Understanding and Envisioning Complex Human-Environment Systems: A Multi-Scale Integrated Approach

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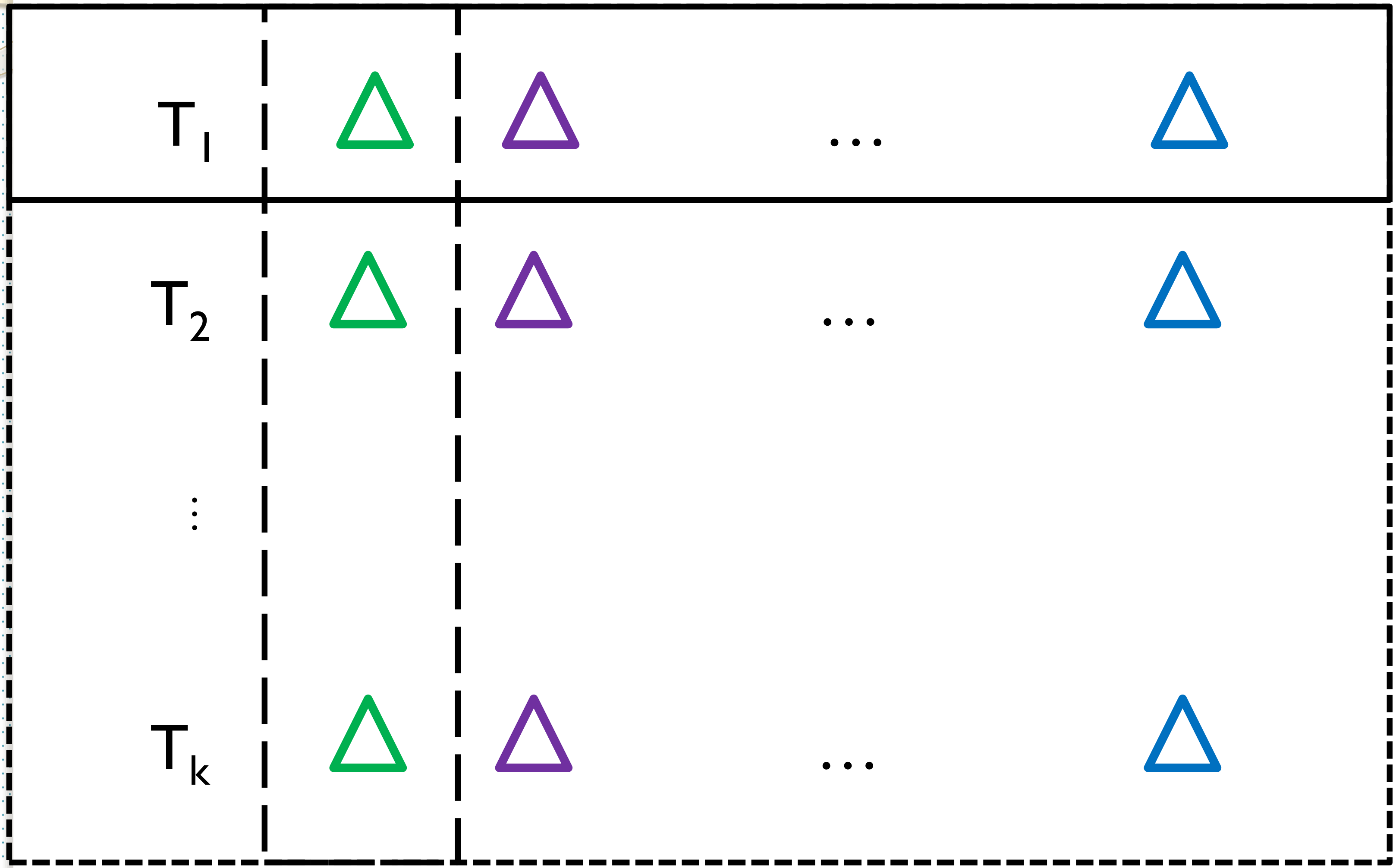
Complex H-E Systems

- Complexity features
  - Heterogeneity (space & time), scales, etc.
  - Feedback
  - Nonlinearity
  - Emergence
  - Self learning / adaptation
  - Legendary
- Similar terms:
  - SENCE (Ma and Wang 1990)
  - SES
  - CHANS (Liu et al. 2008)

CHES Data (X_1, X_2, X_3)



Data types2	Major challenge (s)	Exemplar approaches	Applications		
			H → E	E → H	H—E
Cross-sectional data	Multicollinearity; cluster effects	Variable orthogonality, multilevel modeling (MLM)			
Panel / longitudinal data (Time series & cross-sectional)	Temporal correlation, measure coarseness	Latent trajectory models LTM, MLM, survival models SA)			
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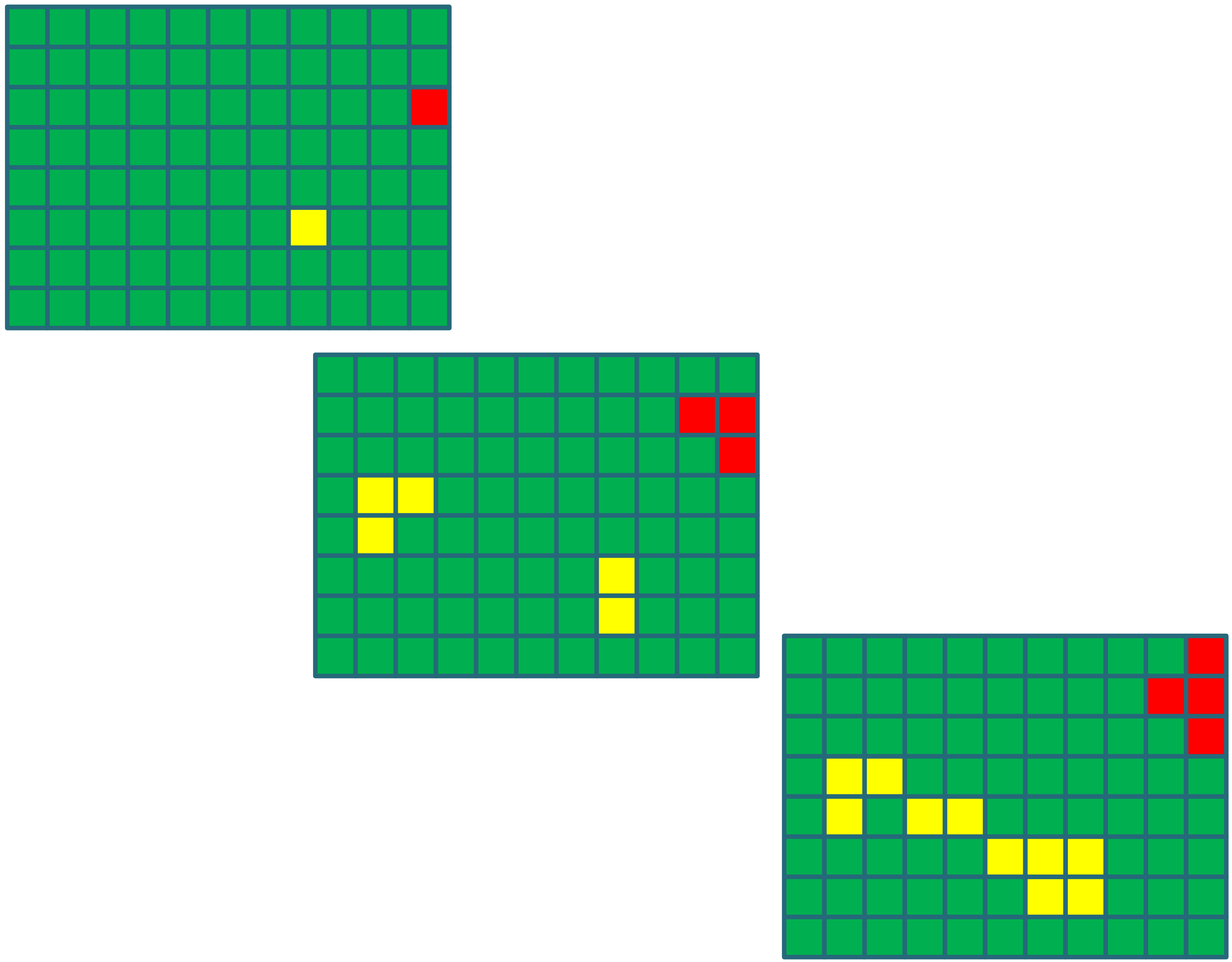
Data models (Snapshot model)

T1

T2

T3



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Case 1: PES interaction (Global)

- Major goal: how to address policy interaction and coordination

Detail in An et al. (in preparation-a)

Ecosystem services

- “The benefits people obtain from ecosystems”, or the “aspects of ecosystems utilized (actively or passively) to produce human wellbeing” (Fisher et al. 2008)
  - Components of nature, directly enjoyed, consumed, or used to yield human well-being (Boyd and Banzhaf 2007).
  - Twenty-four specific ecosystem services identified (e.g., food, water, air, soil, forests, biodiversity, etc. by a UN report).

Payments for Ecosystem Services (PES)

- Incentives paid to users of natural resources
  - Protect the **environment**: ecosystem structure, function, and services
  - Protect the **people**: economic incentives help maintain quality of life and well-being
- Lack of sustainability
  - Resource users return to pre-PES behavior
  - Effective for a short time (The curse of no "permanence")
  - **PES mutual relationships**

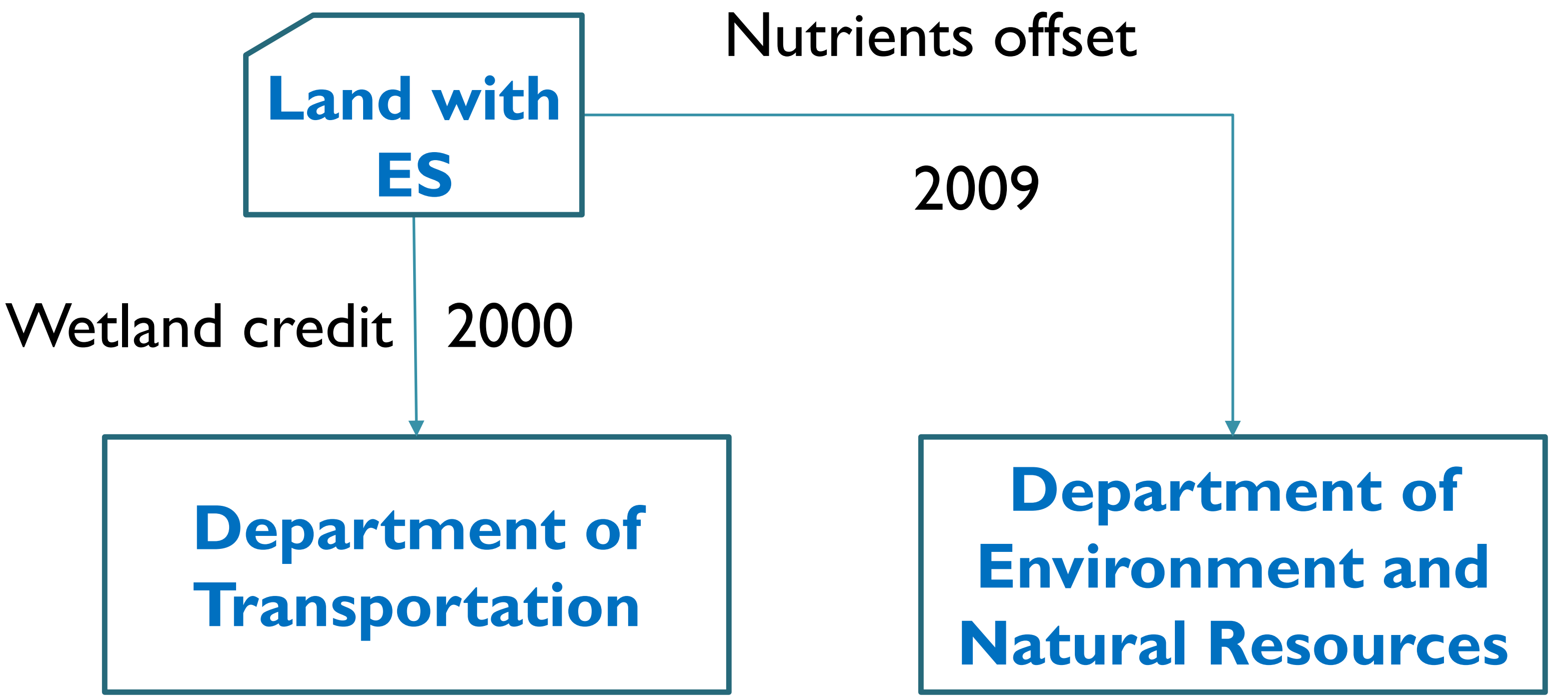
Concurrent PES programs

- Multiple PES goals (programs) simultaneously implemented on same spatial units or charged to same entities (e.g., persons, households, farms, groups)
- Popularity
  - Out of 58 exemplar PES programs worldwide (Ezzine-de-Blas et al. 2016), 28 had concurrent PES programs
  - Grain-To-Green Program (GTGP) vs. Forest Ecological Benefit Compensation (FEBC) /National Forest Conservation Program (NFCP)

PES stacking and bundling (USA)

- Multiple recognized ecosystem services are tradable on markets through the corresponding credits (or payments)
  - Horizontal
  - Vertical ("double dipping" or "piggy-backing)
  - Temporal
- Bundling of multiple ecosystem services to one single credit, which is tradable in markets

North Carolina, USA

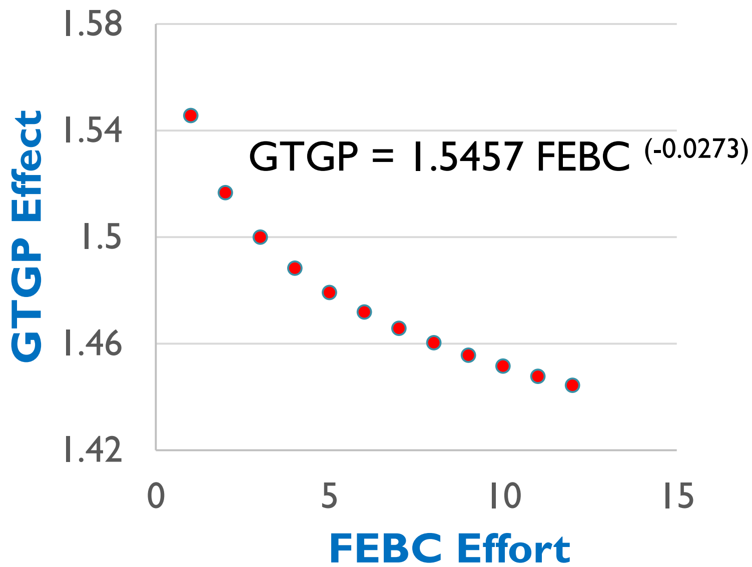


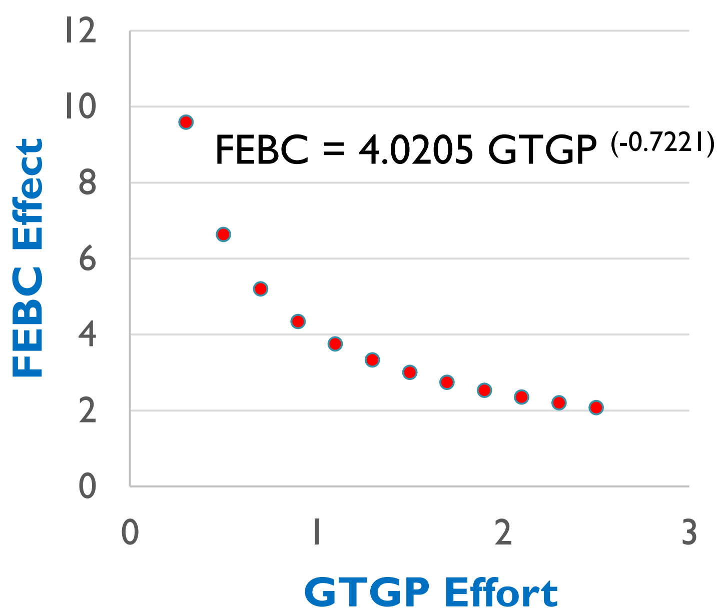
- $698,372 of the $910,920 that DENR paid for nutrient credits in 2009 were “wasted” (additionality = 0)
- Policy change: no future temporal stacking,

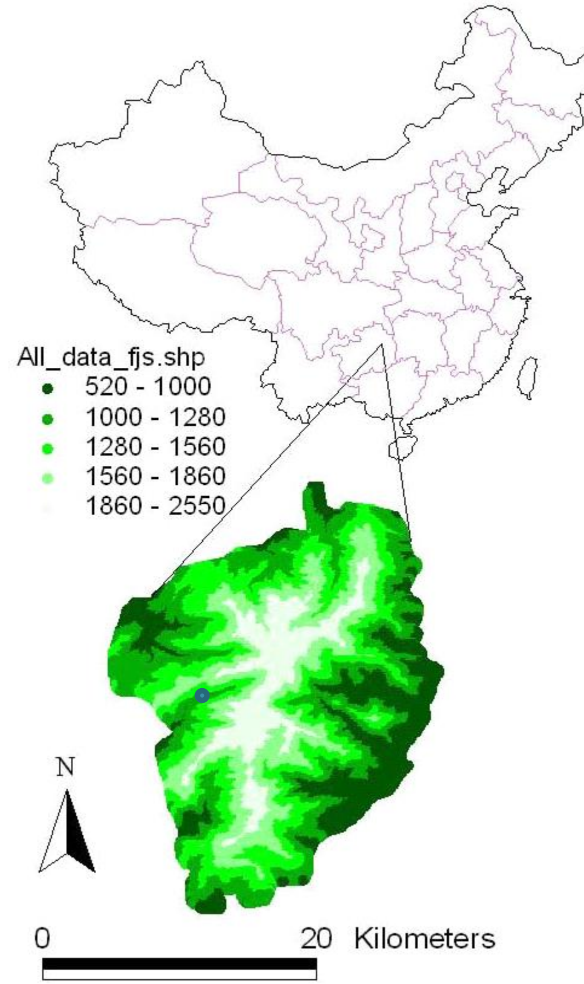
Mexico

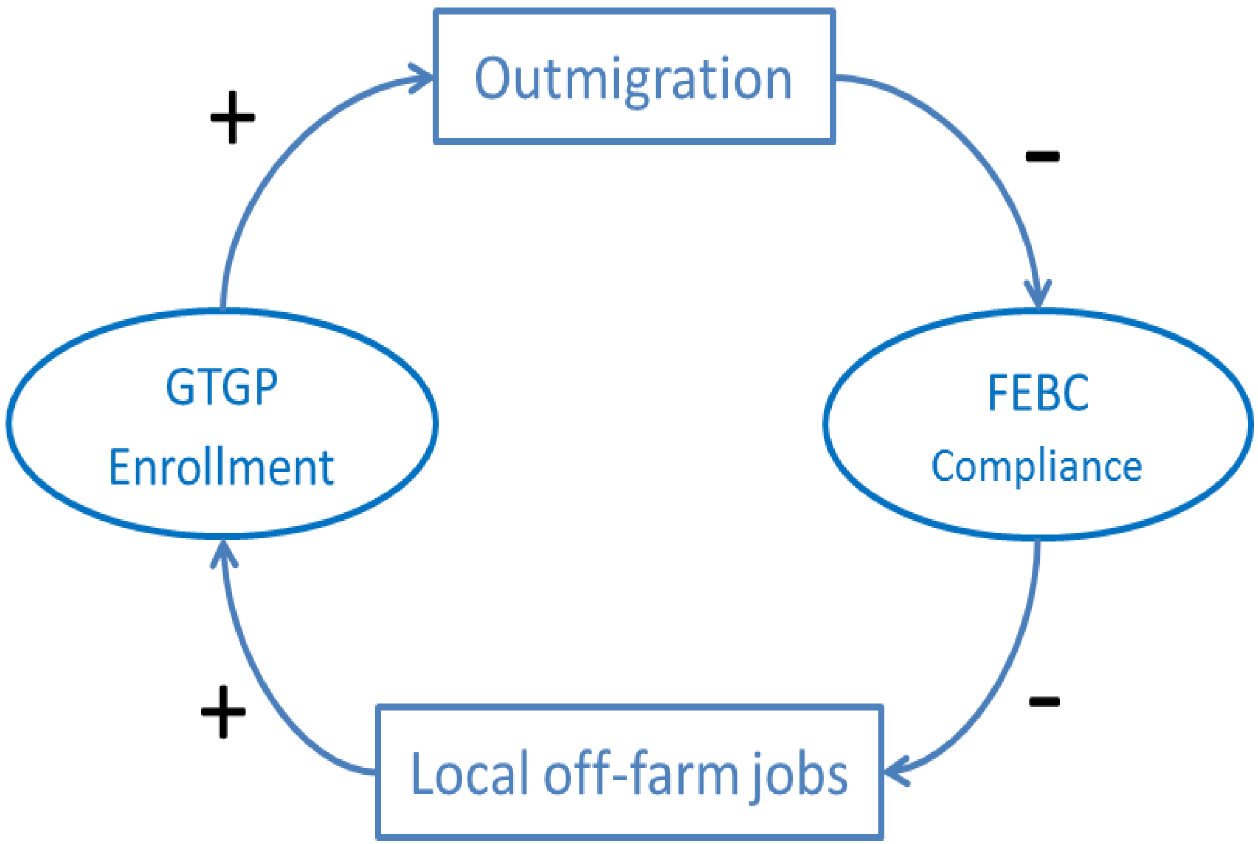
- Federal government:
  - 50% funding
  - Goals A and B
- Local government
  - 50% match-up funding
  - Goals C and D

Fanjingshan National Nature Reserve

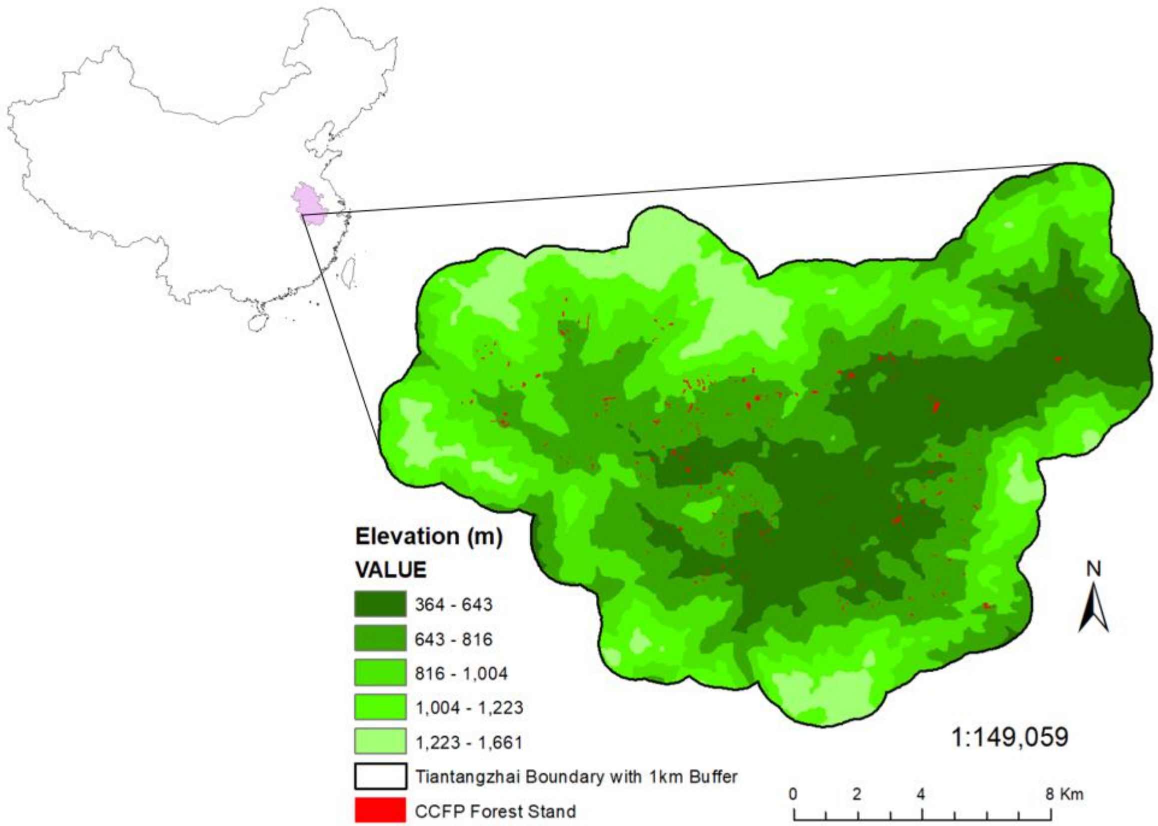






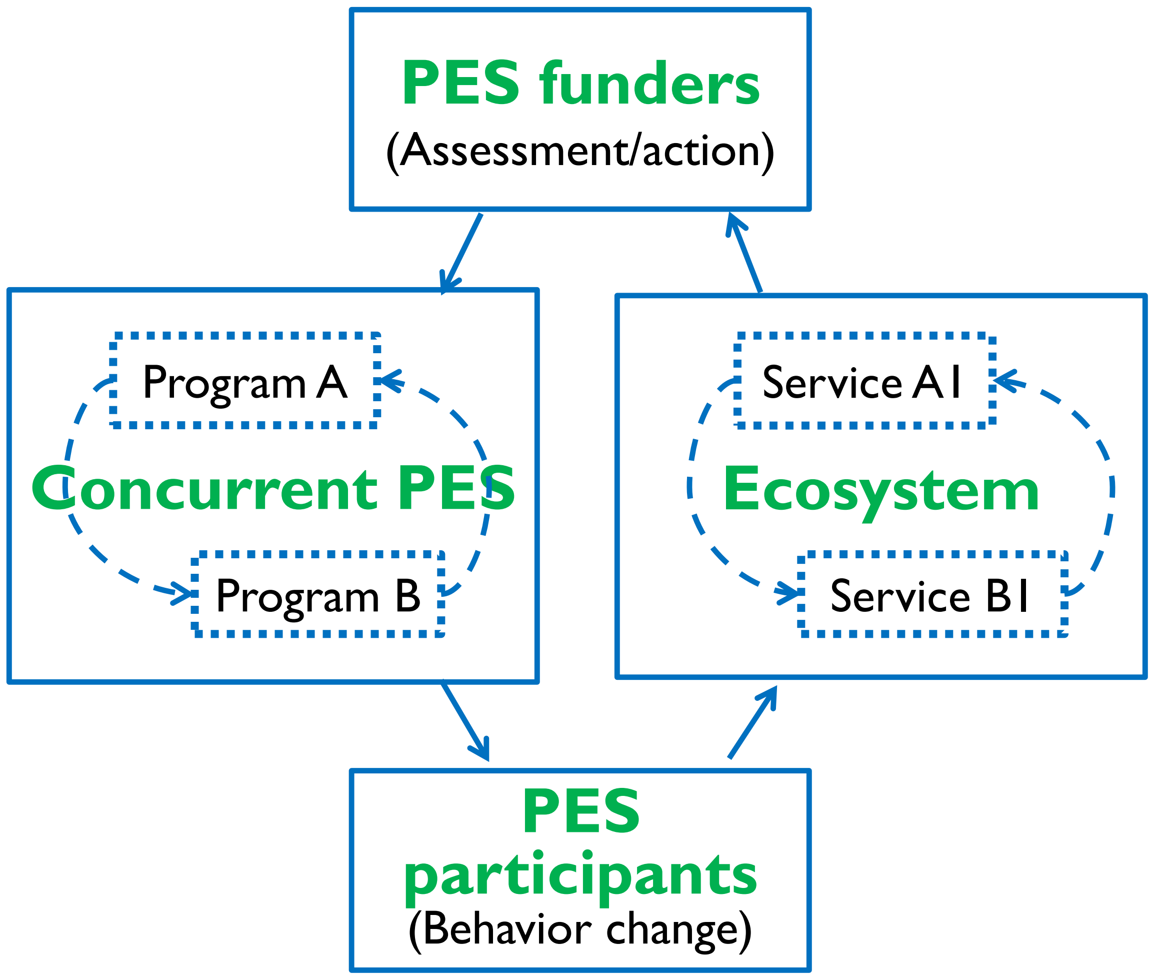

Outmigration
+
-
GTGP
Enrollment
FEBC
Compliance
+
-
Local off-farm jobs

Tianma National Nature Reserve



- GTGP promotes outmigration
- FEBC reduces outmigration

Conceptual model



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Case 2: Perceived global warming

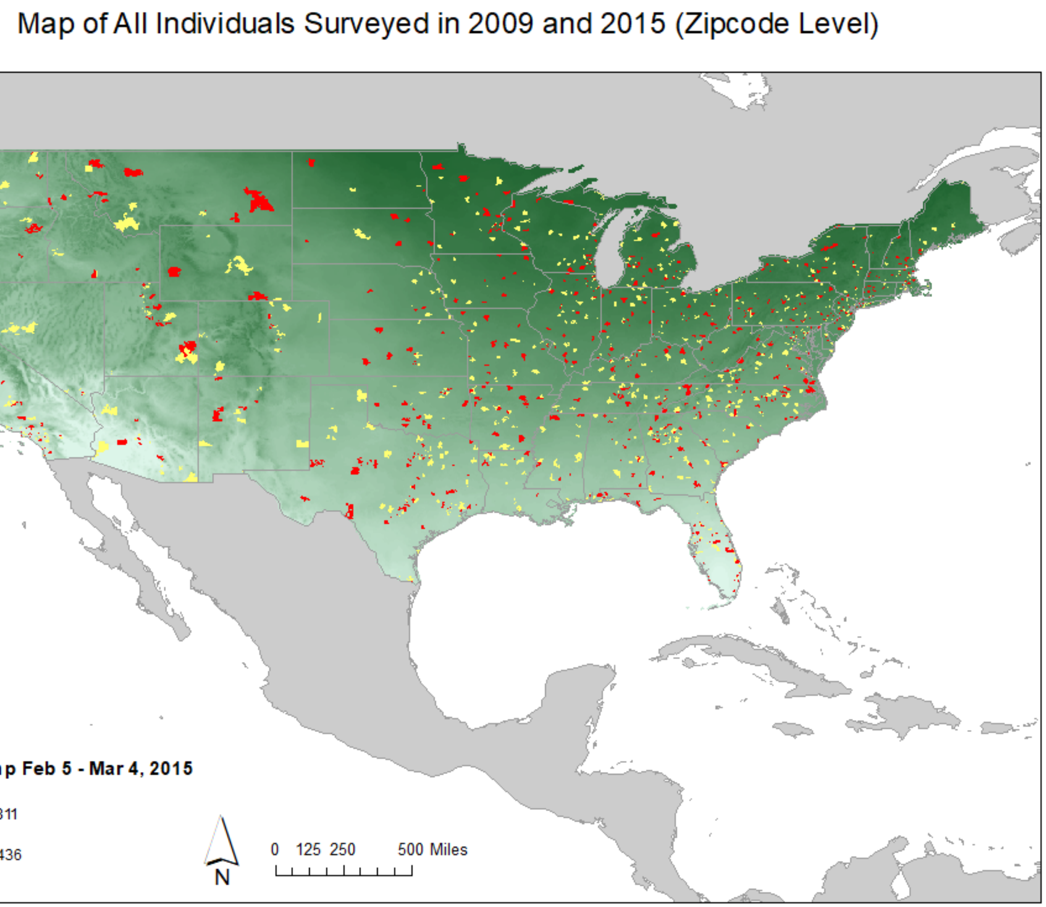
- Major goals:
  - What is the impact of CHANGE of natural climate on people's perception?
  - How to address bias from spatial autocorrelation

Detail in An et al. (in preparation-b)

Background

- Big disparity between scientists and the public about existence and the reason of global warming
  - Socioeconomic, demographic, political, and ideological impacts are assessed
  - Also impacts of climate and weather (perceived and measured) are somewhat assessed
- Yet: how about changes in climate?

Data: Gallop poll (盖洛普民意调查)



Daily max temperature & precipitation 1-, 7-, and 28-day before the survey

Adding climate change as predictor(s)?

- Personal threat of GW

  =f (control variables + measured and perceived CC variables)

- Problem:
  - CC variables are spatially autocorrelated
  - Violation of regression assumption
  - Biased coefficients and standard errors

Eigenvector spatial filtering (ESF)

- Define spatial neighborhoods (matrix of 1s and 0s)
- Generate eigenvectors
- Use the top eigenvectors as "predictors" as regression predictors

For detail see Griffith 2003
Also http://www.complexities.org/Methodology/LTMs/LTMs.htm

Updated model

Perception of GW =

f (control variables

+ measured and perceived CC variables

$\boxed{+ EV_1 + EV_2 + \cdots)}$

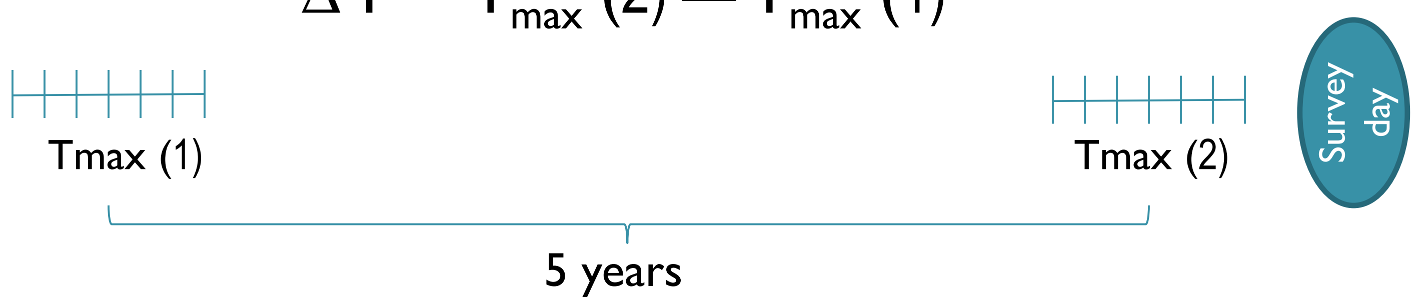
Improve model fit

No change on significance level

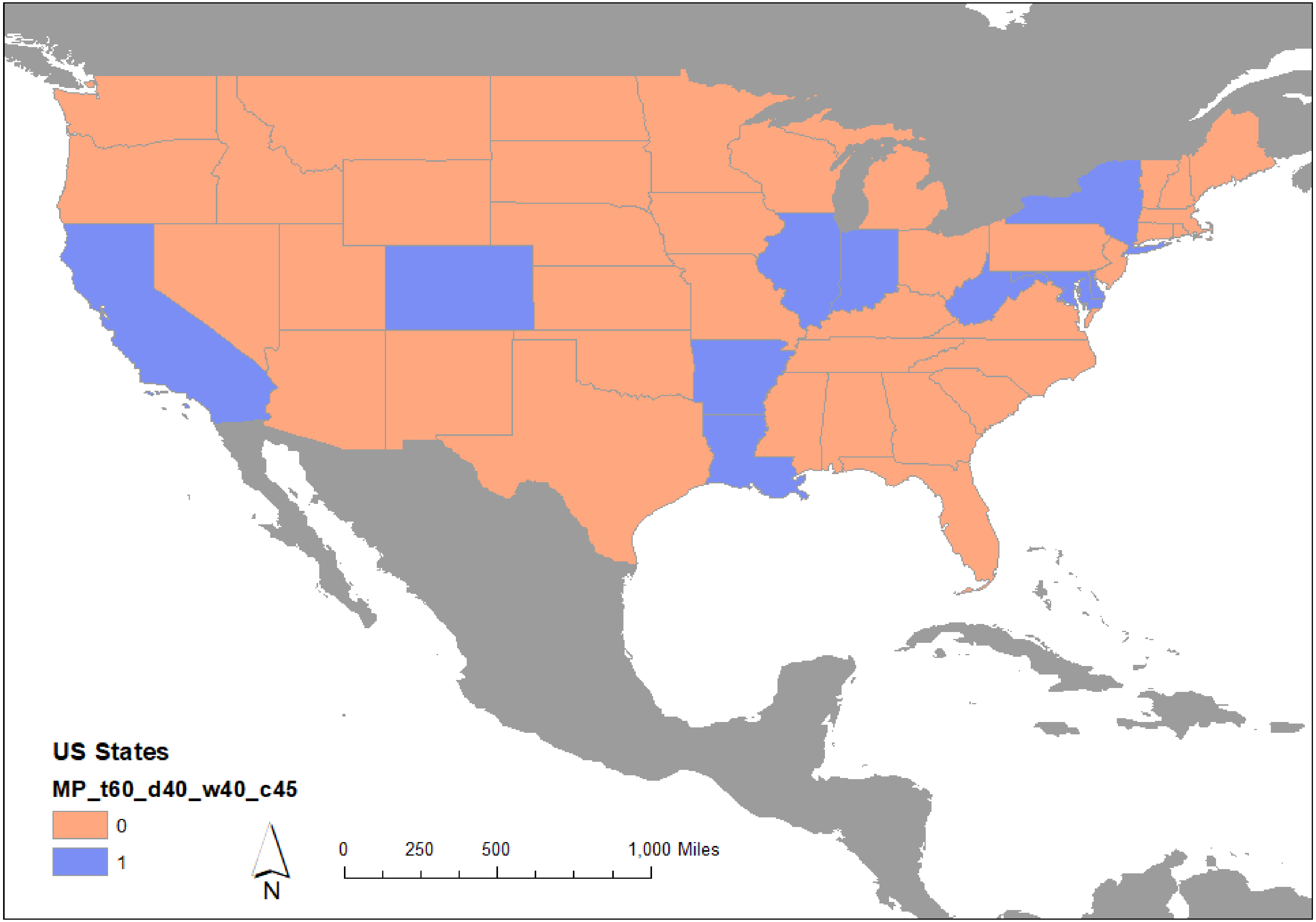
Impact on GW perception

- Control variables have expected effects
  - Perceived warming and drought have positive impact on the perceived threat
  - Among measured climate variables, weekly and monthly average of max. temperatures have positive impact
- Among climate <u>change</u> variables, temperature, **<u>not</u>** precipitation DOES have a significant, positive impact:

$$\Delta T = T_{max}(2) - T_{max}(1)$$



States Meeting Classification Threshold



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Case 3: Ghana BMI

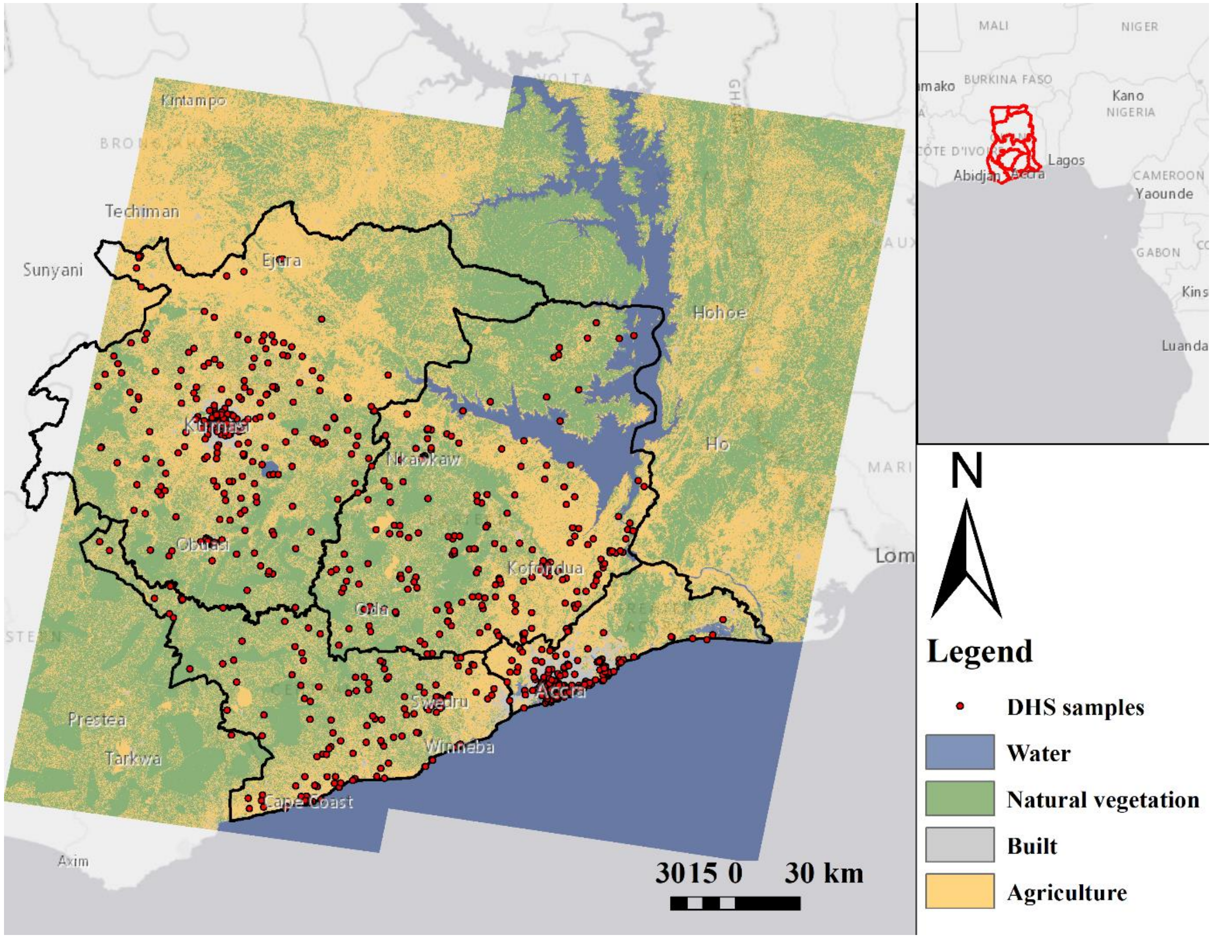
- Do land cover variables affect body mass index (BMI)?
- How to address both spatial and temporal autocorrelation?

$$BMI = \frac{Weigh\ (kg)}{Height\ (m)^2!}$$

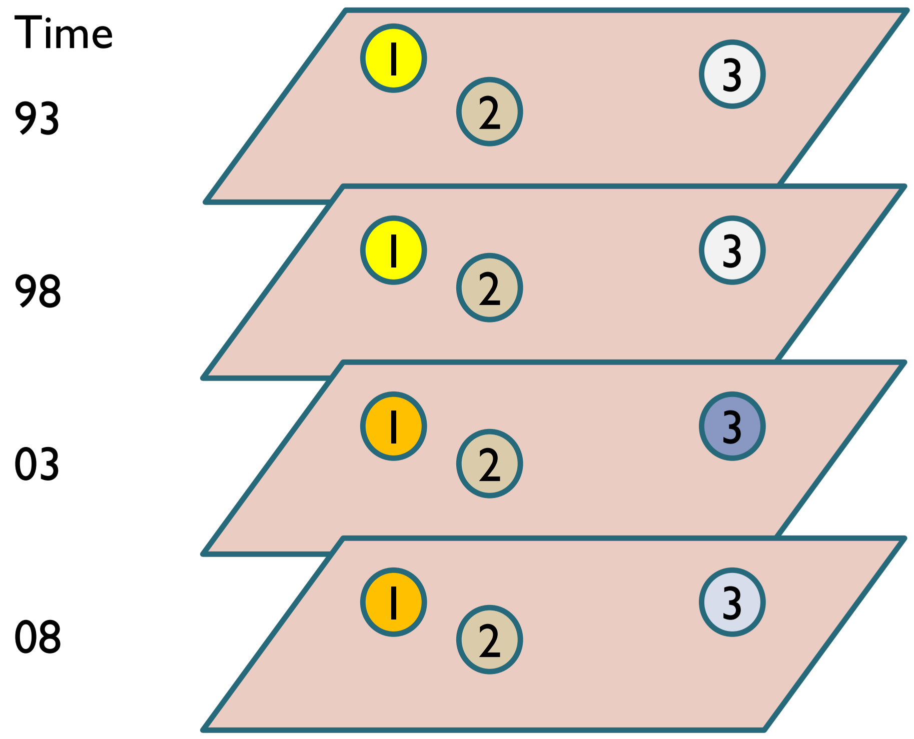
where 18.5<BMI<25 is good

Detail in Shih et al. (in preparation)

Southeastern Ghana



Data



BMI

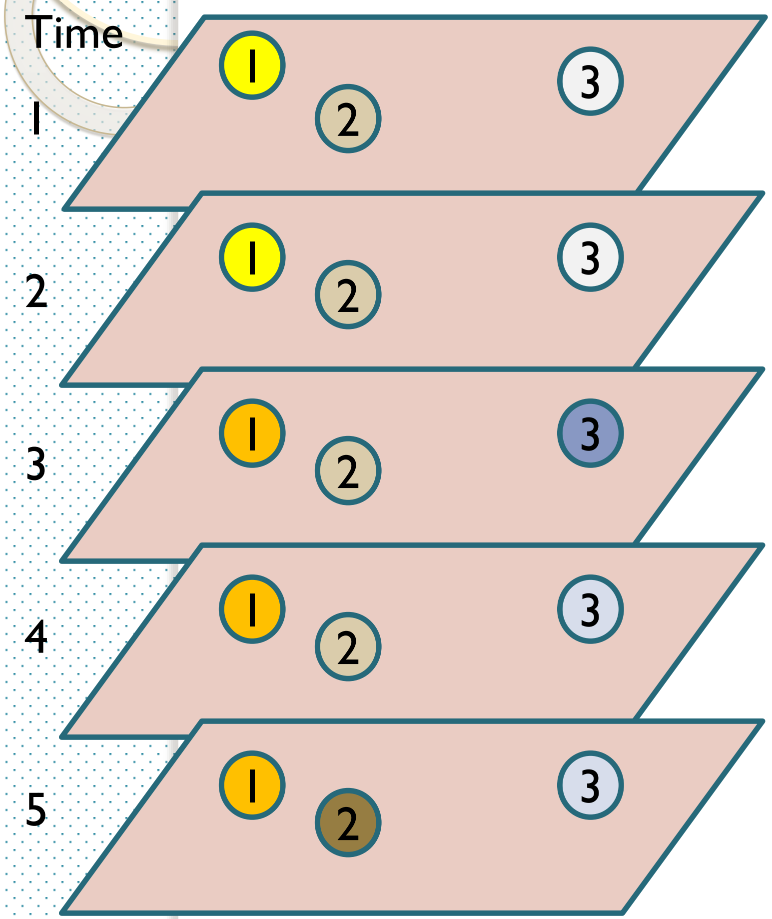
Demographic and Health Surveys (DHS)

Land cover data (from satellite imagery)

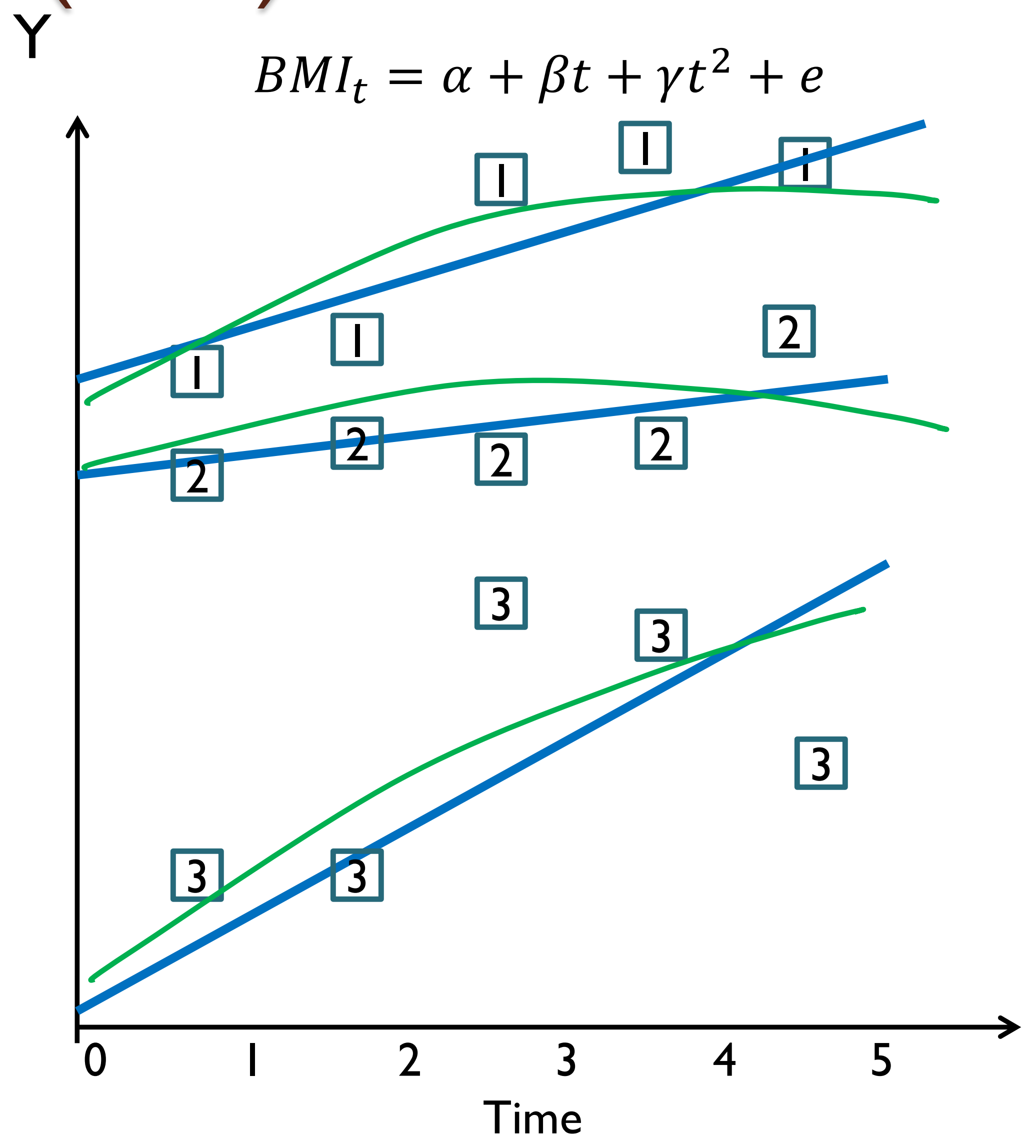
Generic model

$$BMI_t = \alpha + \beta t + \gamma t^2 + e$$

Trajectories (BMI):



The numbers are unique IDs of spatial units



Latent trajectory modeling

- Repeated measures for each study unit are assumed to come from a continuous underlying trajectory
- Trajectory parameters are modeled, e.g.,
  - Intercepts = f (chosen covariates)
  - Slope = f (chosen covariates)
  - Slope-square= f (chosen covariates)
- But trajectories may be subject to spatial autocorrelation…

Keep in mind:

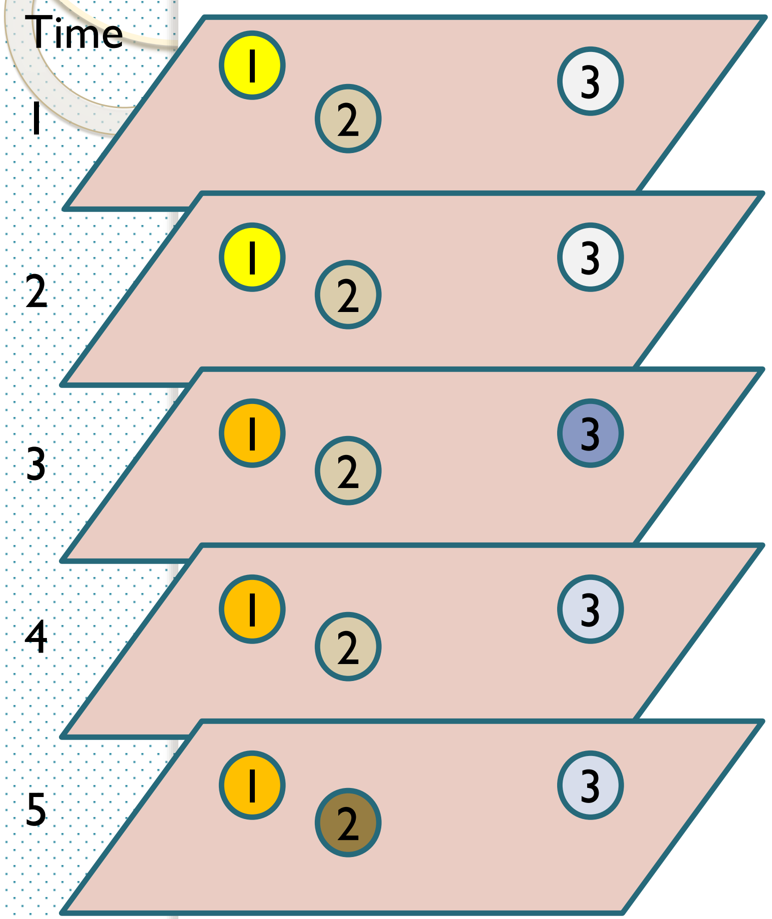
$$Y = \beta_0 + \beta_1 T + e$$

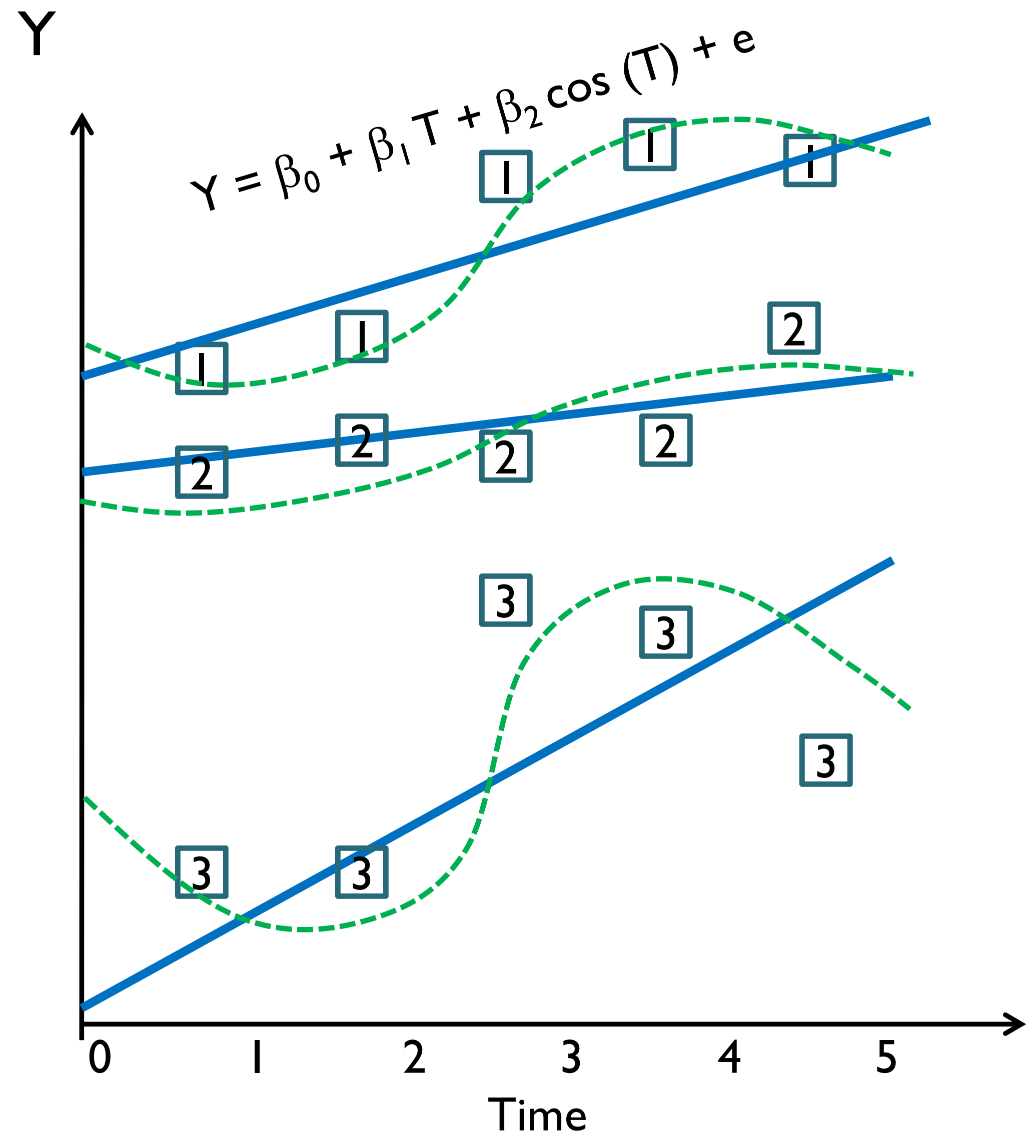
$$BMI_t = \alpha + \beta t + \gamma t^2 + e$$

$$Y = \beta_0 + \beta_1 T + \beta_2 \cos(T) + e$$

- The trajectory function and parameters (e.g., β_0, β_1, and β_2) determine the shape and trend of each trajectory
- Temporal variability (or correlation) is built-in
    - Think about each trajectory (trend line) is a regression of ALL measurements (over time) at one place

Trajectories 1 and 2 are more similar





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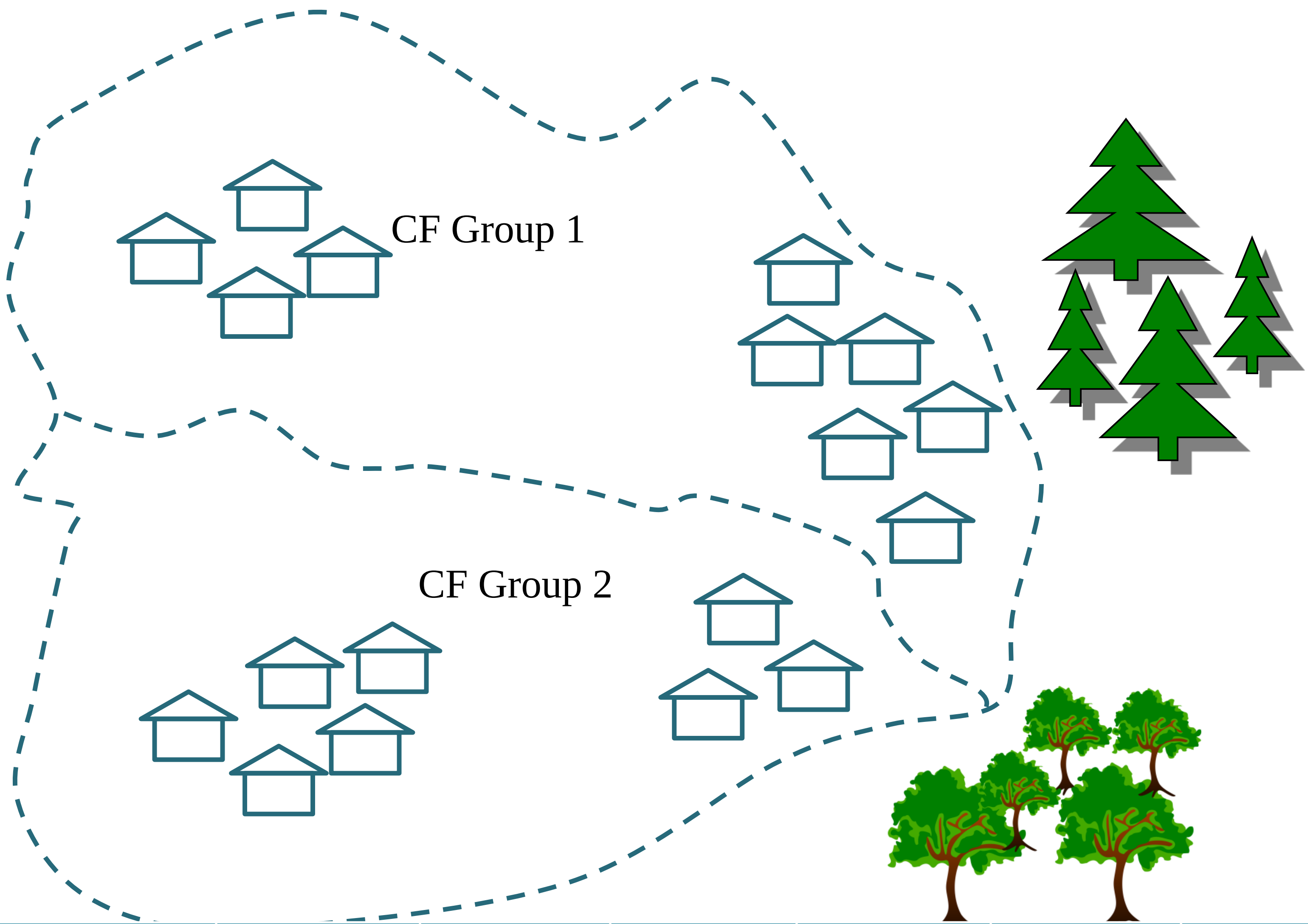
	Model (g)0 (with spatial autocorrelation)	Model (g)1	Model (g)2	Model (g)3	Model (g)4
AICc	5244.7	5000.2	5013.9	5025.9	5143.9
t^0 (α_0)	1552.16***	1928.48***	1848.51***	1851.37***	1821.63***
HHSize (α_1)	126.44*	43.89	70.27	73.79	61.95
FlushToilet (α_2)	2187.26***	1558.57***	1537.93***	1439.59***	1771.80***
NoToilet (α_3)	470.30**	129.74	25.45	-7.46	151.39
Built (α_4)	1.2×10^{-5}***	5.182×10^{-6}	5.430×10^{-6}	6.119×10^{-6}*	8.963×10^{-6}**
NaturalVeg (α_5)	7.986×10^{-6}	1.400×10^{-5}	1.600×10^{-5}	1.200×10^{-5}	1.3×10^{-5}
t^1 (β_0)	437.88**	265.95	315.32	320.43*	342.92*
HHSize (β_1)	-54.27	-16.79	-33.76	-41.98	-37.39
FlushToilet (β_2)	-989.25***	-784.53***	-793.10***	-710.03***	-951.91***
NoToilet (β_3)	-595.56***	-270.17	-205.67	-141.11	-322.51*
Built (β_4)	-1×10^{-5}***	-3.760×10^{-6}	-3.280×10^{-6}	-3.290×10^{-7}	-4.260×10^{-6}
NaturalVeg (β_5)	-2×10^{-5}	-2.000×10^{-5}*	-2.000×10^{-5}*	-2.000×10^{-5}*	-2.000×10^{-5}*
t^2 (γ_0)	-53.62	-17.99	-26.09	-29.18	-50.09
HHSize (γ_1)	2.97	-3.80	-1.32	0.93	3.65
FlushToilet (γ_2)	125.08***	104.36**	107.08***	93.79**	141.85***
NoToilet (γ_3)	157.38***	63.45	56.53*	36.77	94.58**
Built (γ_4)	2.637×10^{-6}***	9.639×10^{-7}***	9.051×10^{-7}***	8.875×10^{-7}***	1.112×10^{-7}***
NaturalVeg (γ_5)	2.903×10^{-6}	3.356×10^{-6}*	3.722×10^{-6}*	3.391×10^{-6}*	3.581×10^{-6}*

* p-value <0.05; ** p-value <0.01; ***p-value <0.0001. From Shih et al. (in preparation).



Model	No filtering	NBH 10	NBH 20	NBH 30	NBH 40	NBH 50
CF perceived threat	**-0.5974***	**-0.8761****	**-0.7266***	0.3549	0.1596	0.0084

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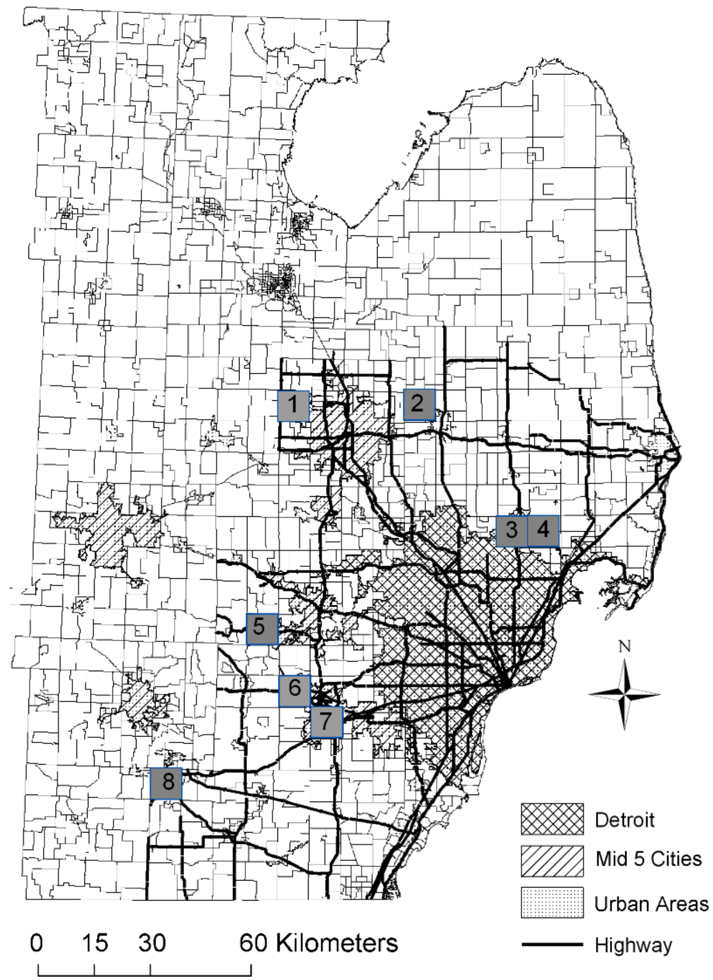
Case 4: Land change

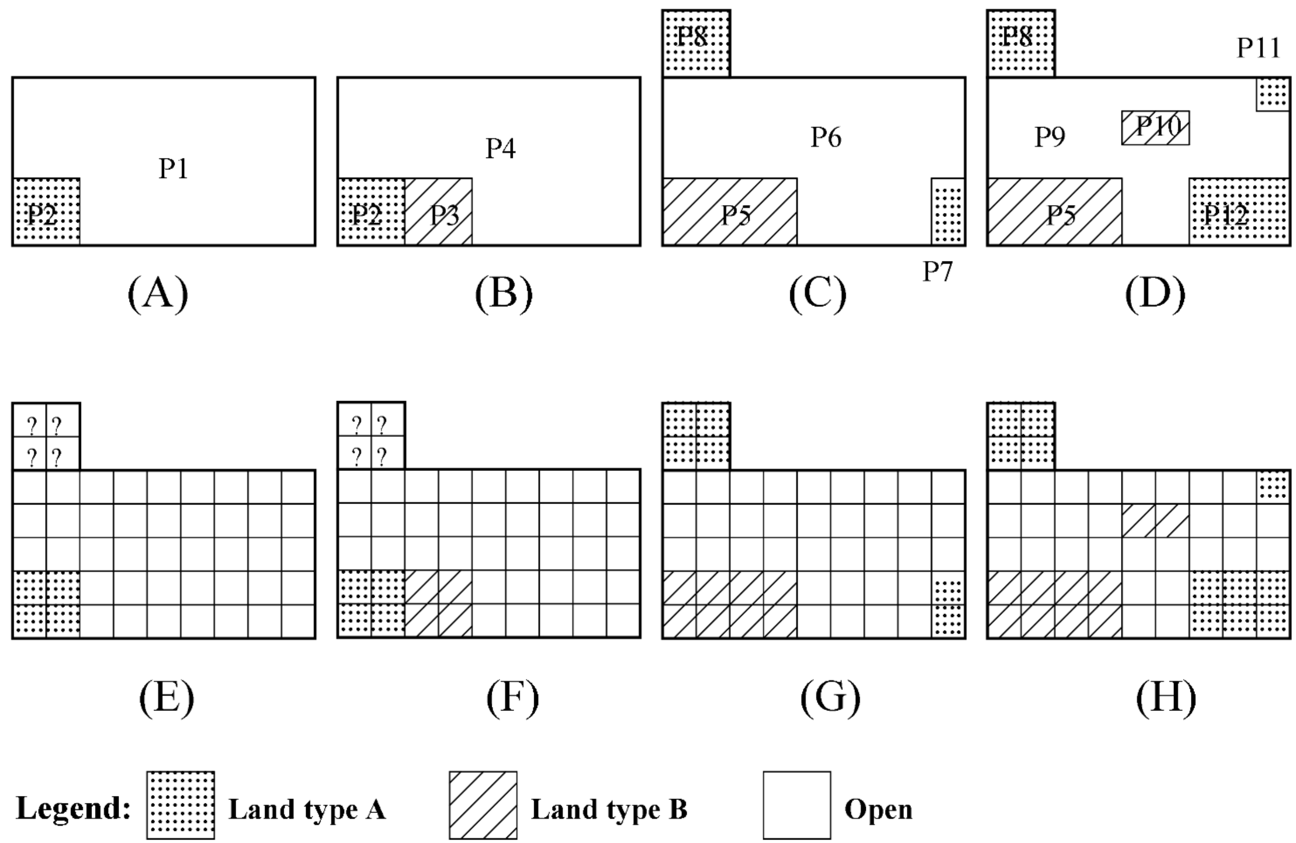
- Major goal: how to address uncertainty in time measurements?
- What drives Southeast Michigan land changes?

An et al. 2008, 2011

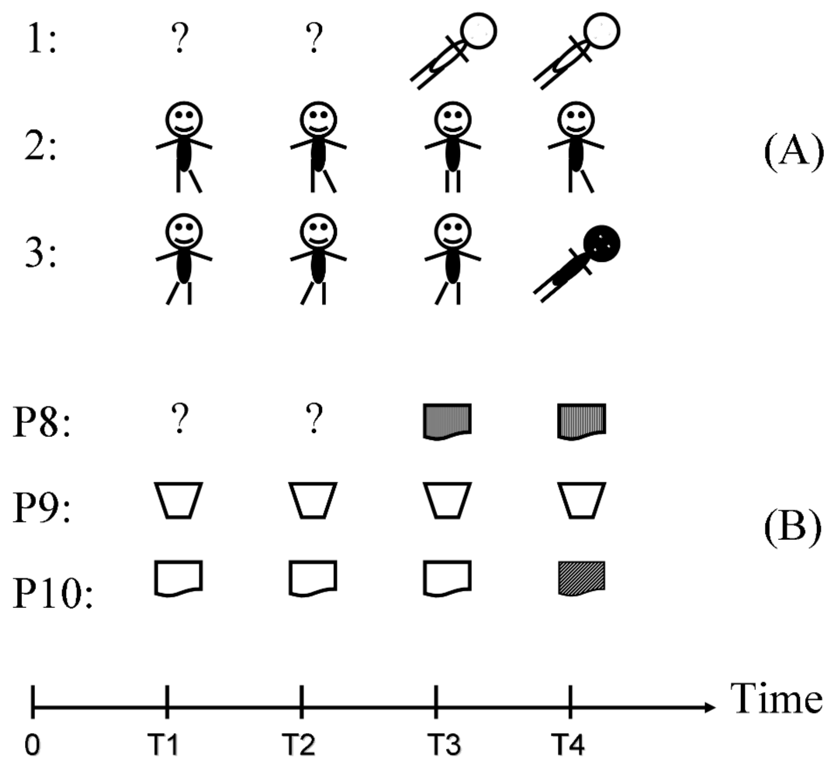
Study site


1
2
3
4
5
6
7
8
N
Detroit
Mid 5 Cities
Urban Areas
Highway
0 15 30 60 Kilometers

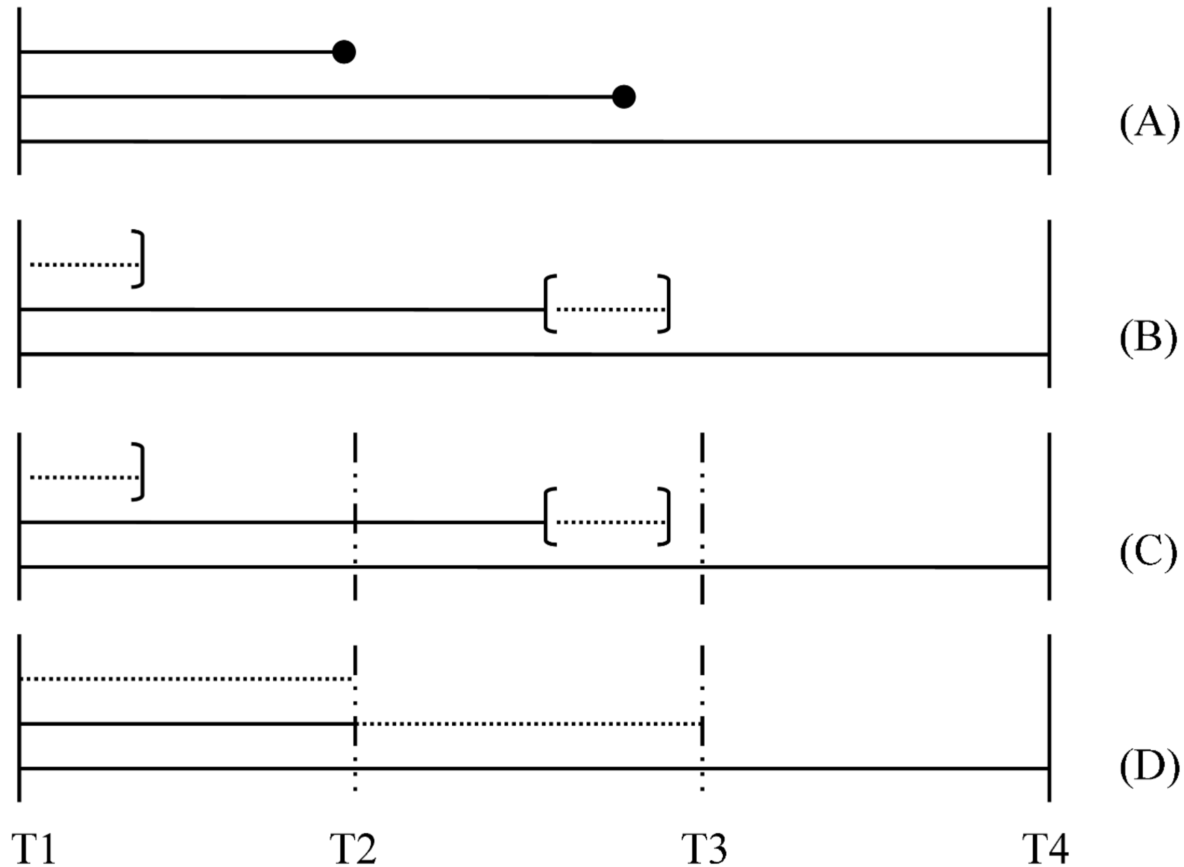
Land change conceptual model



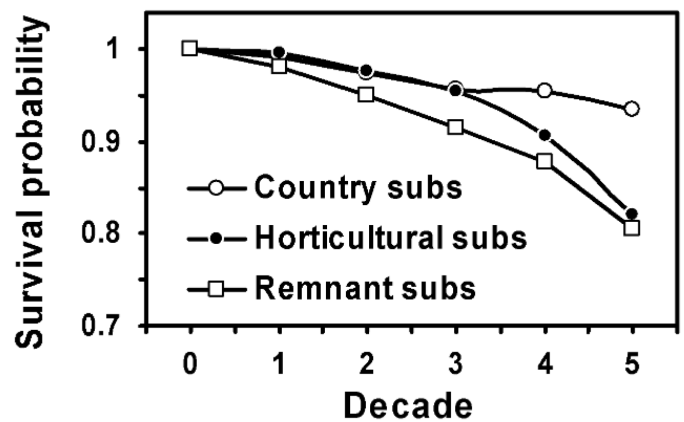
Survival analysis (traditional)



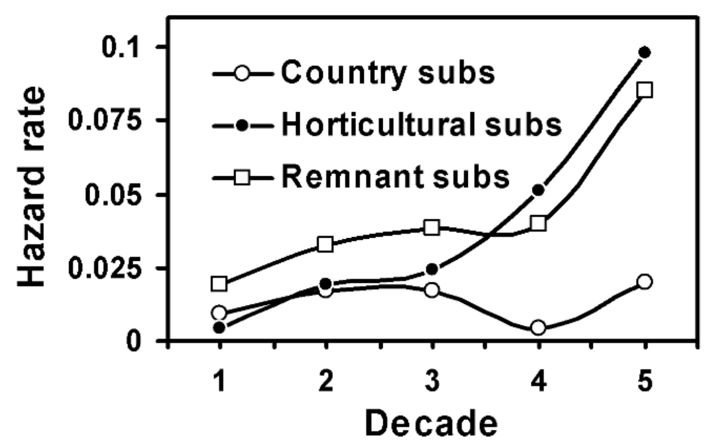
Time imprecision



Change measurements



(A)



(B)

Modeling hazards

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr\{t \leq T \leq t + \Delta t | T \geq t\}}{\Delta t}$$

$$\text{Log}\, h_i(t) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik}$$

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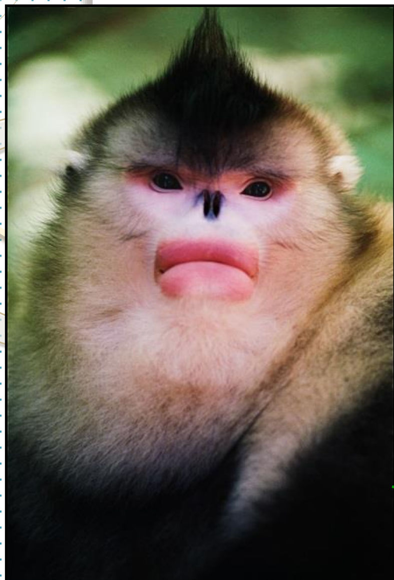
Case 5: Habitat occupancy

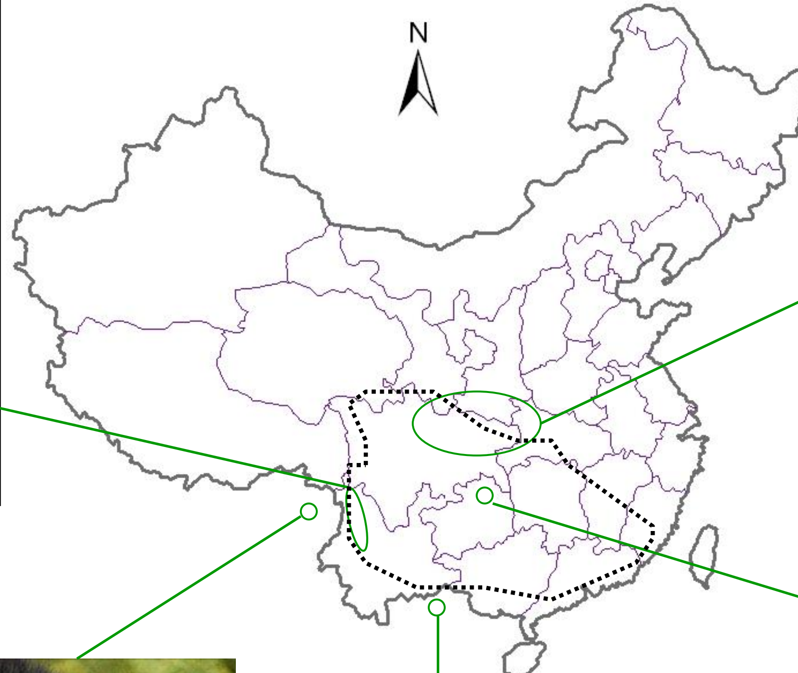
- How to address human-human, environment-environment, and human-environment feedbacks
- When, why, and how does emergence come out?

An et al. (in preparation-c)
Mak (2018)

Rhinopithecus

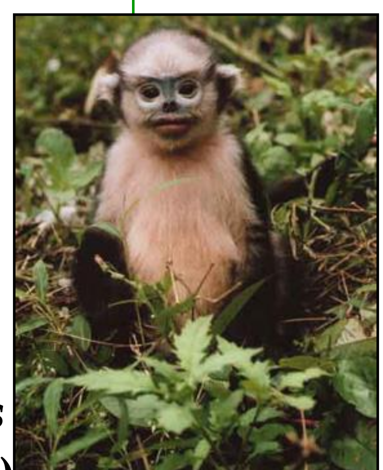


R. bieti 1,500
(Yunan)



R. roxellana
15,000 (Sichuan)

R. Strykeri
<300 (Myanmar)



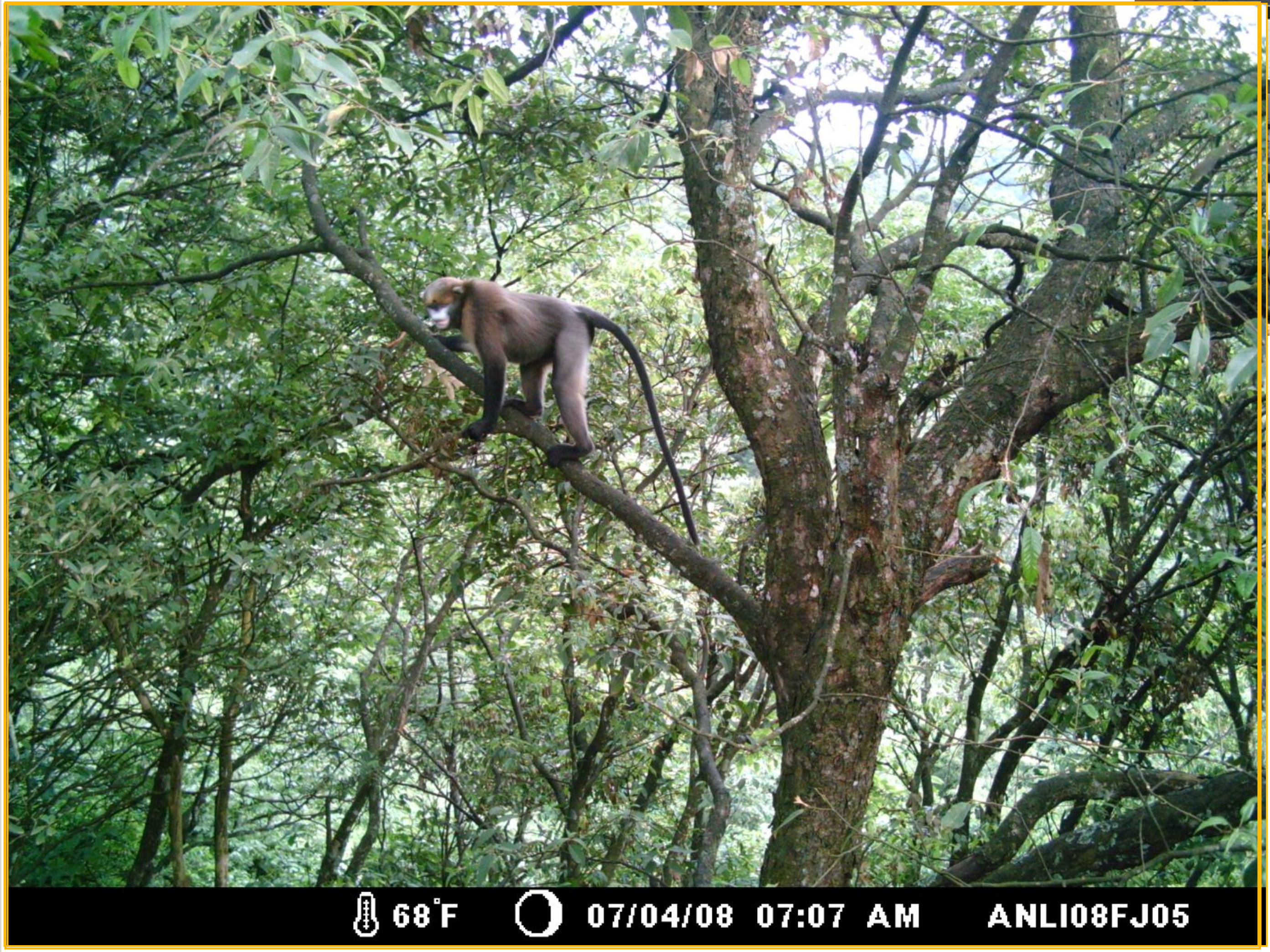
R. avunculus
<200 (Vietnam)

R. brelichi
800 (Guizhou)

Photo courtesy: Chia Tan, Xiaoping Lei, www.ibn-tv.com

Forest changes due to PES?

Changes in monkey occupancy



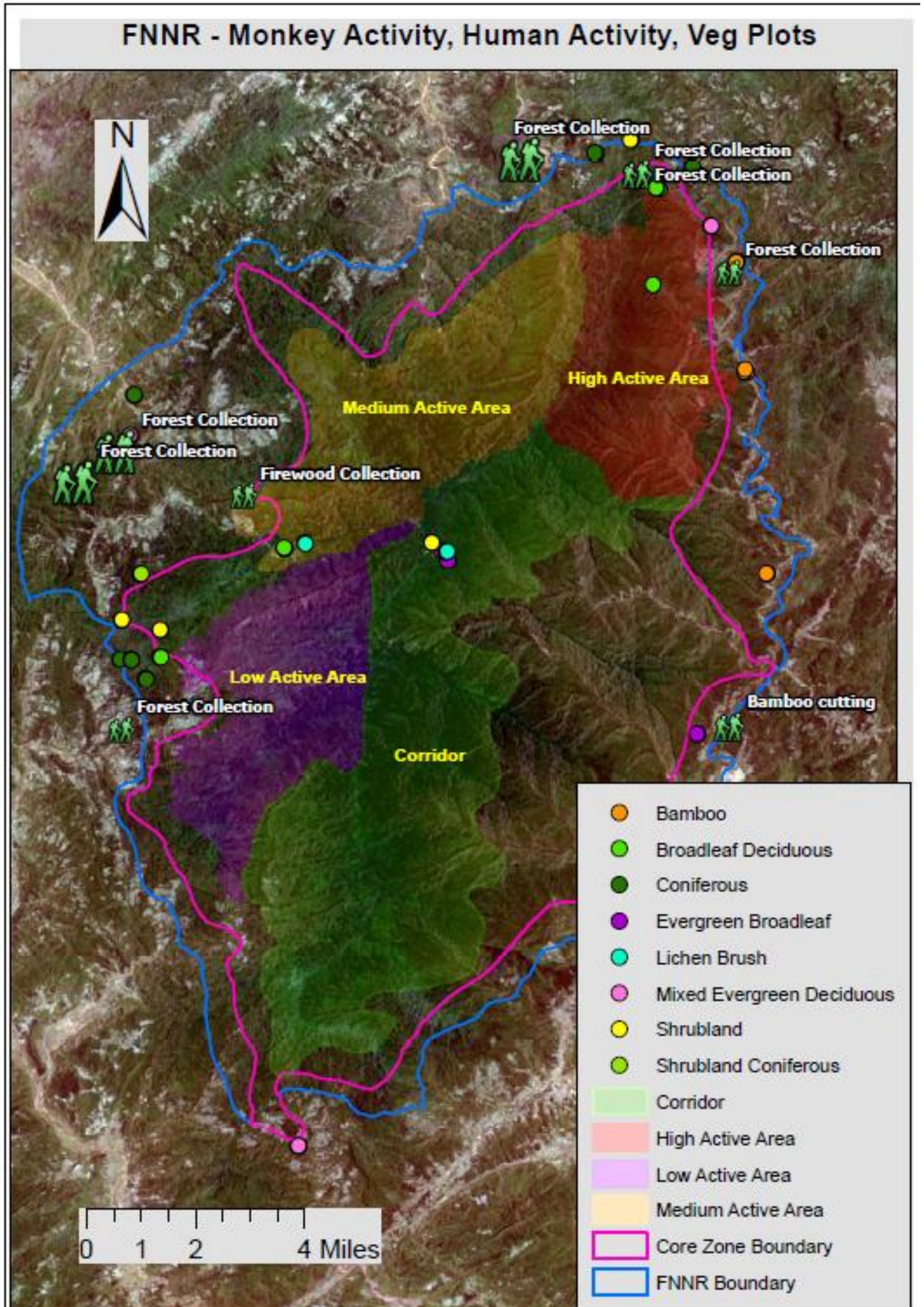
Envision mechanisms **Changes**

Changes in human activity?

Envision
mechanisms
Changes

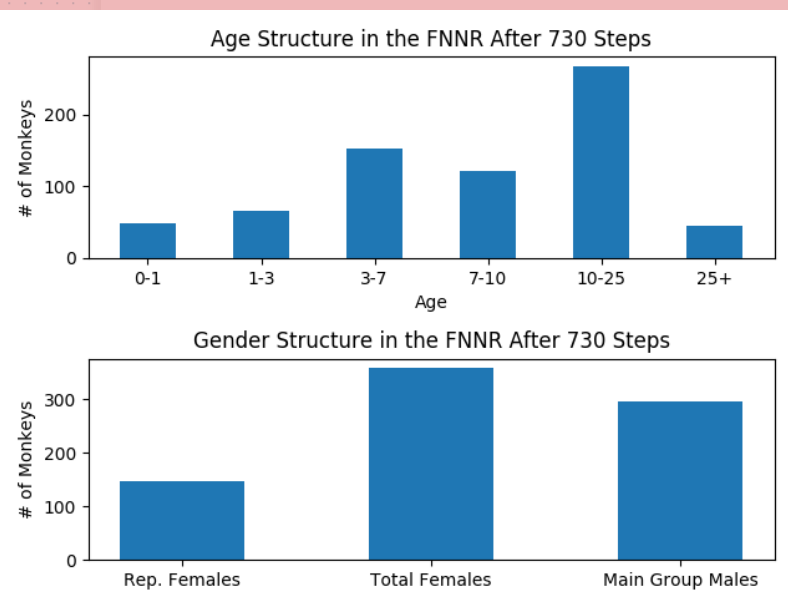
Changes mechanisms Envision

Participatory mapping



Demographic submodel:

What level of biological traits (birth rates, between-birth intervals, and death rates), if affected by human or natural disturbances, would make the population o the Guizhou snub-nosed monkey vulnerable?



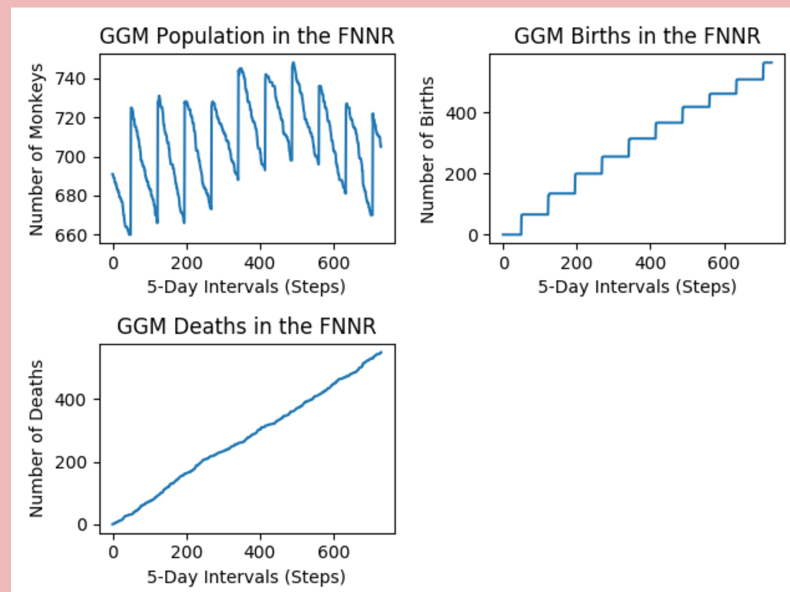
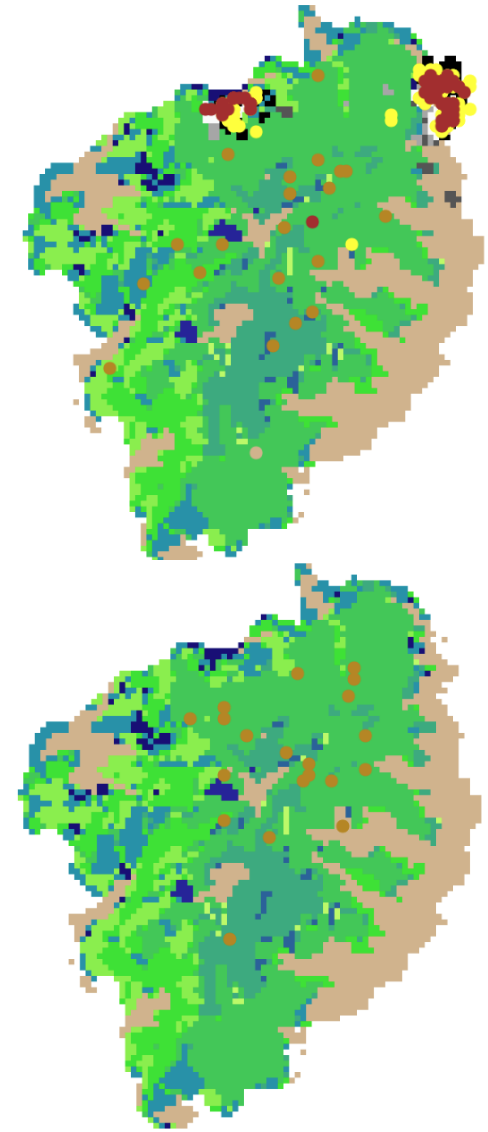


Figure acknowledgement: Judy Mak 2018 (thesis)

Habitat occupancy modeling

- Input:
  - Family-group agents (25-40 monkeys per group)
  - Environmental layers: elevation, vegetation
- Input for "With-humans" scenario only:
  - Human agents (starting points at homes)
  - Resources (gathered by humans)
  - Data from Yang et al. 2014, 2016



系統 × Agent-Based Modeling (ABM) × +

complexities.org/ABM17/ 80% Search

d Getting Started

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Complex H-E Systems

- Complexity features
  - Feedback
  - Nonlinearity
  - Emergence
  - Self learning / adaptation
  - Legendary
  - Heterogeneity (space & time), scales, etc.
- Similar terms:
  - SENCE (Ma and Wang 1990)
  - SES
  - CHANS (Liu et al. 2008)

Data types	Major challenge (s)	Exemplar approaches	Applications		
			H → E	E → H	H—E
Cross-sectional data	Multicollinearity; cluster effects	Variable orthogonality, multilevel modeling (MLM)			
Panel / longitudinal data (Time series & cross-sectional)	Temporal correlation, measure coarseness	Latent trajectory models LTM, MLM, survival models SA)			
Special: Spatial data	Spatial autocorrelation	GWR, ESF		Case 3: Perception of Global warming (country)	Case 5: Habitat occupancy (local)
Spatial panel data (Space-time data)	Spatial autocorrelation & temporal correlation	LTM-ESF, agent-based model	Case 4: Land change (region)	Case 2 Ghana BMI (region)	Case 1: PES interaction (global)

Extremely important

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Questions??