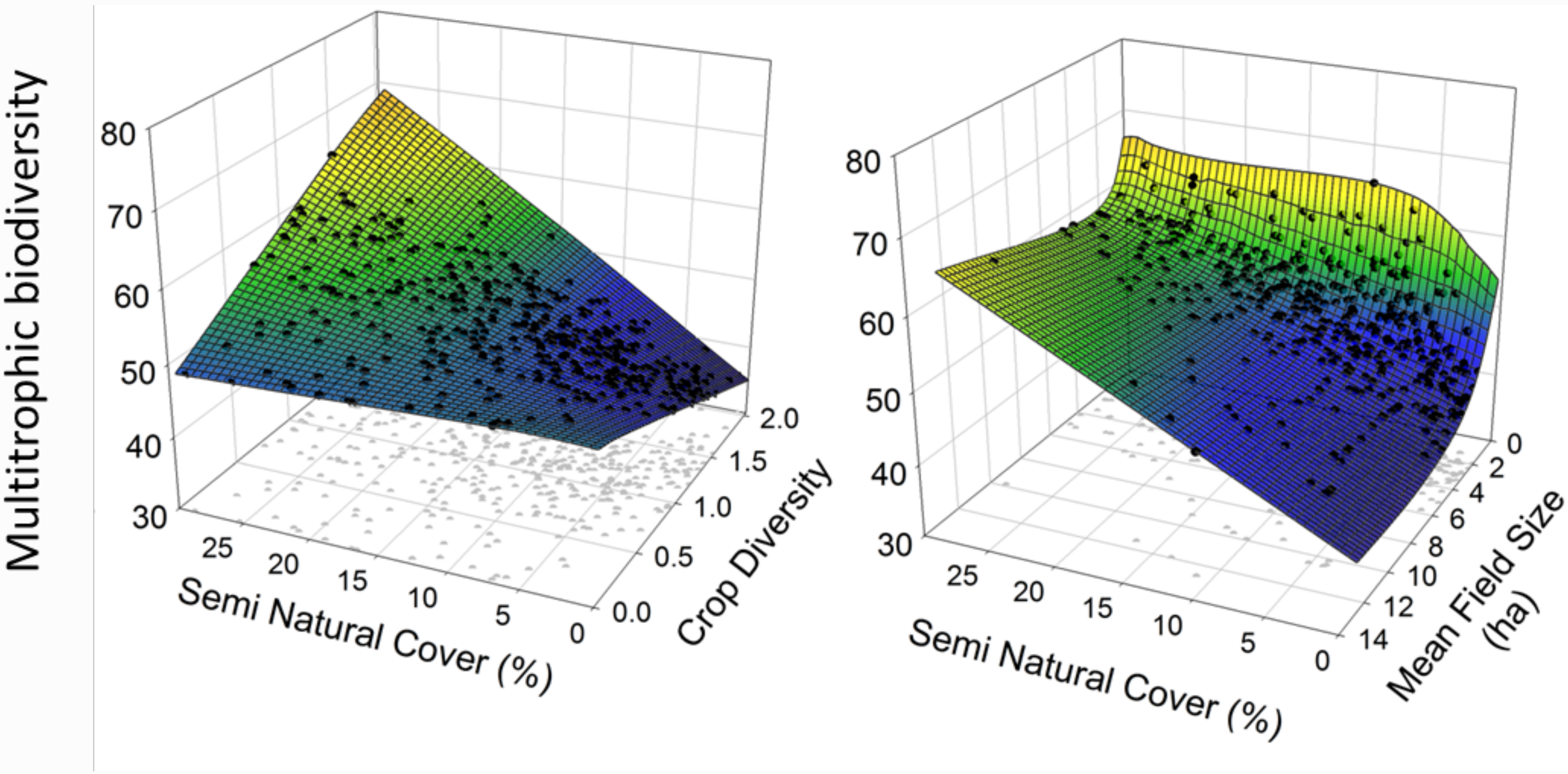


Fig. 1: Illustration of the two

C D



Multitrophic biodiversity
80
70
60
50
40
30
25
20
15
10
5
0
Semi Natural Cover (%)
0.0
0.5
1.0
1.5
2.0
Crop Diversity
Semi Natural Cover (%)
0
2
4
6
8
10
12
14
Mean Field Size (ha)

Extreme weather: envisioning Ontario agriculture

Scott Mitchell[1], Anna Zaytseva[1], Dan MacDonald[2], and Ruth Waldick[1,2]

Adaptation Canada 2016

(1) Carleton University
Department of Geography & Environmental Studies

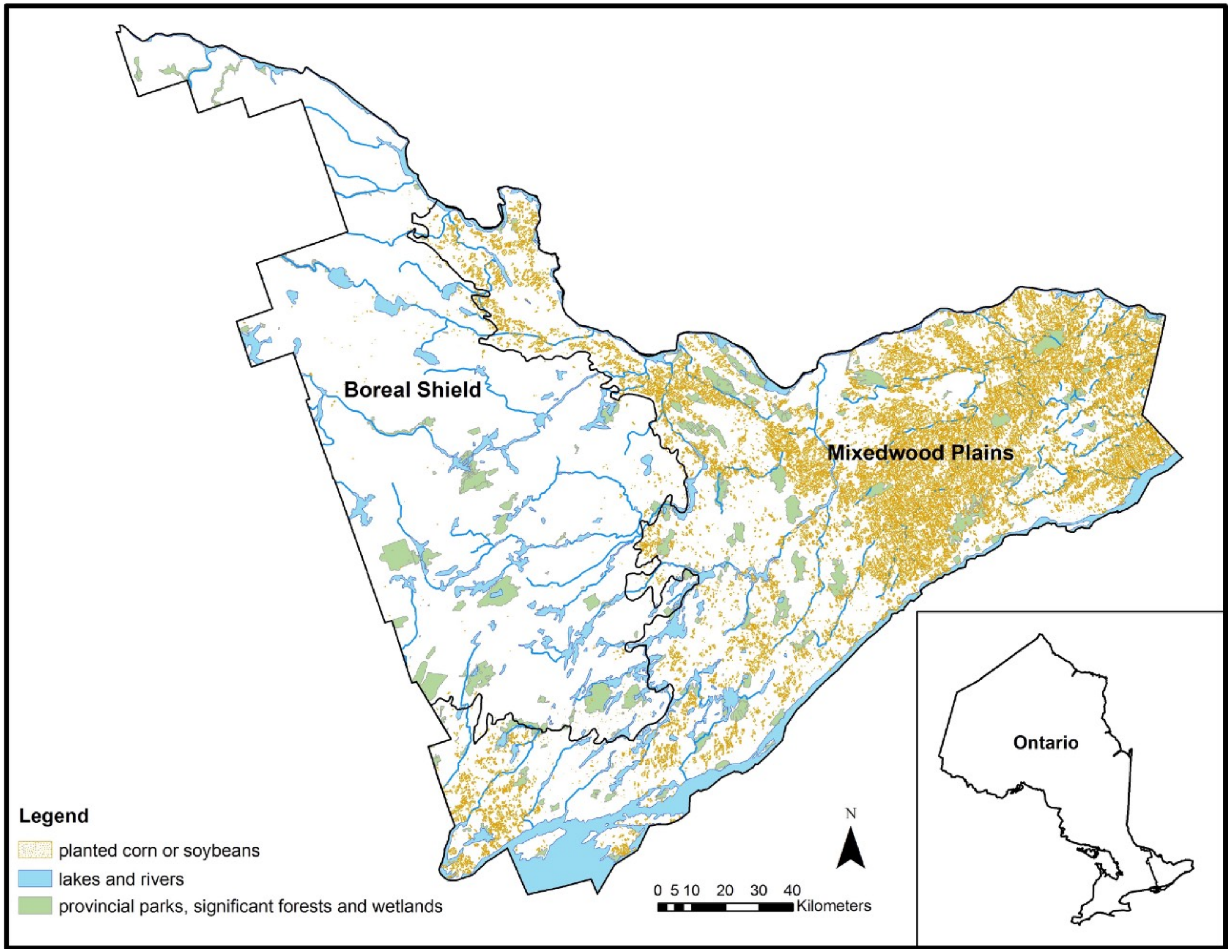
Ontario
Ministry of Agriculture, Food and Rural Affairs

(2) Agriculture and Agri-Food Canada
Agriculture et Agroalimentaire Canada

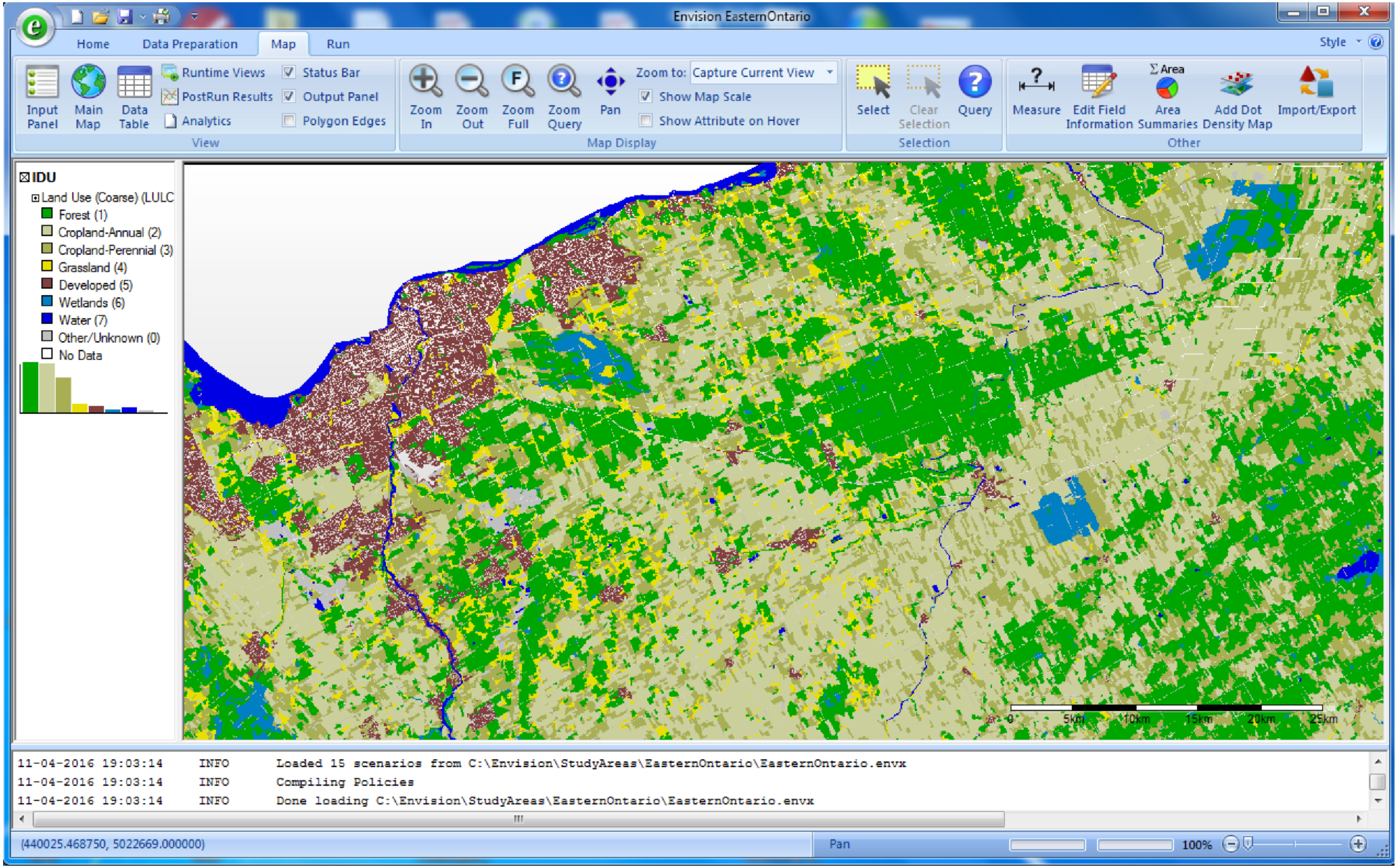
Purpose -> constraints

- "… create and deliver information about prospective climate extremes that will affect Ontario's agriculture sector and rural communities. We will develop a decision support model (DSM) to characterize risk and vulnerabilities associated with climate change and extremes in agriculture, allowing users to plan for and mitigate risks by evaluating different adaptation choices."
  - spatial scenario modelling framework – impacts on crops and livestock*
    - map-based, field-level mapping; expectations
    - data realities: weather stations (time), GCM resolution
    - temporal scales at which can say much about future extreme events are hard to translate to impacts to crops and livestock
- use of seasonal, phenology-linked indices with links to specific crops

Study area: eastern Ontario



(Zaytseva M.Sc. Thesis)


Envision EasternOntario
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Map
Run
Style
Input Panel
Main Map
Data Table
Runtime Views
PostRun Results
Analytics
Status Bar
Output Panel
Polygon Edges
View
Zoom In
Zoom Out
Zoom Full
Zoom Query
Pan
Zoom to: Capture Current View
Show Map Scale
Show Attribute on Hover
Map Display
Select
Clear Selection
Query
Selection
Measure
Edit Field Information
Σ Area
Area Summaries
Add Dot Density Map
Import/Export
Other
IDU
Land Use (Coarse) (LULC
Forest (1)
Cropland-Annual (2)
Cropland-Perennial (3)
Grassland (4)
Developed (5)
Wetlands (6)
Water (7)
Other/Unknown (0)
No Data
0
5km
10km
15km
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25km
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11-04-2016 19:03:14 INFO Compiling Policies
11-04-2016 19:03:14 INFO Done loading C:\Envision\StudyAreas\EasternOntario\EasternOntario.envx
(440025.468750, 5022669.000000)
Pan
100%

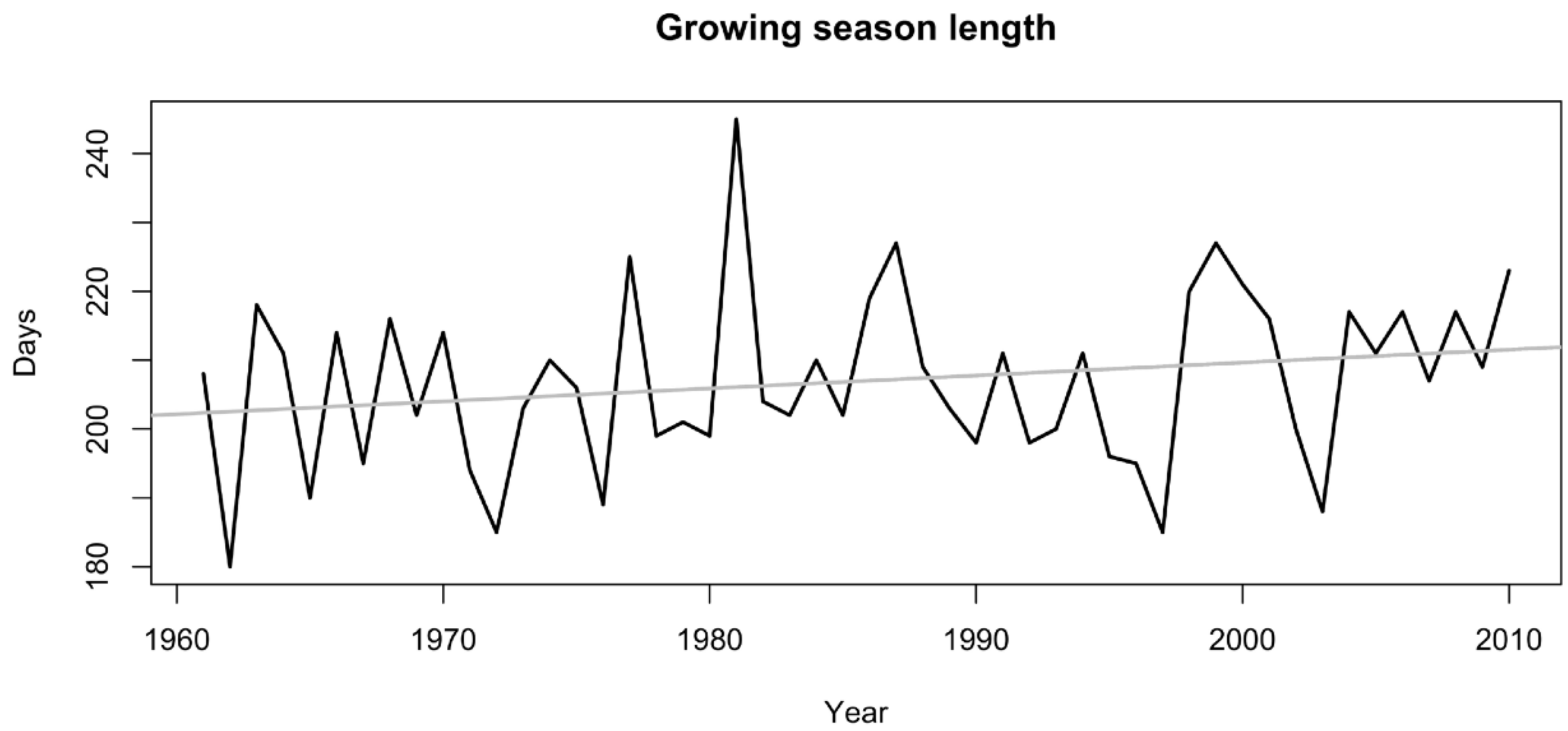
Indices derived from "just" weather data

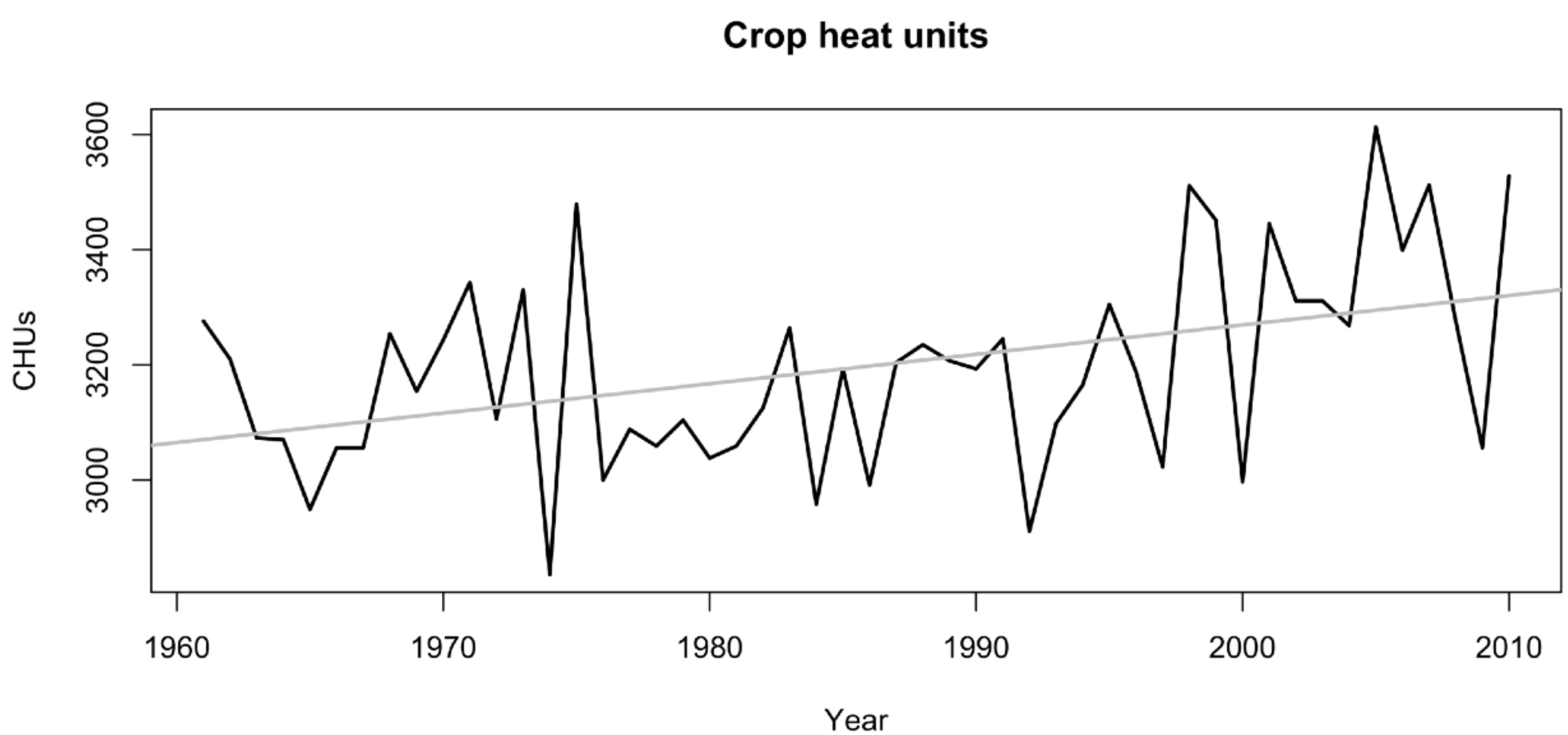
- E. Ontario not expected to be a hotspot of weather extremes
  - but types of extremes of particular relevance in "regular" agricultural operations are not necessarily what people first think of as "extreme"

- "standard" indices are available to analyse and compare weather / extremes
  - useful to describe general trends

- some, however, mask processes that are important to agriculture

Why extremes? This is NOT the whole story!





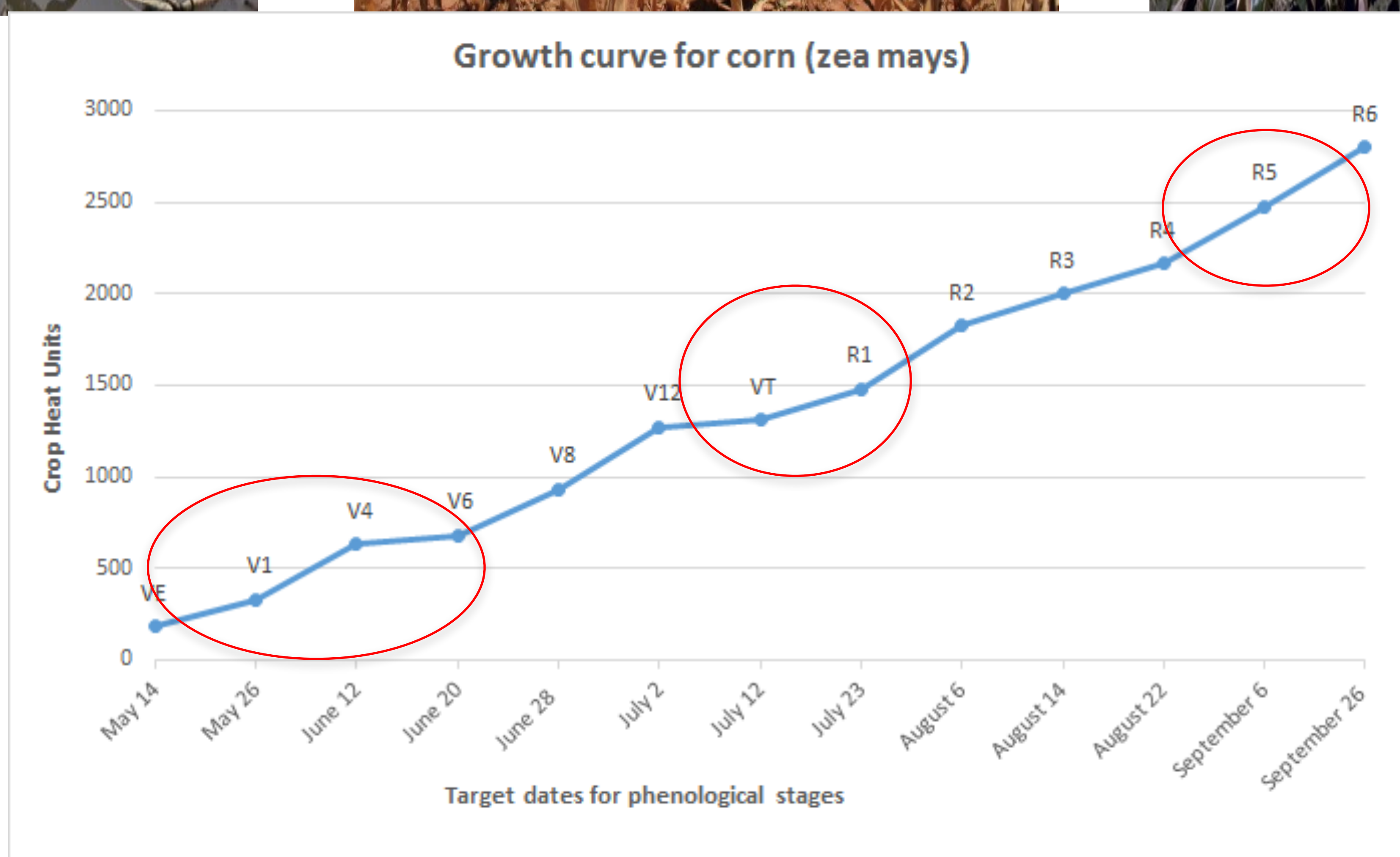
(Zaytseva M.Sc. Thesis)

The Question

- How will day to day farm operations be affected by changing weather patterns?

- Focus on seeding operations for cash crop farms.
- Corn/soy/cereal based rotations.

Crop-specific weather extremes



Indicator development

- Extensive literature review (close to 100 sources reviewed)
- Expert consultations (AAFC, OMAFRA)
- Crop tolerance thresholds to T and P conditions at various phenological stages were identified
- Yield loss percentages associated with threshold exceedance were studied

MORE CROP RELEVANT INDICES: FOCUS ON SEASONAL PHENOLOGY

- Corn (for example):

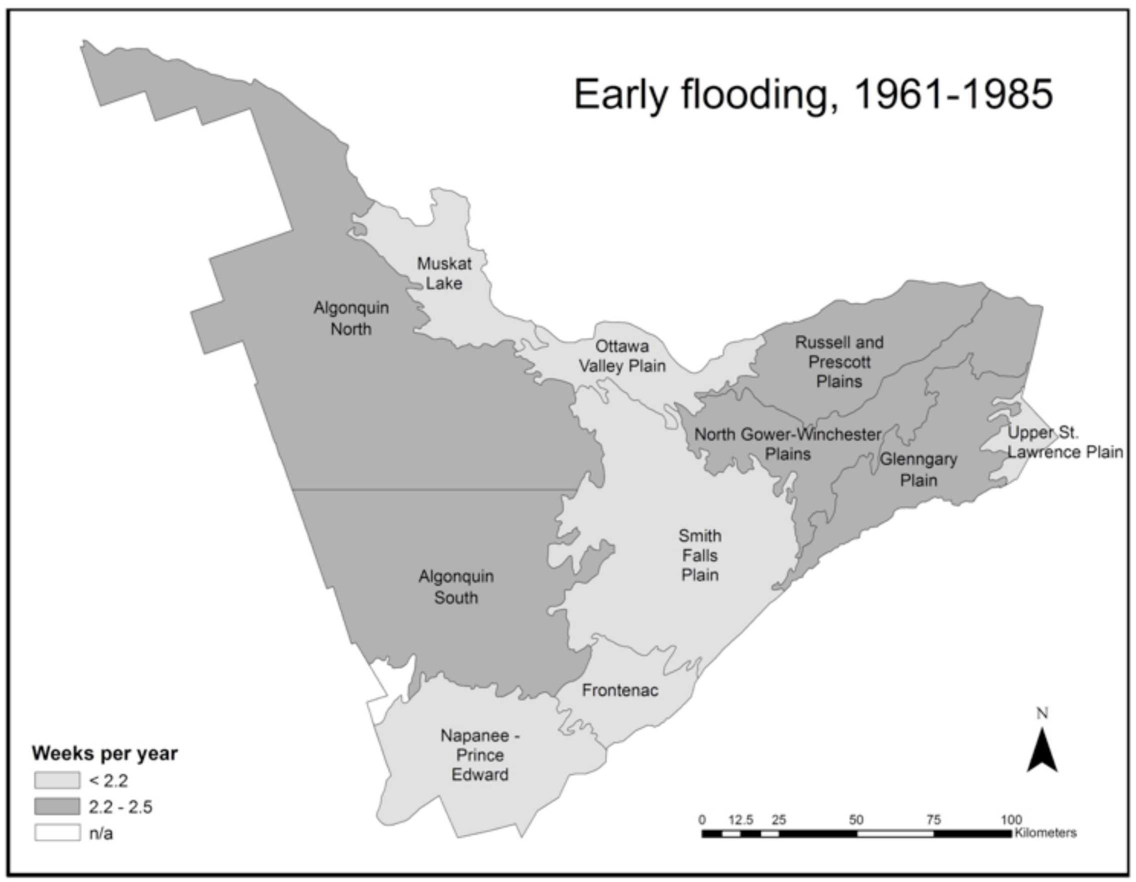
Index name	Definition	Units
Corn:		
Poor seeding conditions	Weekly precipitation 30% greater than weekly mean precipitation (between April 23 and May 20)	weeks/year
Early flooding	Weekly precipitation 30% greater than weekly mean precipitation with 1 to 780 accumulated CHUs	weeks/year
Pollination drought	CDD >10 with 1,301 to 1,600 accumulated CHUs	annual occurrence (Yes or No)
R2 (blister) drought	P<45mm with 1,601 to 1,825 accumulated CHUs	annual occurrence (Yes or No)
R3 (milk) drought	P<45mm with 1,826 to 2,000 accumulated CHUs	annual occurrence (Yes or No)
Early killing frost	Tmin <=-2°C with 2,165 to 2,475 accumulated CHUs	days/year
R4 (dough) drought	P<8mm with 2,001 to 2,165 accumulated CHUs	annual occurrence (Yes or No)
Fall killing frost	Tmin <=-2°C with 2,476 to 2,600 accumulated CHUs	days/year

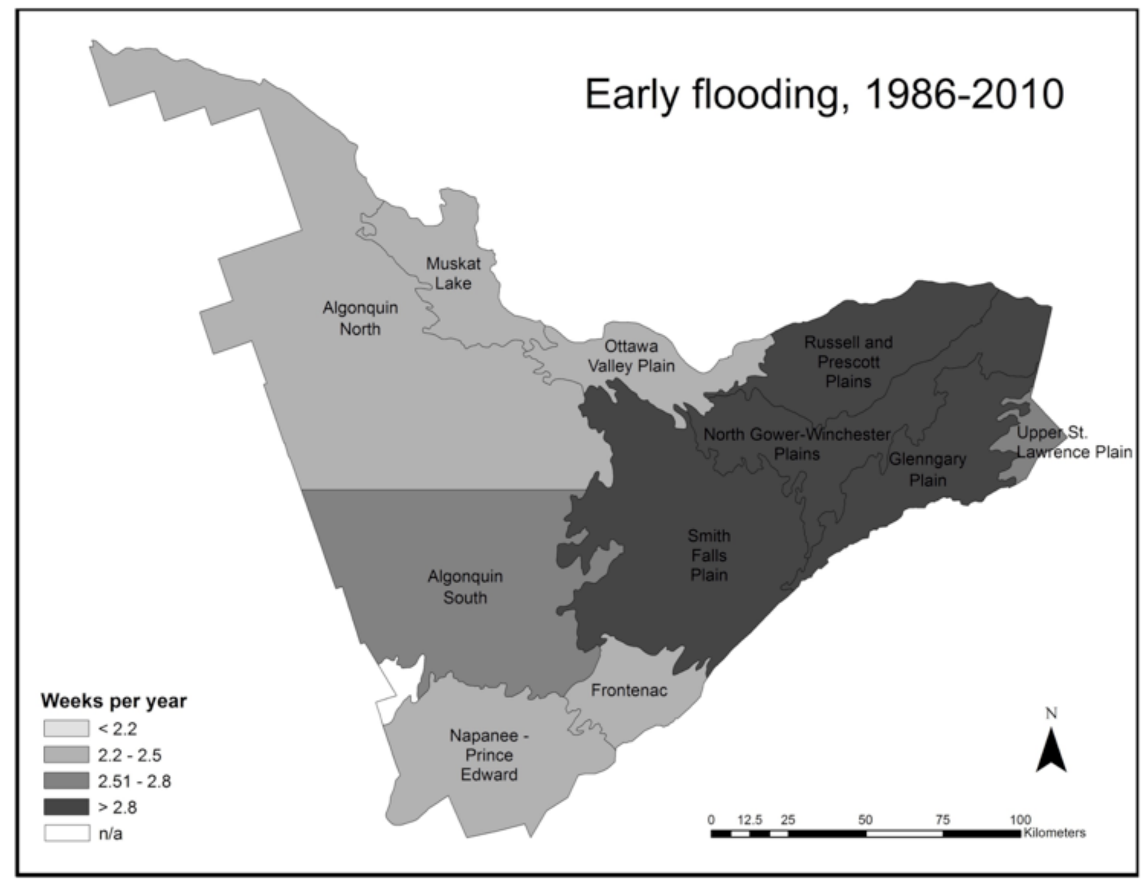
(Zaytseva M.Sc. Thesis)

Soybean-specific indices

Index name	Definition	Units
Soybeans:		
Poor seeding conditions	**Weekly precipitation 30% greater than weekly mean precipitation (weeks between May 7 and June 10)**	**weeks/year**
Spring killing frost	Tmin <0°C 26 to 50 days after seeding	days/year
Early flooding	Precipitation 30% greater than weekly precipitation 25 to 45 days after seeding	weeks/year
Cool nights	Tmin <10°C for 5+ days 45-55 days after seeding	annual occurrence (Yes or No)
Warm nights	Tmin>=24°C 55 to 100 days after seeding	days/year
Mid-season flooding	Precipitation >90mm 60 to 80 days after seeding	annual occurrence (Yes or No)
Pod filling drought	**Precipitation <10mm 81 to 95 days after seeding**	**annual occurrence (Yes or No)**
Early killing frost	Tmin <-1°C between 90 and 100 days after seeding	days/year
Extreme heat	Mean Tmax>33°C 95-120 days after seeding	days/year
Fall killing frost	Tmin <-1°C 101 to 110 days after seeding;	days/year
Seed development drought	**P<5mm 96-115 days after seeding**	**annual occurrence (Yes or No)**

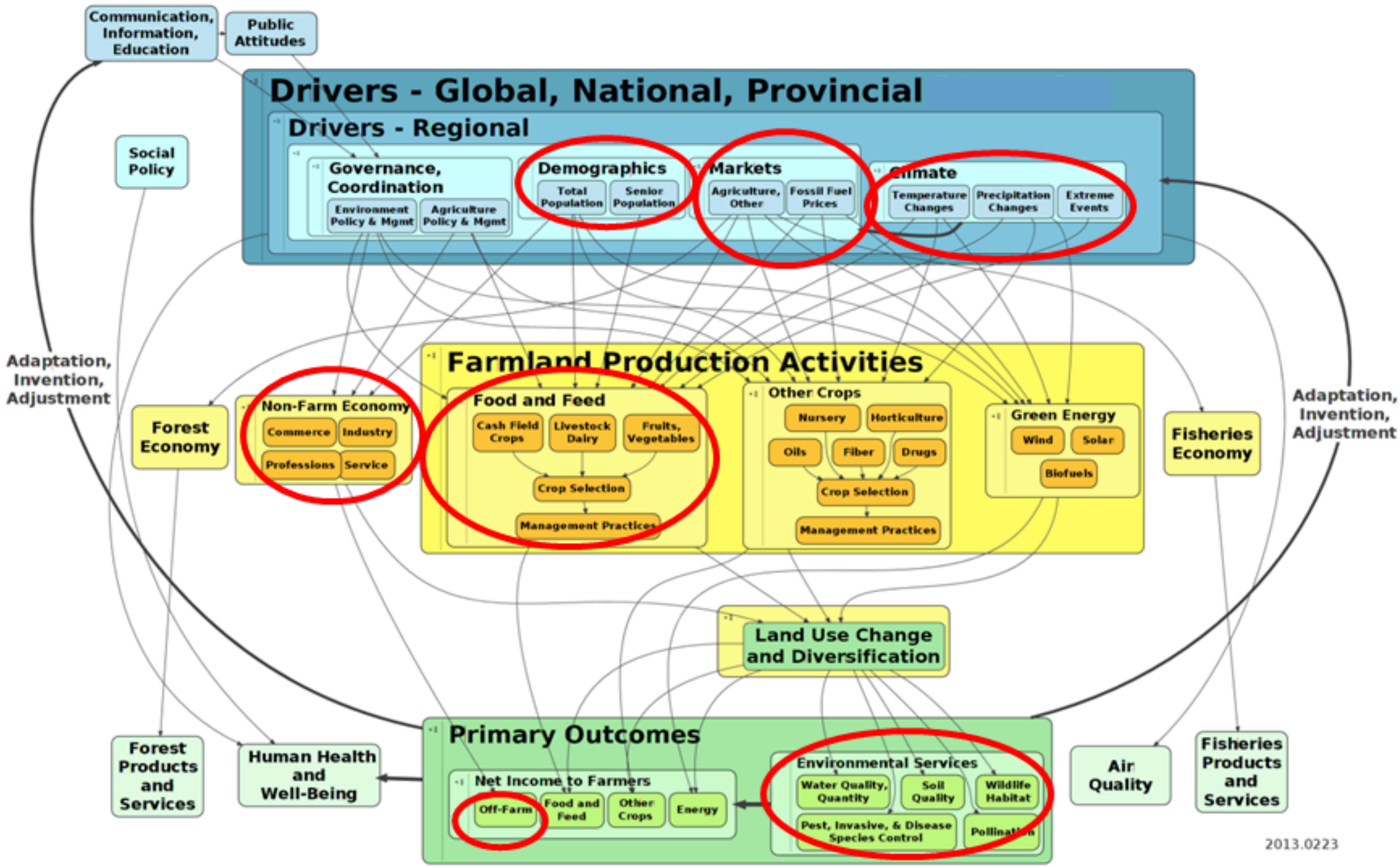
Example: early flooding

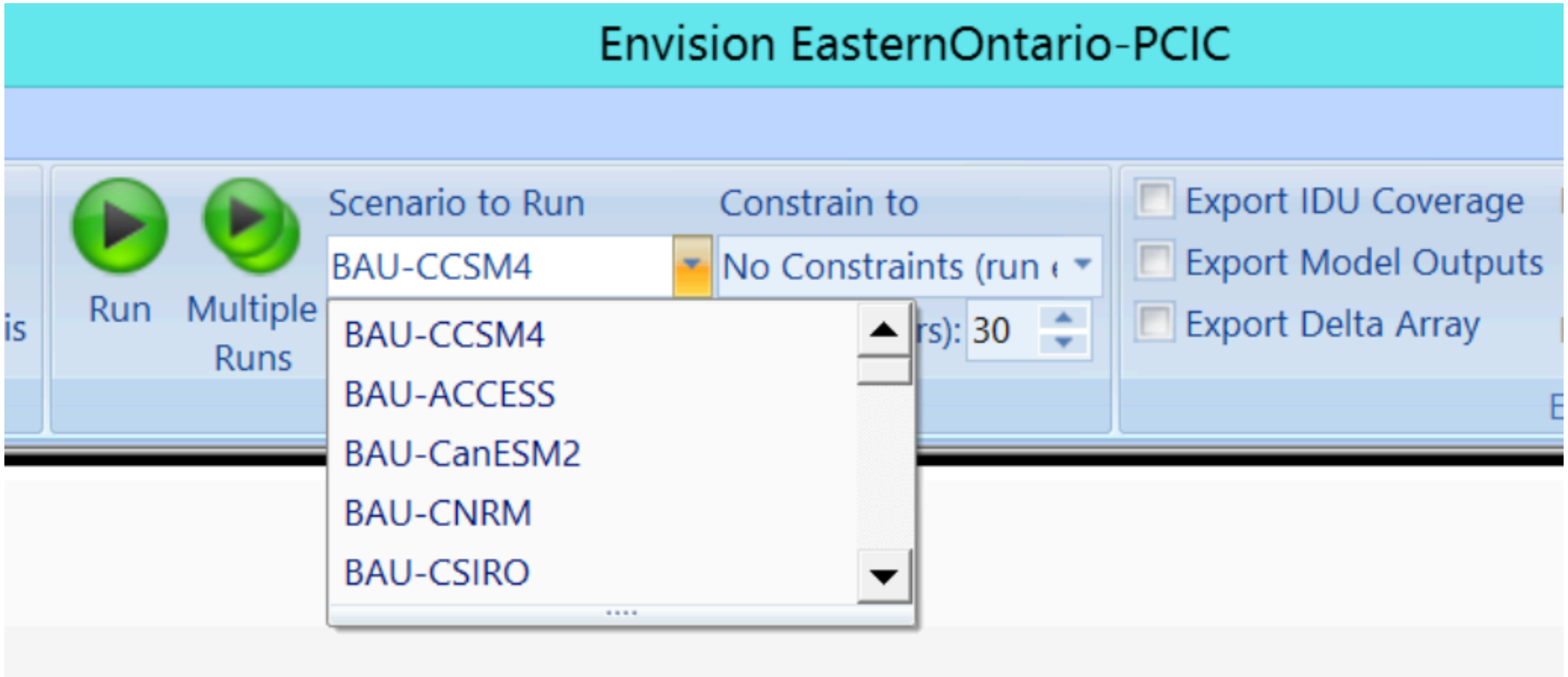




A. Zaytseva's DRAFT M.Sc. Thesis (Carleton University).

Simulation model for Eastern Ontario


Communication, Information, Education
Public Attitudes
Social Policy
Drivers - Global, National, Provincial
Drivers - Regional
Governance, Coordination
Environment Policy & Mgmt
Agriculture Policy & Mgmt
Demographics
Total Population
Senior Population
Markets
Agriculture, Other
Fossil Fuel Prices
Climate
Temperature Changes
Precipitation Changes
Extreme Events
Adaptation, Invention, Adjustment
Forest Economy
Non-Farm Economy
Commerce
Industry
Professions
Service
Farmland Production Activities
Food and Feed
Cash Field Crops
Livestock Dairy
Fruits, Vegetables
Crop Selection
Management Practices
Other Crops
Nursery
Horticulture
Oils
Fiber
Drugs
Crop Selection
Management Practices
Green Energy
Wind
Solar
Biofuels
Fisheries Economy
Adaptation, Invention, Adjustment
Land Use Change and Diversification
Primary Outcomes
Net Income to Farmers
Off-Farm
Food and Feed
Other Crops
Energy
Environmental Services
Water Quality, Quantity
Soil Quality
Wildlife Habitat
Pest, Invasive, & Disease Species Control
Forest Products and Services
Human Health and Well-Being
Air Quality
Fisheries Products and Services
2013.0223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Run
Multiple Runs
Scenario to Run
Constrain to
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No Constraints (run
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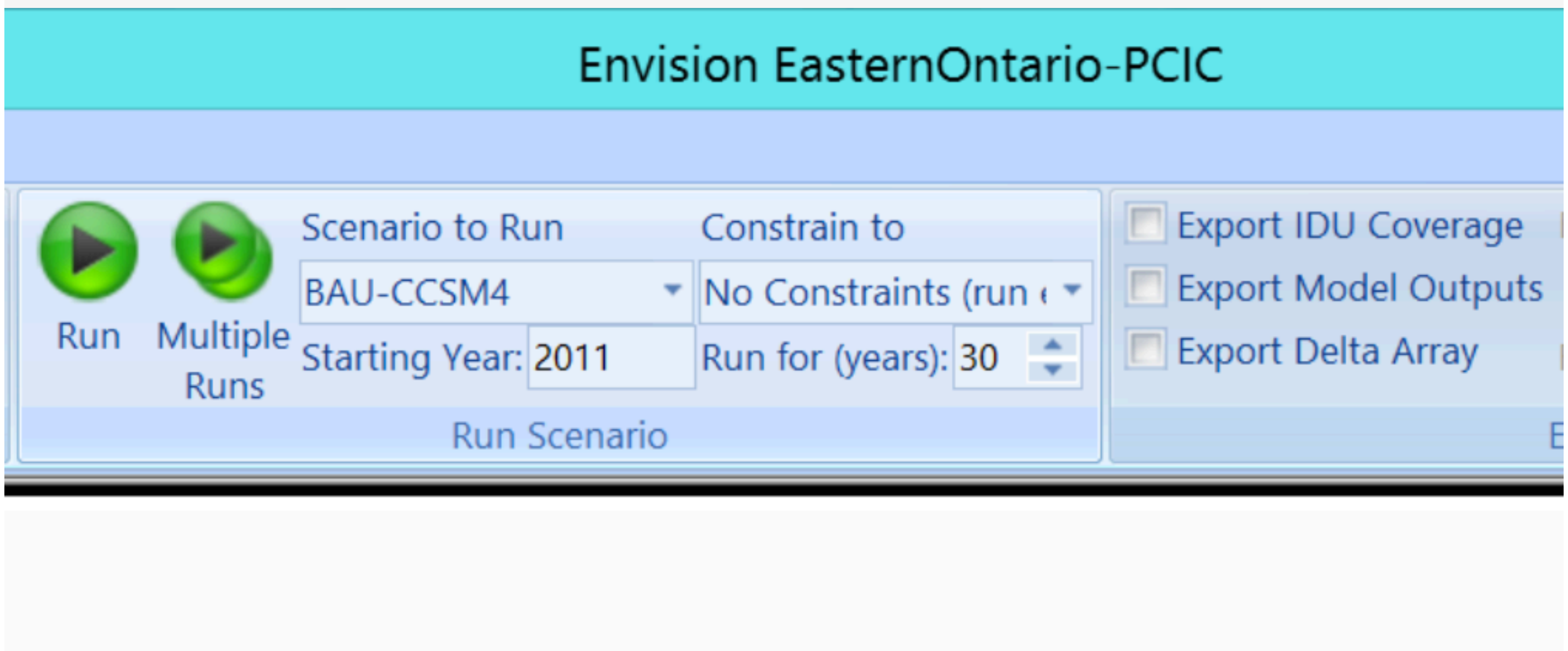
30
Export IDU Coverage
Export Model Outputs
Export Delta Array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Run
Multiple Runs
Scenario to Run
Constrain to
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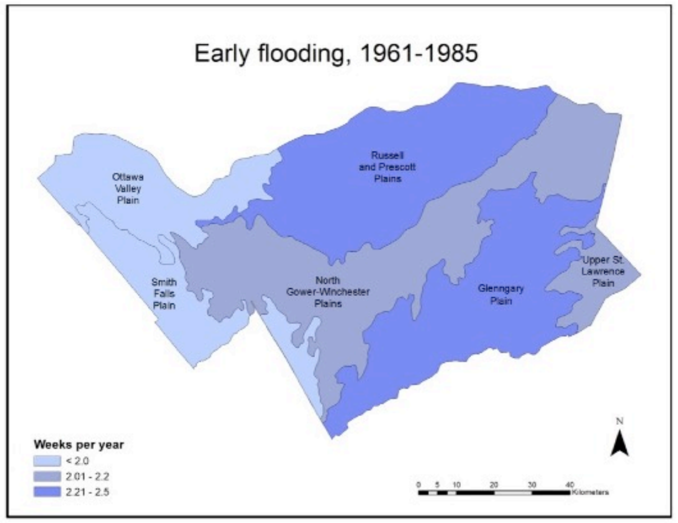
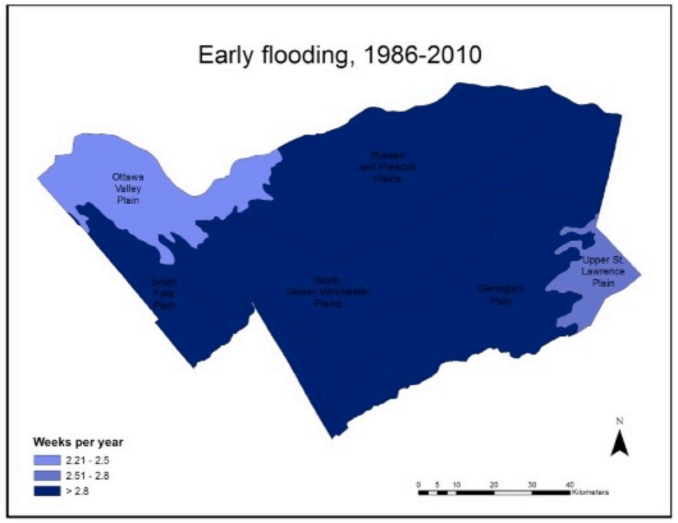
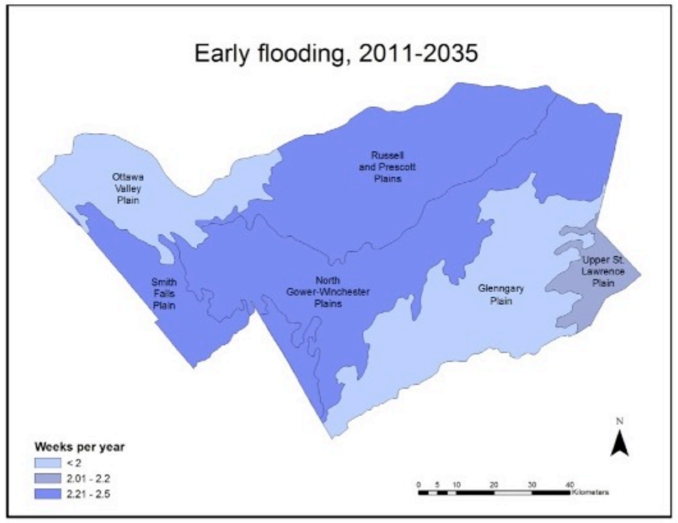
No Constraints (run
Starting Year: 2011
Run for (years): 30
Run Scenario
Export IDU Coverage
Export Model Outputs
Export Delta Array

Processed post-run results (Corn)

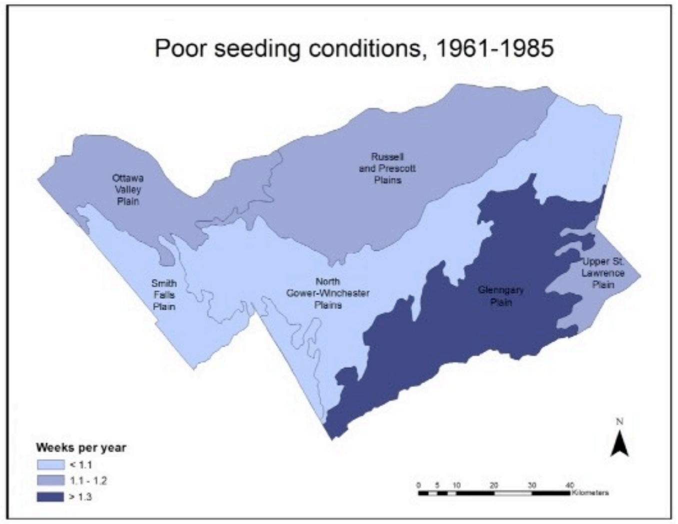


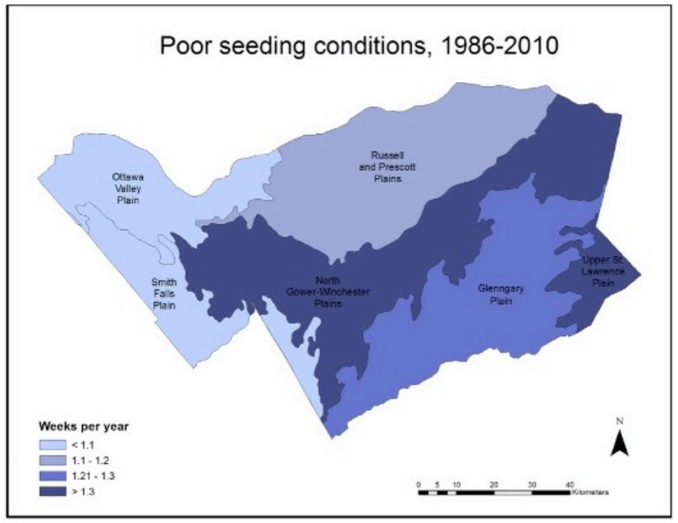


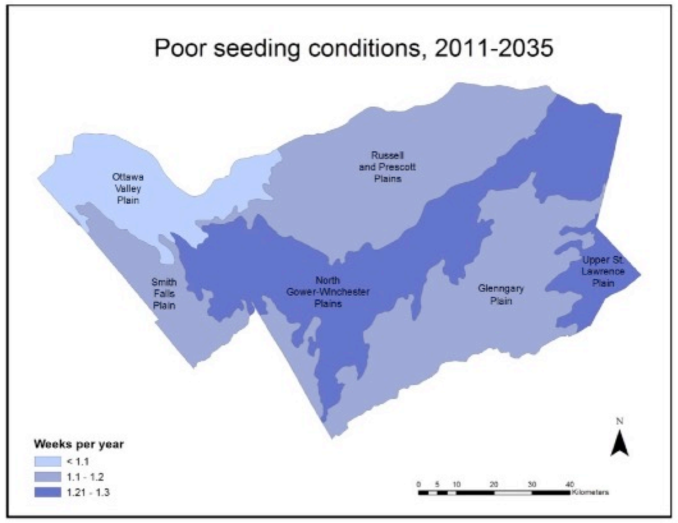


Weeks per year

- < 1.1
- 1.1 - 1.2
- 1.21 - 1.3
- > 1.3







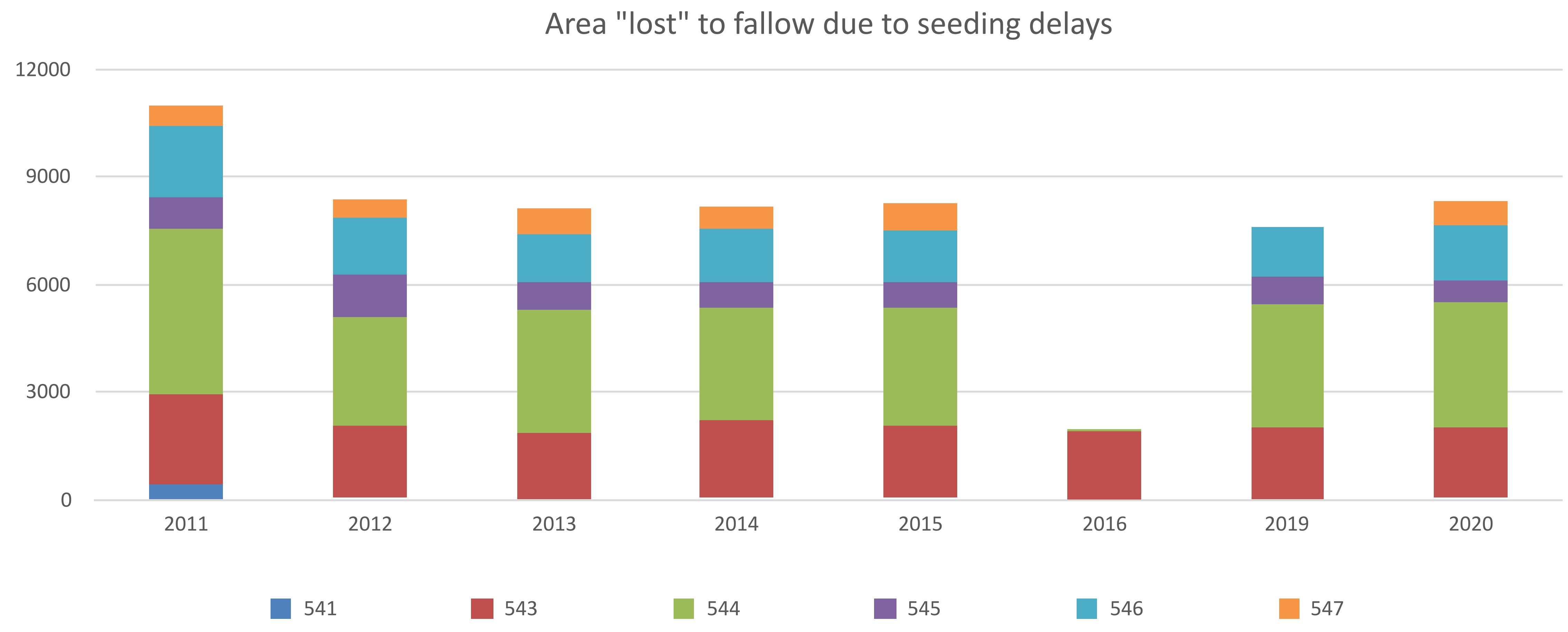
Weeks per year

- < 2
- 2 - 2.2
- 2.21 - 2.5
- 2.51 - 2.8
- > 2.8

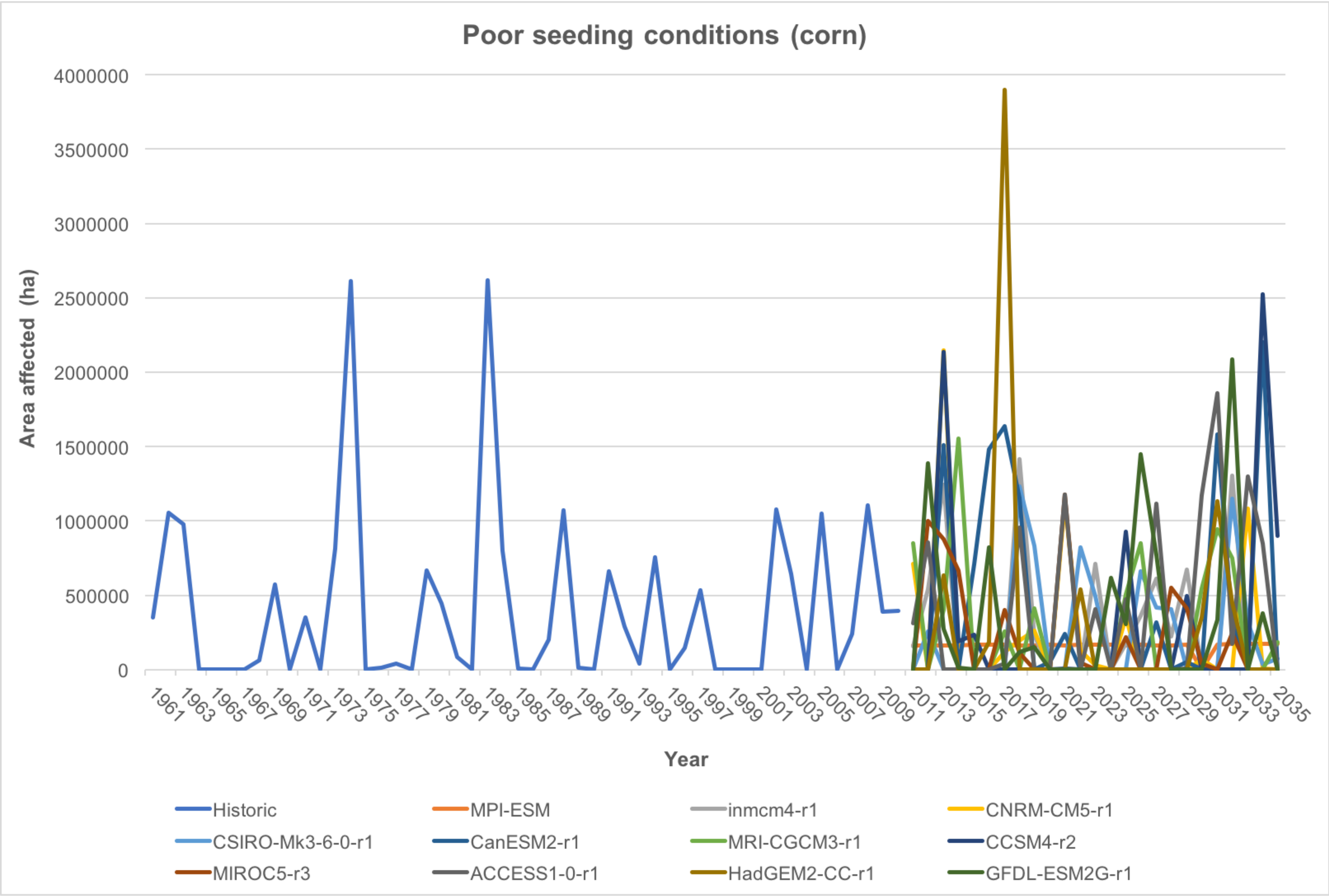
Envision Eastern Ontario Model

- 2844 farms of 22 farm types
  - Based on census of agriculture statistics
  - Spatially distributed on the landscape
    - Average farm size, not their real locations
- Weather and farming operations follow a daily time step.
  - Maximum and minimum temperature and precipitation.
- Crops development - heat unit based growth curves.

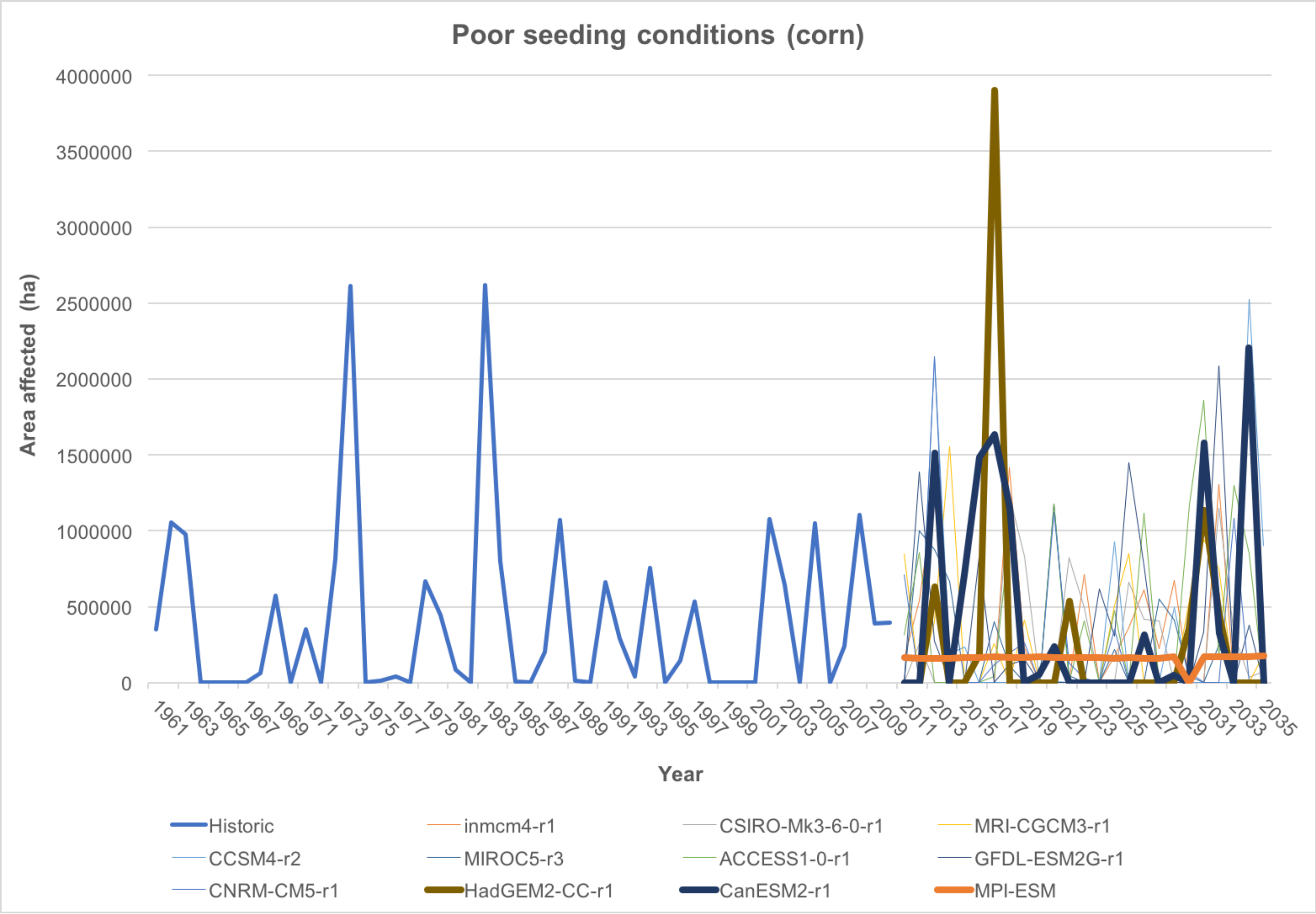
Example: projected seeding delays



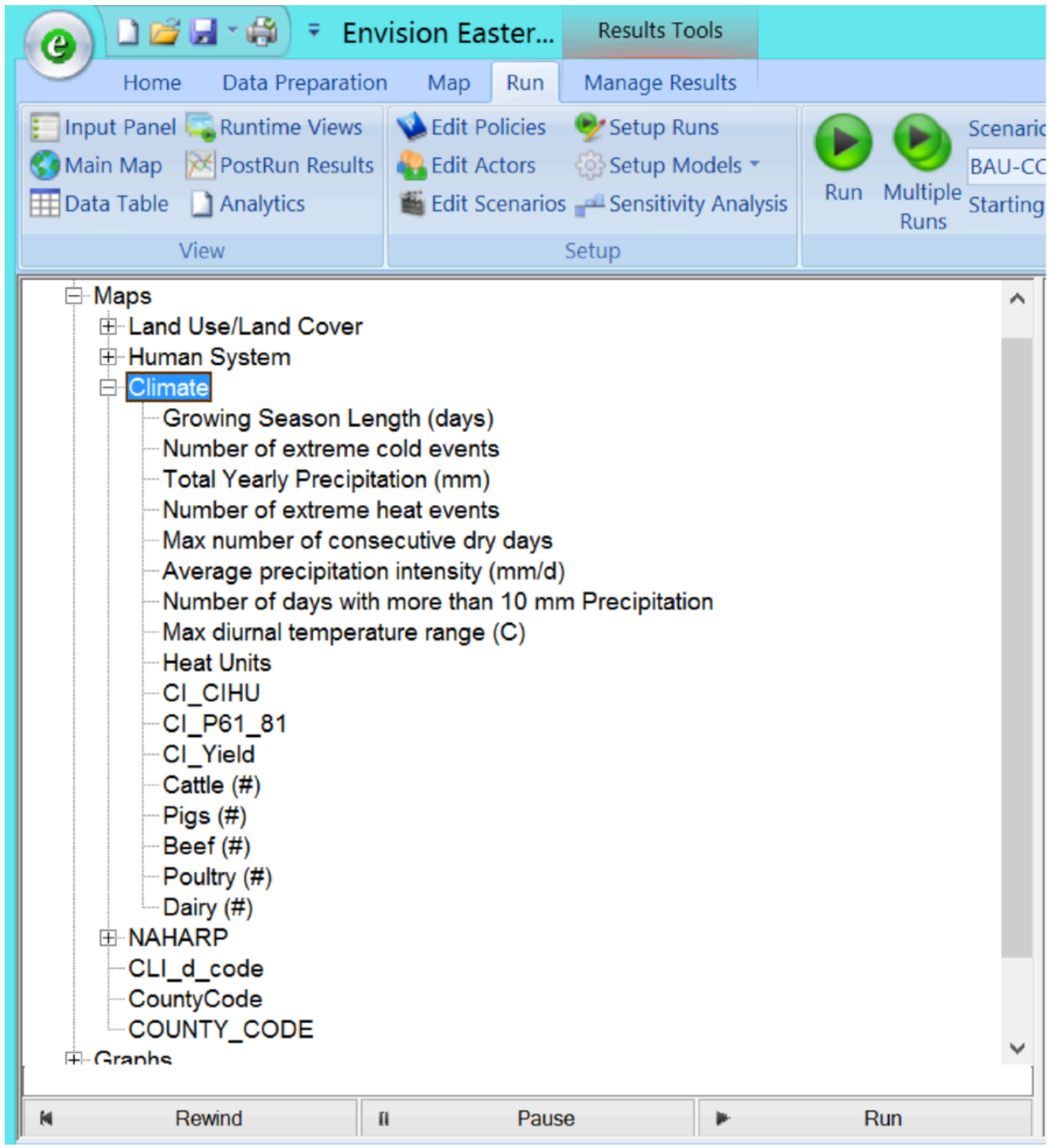
Processed post-run results (Corn)

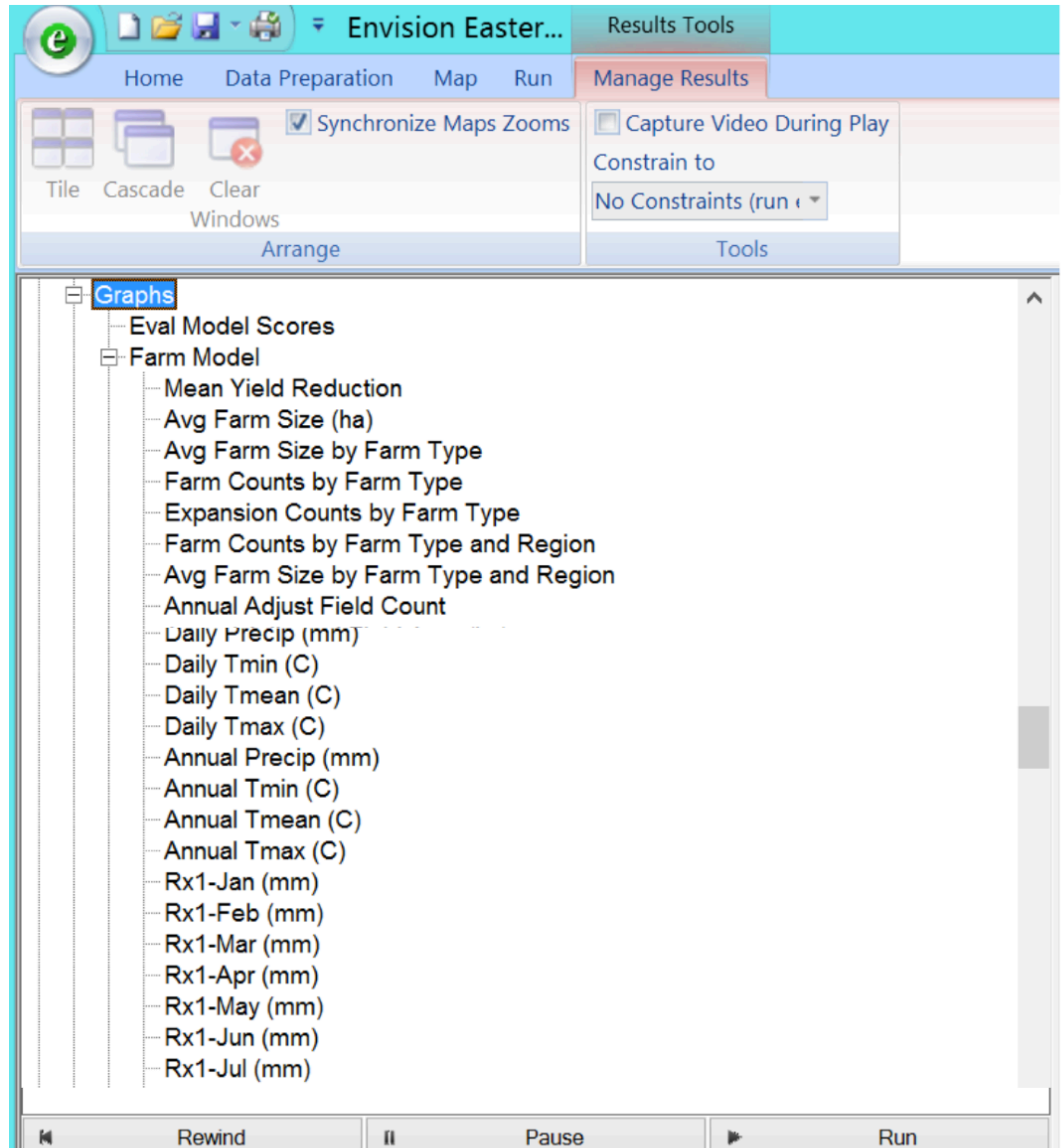


Processed post-run results (Corn)



Output maps and graphs (generic weather variables and extremes)





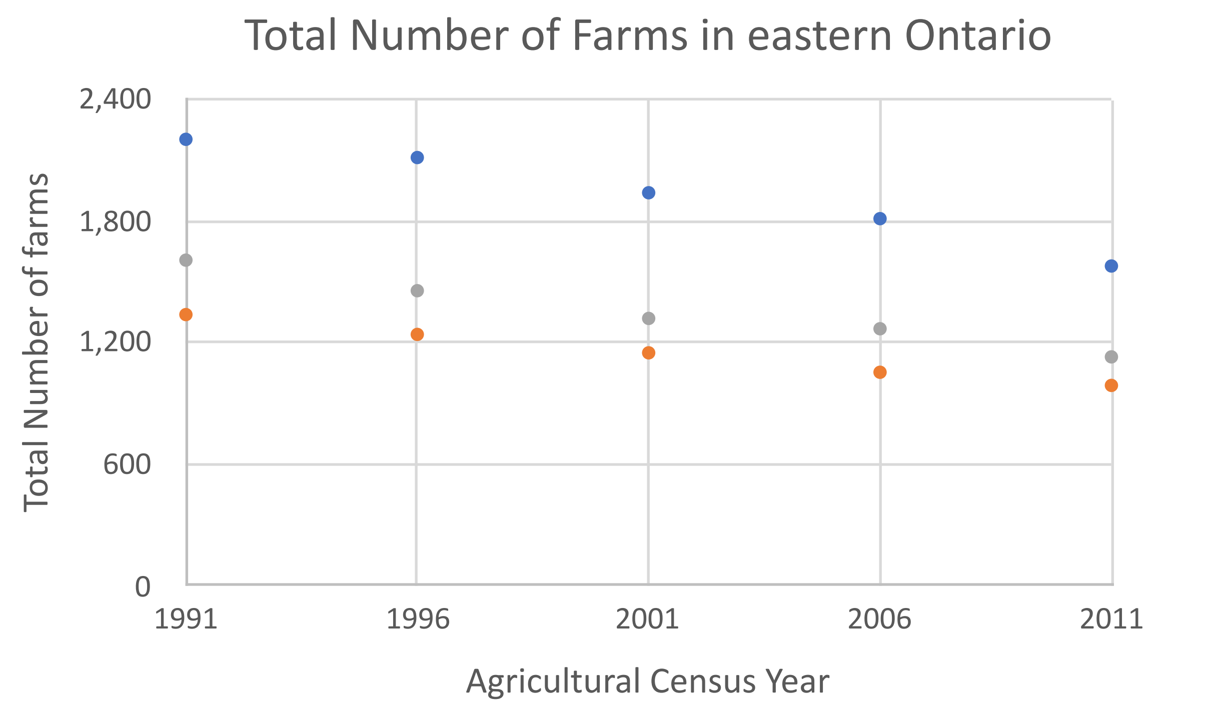
Trends and transitions between farm types and in the spatial layout of farm fields

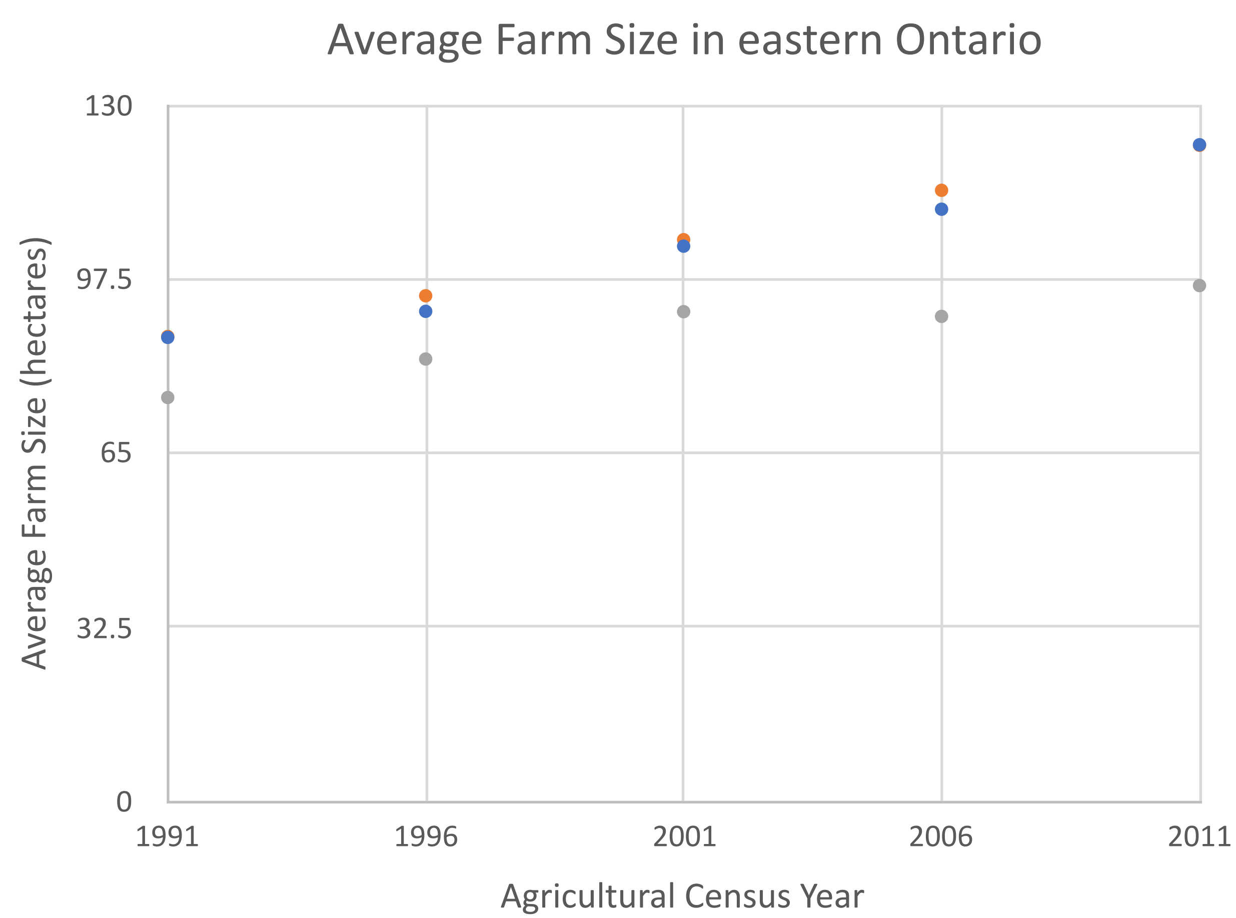
Presentation by: Tonia Tanner

Supervisor: Scott Mitchell

Present Trends in Agriculture:

- Every 5 years the number of farms in eastern Ontario decreases by an average of 364
- Average farm size is increasing at a rate of between 5 to 9 ha every 5 years throughout the region
- As a result, we have fewer larger farms





- Stormont, Dundas and Glengarry United Counties
- Prescott and Russell United Counties
- Ottawa-Carleton Regional Municipality

Farm Type and Size Trends

Farm Types

- Dairy
  - Dairy and Grain
  - Dairy and Hay
  - Dairy
- Beef
  - Beef
    - Cow Calf
    - Feeder
  - Beef and Grain
    - Cow calf and field crop
    - Feeder and Field Crop
- Field Crop
  - Field Crop
  - Field Crop and Dairy
  - Field Crop and Beef
    - Field Crop Cow Calf
    - Field Crop Feeder
  - Field Crop and Other livestock
  - Field Crop Hogs
  - Field Crop and Poultry
- Poultry and Egg
  - Poultry and Egg and Field Crops
  - Poultry and Egg
- Other Livestock
  - Other Livestock and Field Crops
  - Other Livestock
- Hogs
  - Swine and Field Crops
  - Swine
- Fruit and vegetable
- Other Crops

Indicates a decrease in the number of these farm types

Indicates an increase in the number of these farm types

Indicates an increase in the averag size of these farm types

Field sizes are growing

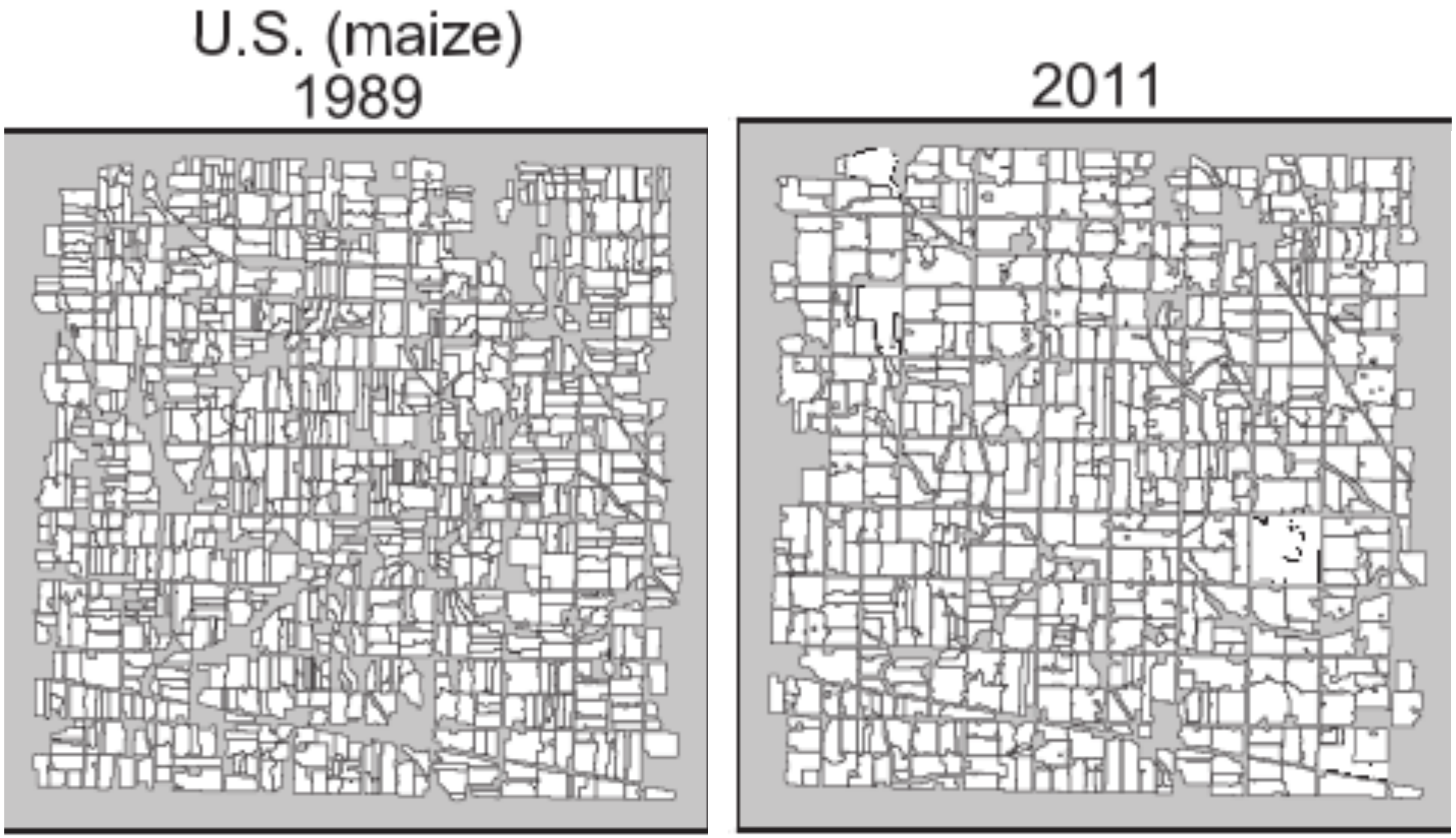


Figure 1. Maps displaying 15km by 15km agricultural landscape showing only corn fields and their size differences between 1989-2011, as extracted from Landsat imagery (White & Roy, 2015).

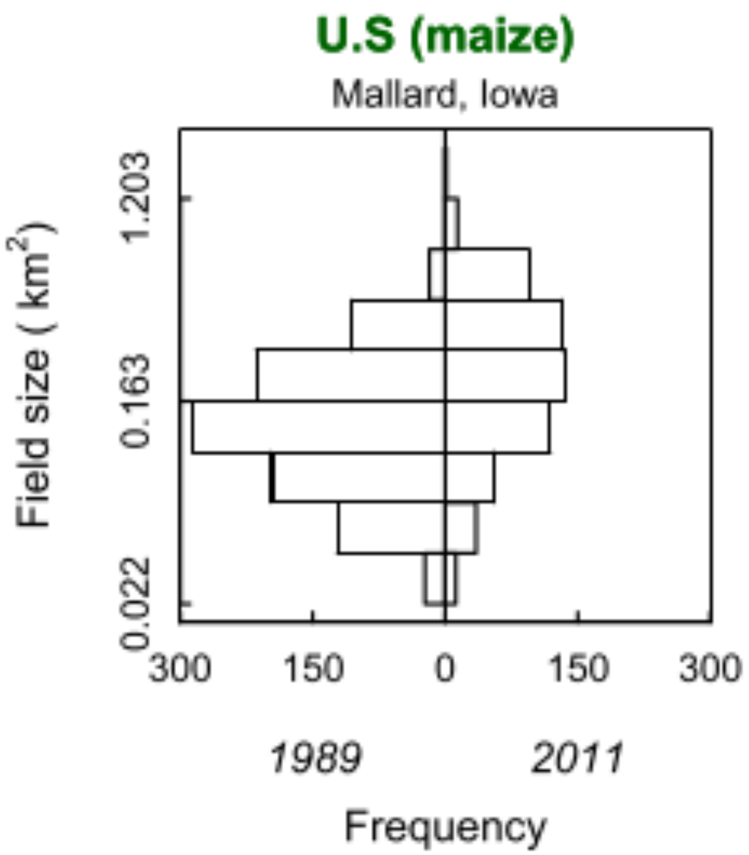


Figure 2. Histogram showing corn field size change from 1989 to 2011 (White & Roy, 2015).

Quantifying field size change in eastern Ontario

2012

2015

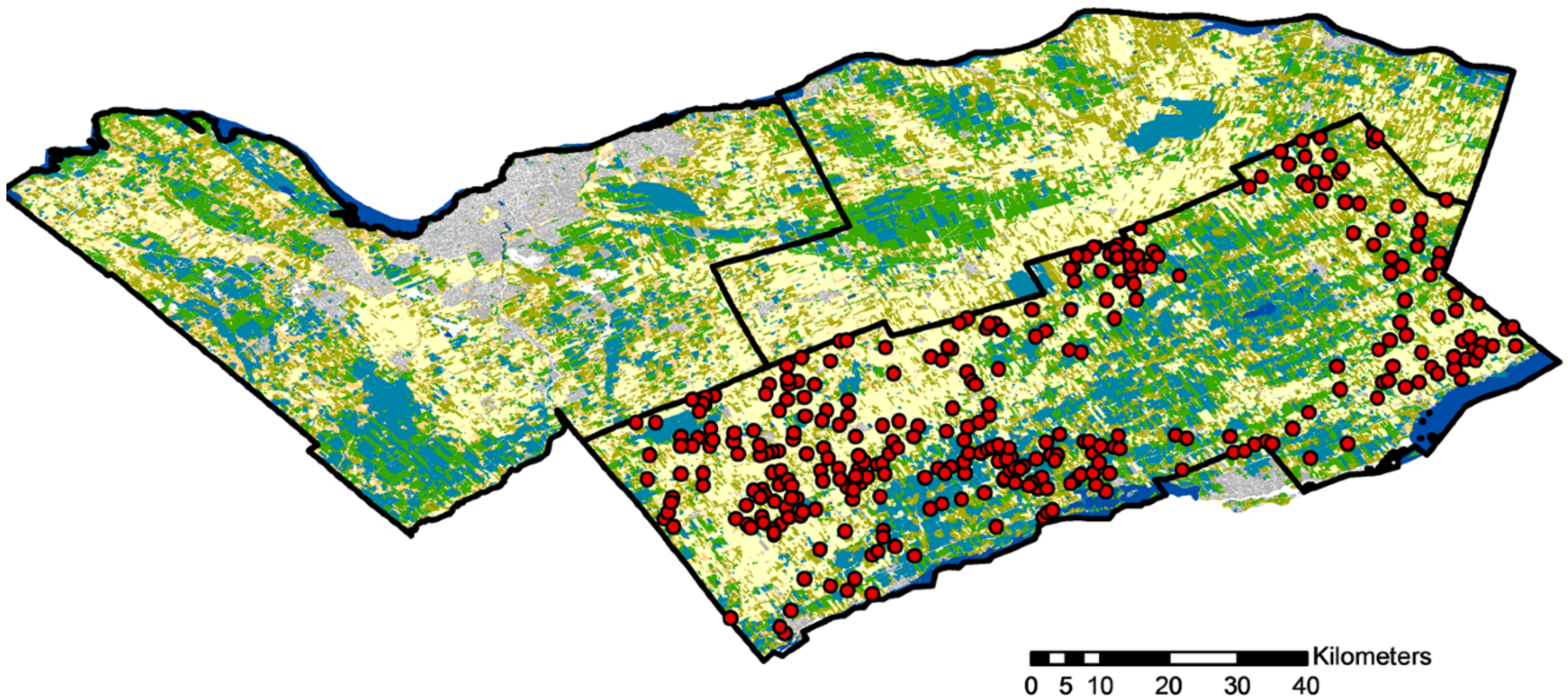
Consolidation of fields

2011
Number of fields: 10
Average field size:
1.81 ha

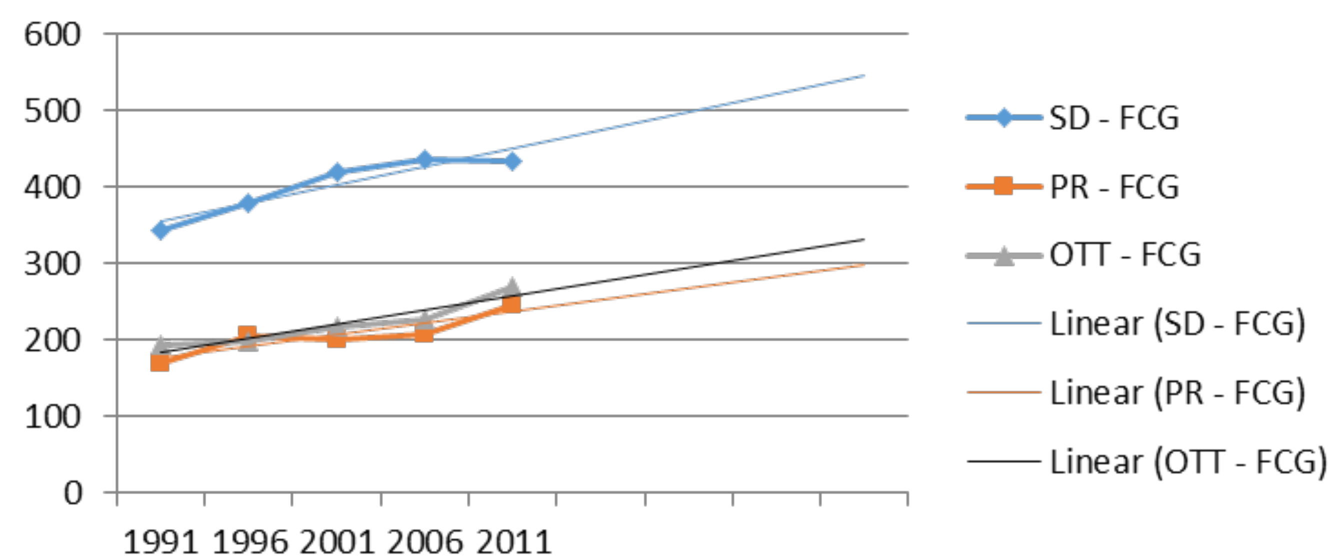
2015
Number of fields: 1
Average field size:
19.56 ha

All satellite images from Google Earth

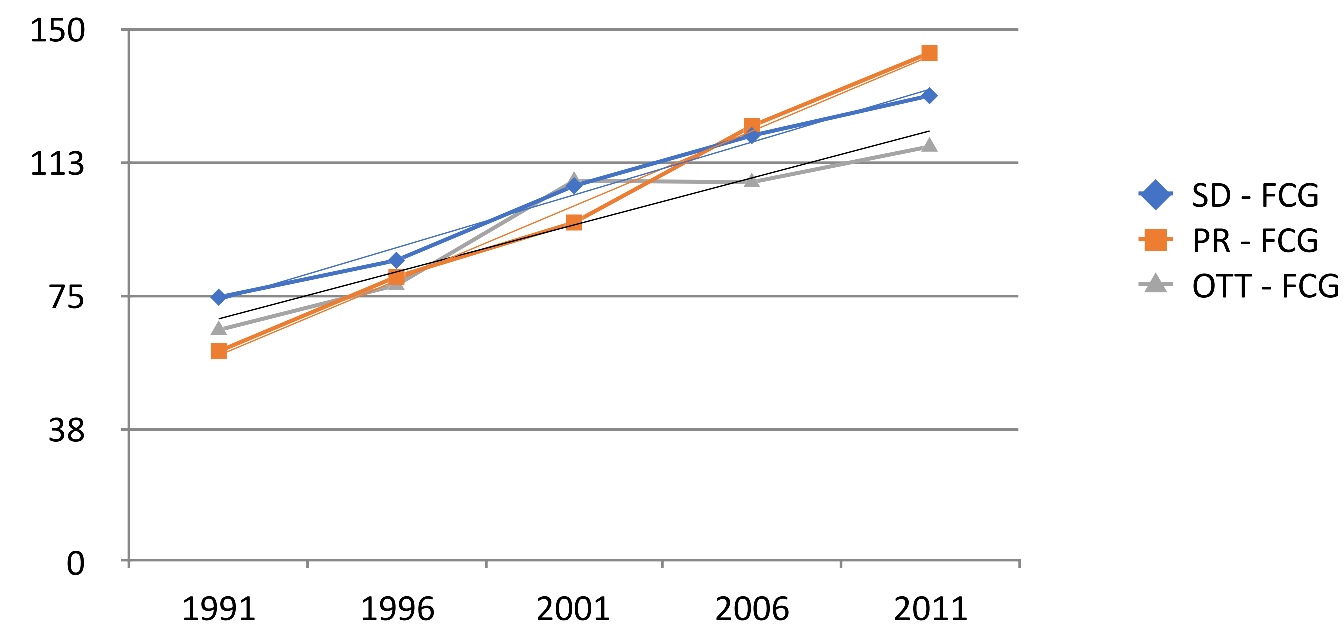
When do expansion events stop, in a given year?



Total Number of Field Crop Grain - Farms reporting



- Field Crop Grain



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"Scenario-based risk assessment decision support modelling tools for regional climate change and climate extremes, impacts and adaptation in agricultural watersheds" is a project funded by the Ontario Ministry of Agriculture, Food, and Rural Affairs' New Directions Research Program. One of our main objectives is to provide a clearing-house for information and resources that are useful for evaluating climate change in Ontario, starting with our pilot program in eastern Ontario.