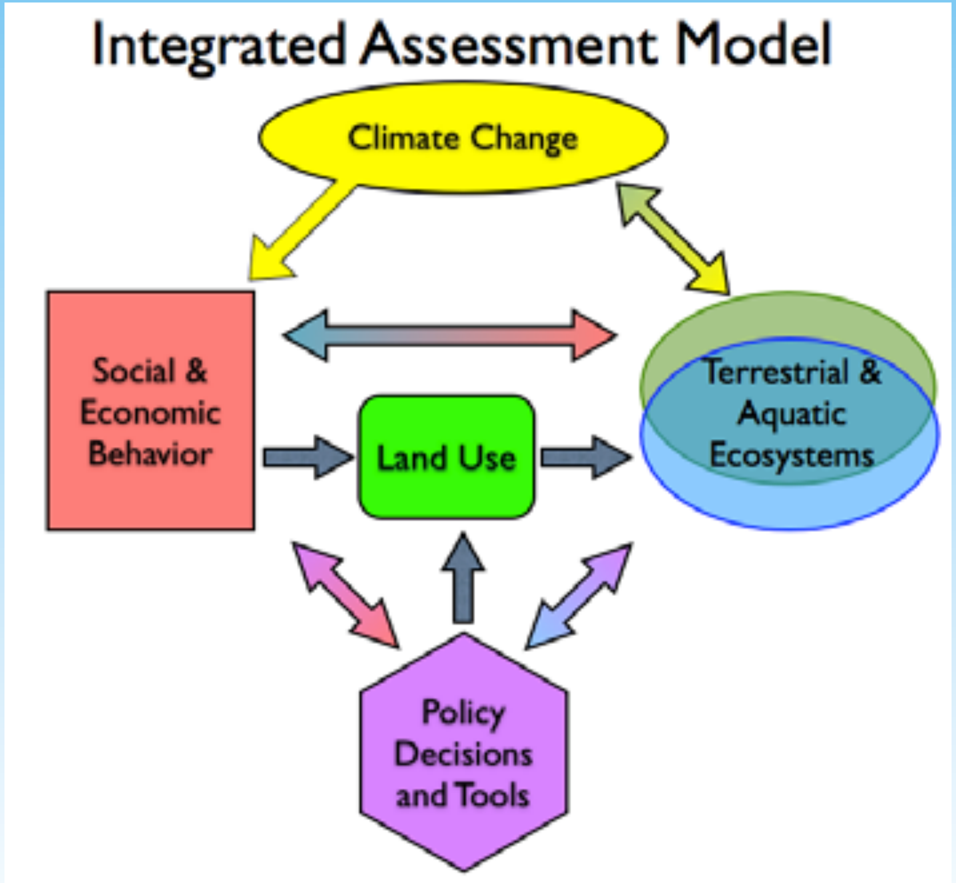
“Integrated Assessment Modeling” of Coupled Natural and Human Systems in LCB

Asim Zia & Scott Turnbull
University of Vermont

The Overarching RACC Question

RACC Research on Adaptation to Climate Change

How will the interactions of climate change and land use alter hydrological processes and nutrient transport from the landscape, internal processing and eutrophic state within the lake, and what are the implications for adaptive management strategies?



Three Distinct Approaches to IAMs

- **Cascading Models**
  - E.g. MIT's IGSM; GB-Quest (Carmichael et al 2005)
- **System Dynamic and/or Bayesian Networks (Hybrid Models)**
  - E.g. World3 (Meadows et al 2003); IIASA's GAINS model; IIASA's EPIC model
- **Qualitative/ Synthetic Impact Assessment Models**
  - E.g. Millennium Ecosystem Assessment (MEA) 2005; Rottmans and Van Asselt approach to "Integrated Assessment"

Cascading Model Example: MIT's IGSM

Research on Adaptation to Climate Change

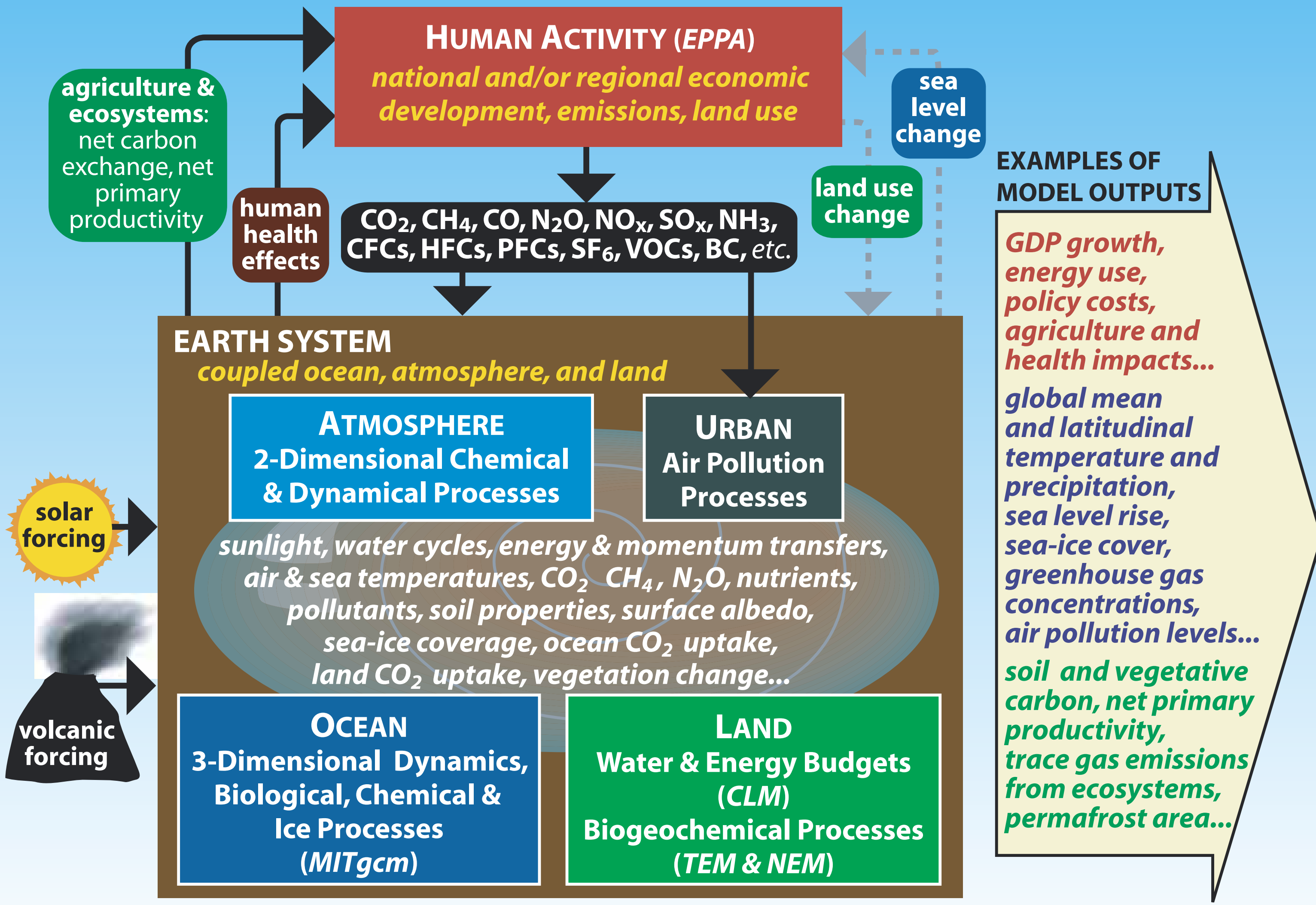


Figure 1. Schematic of the MIT Integrated Global System Model Version 2 (IGSM2).

Cascading Model Example: GB-QUEST

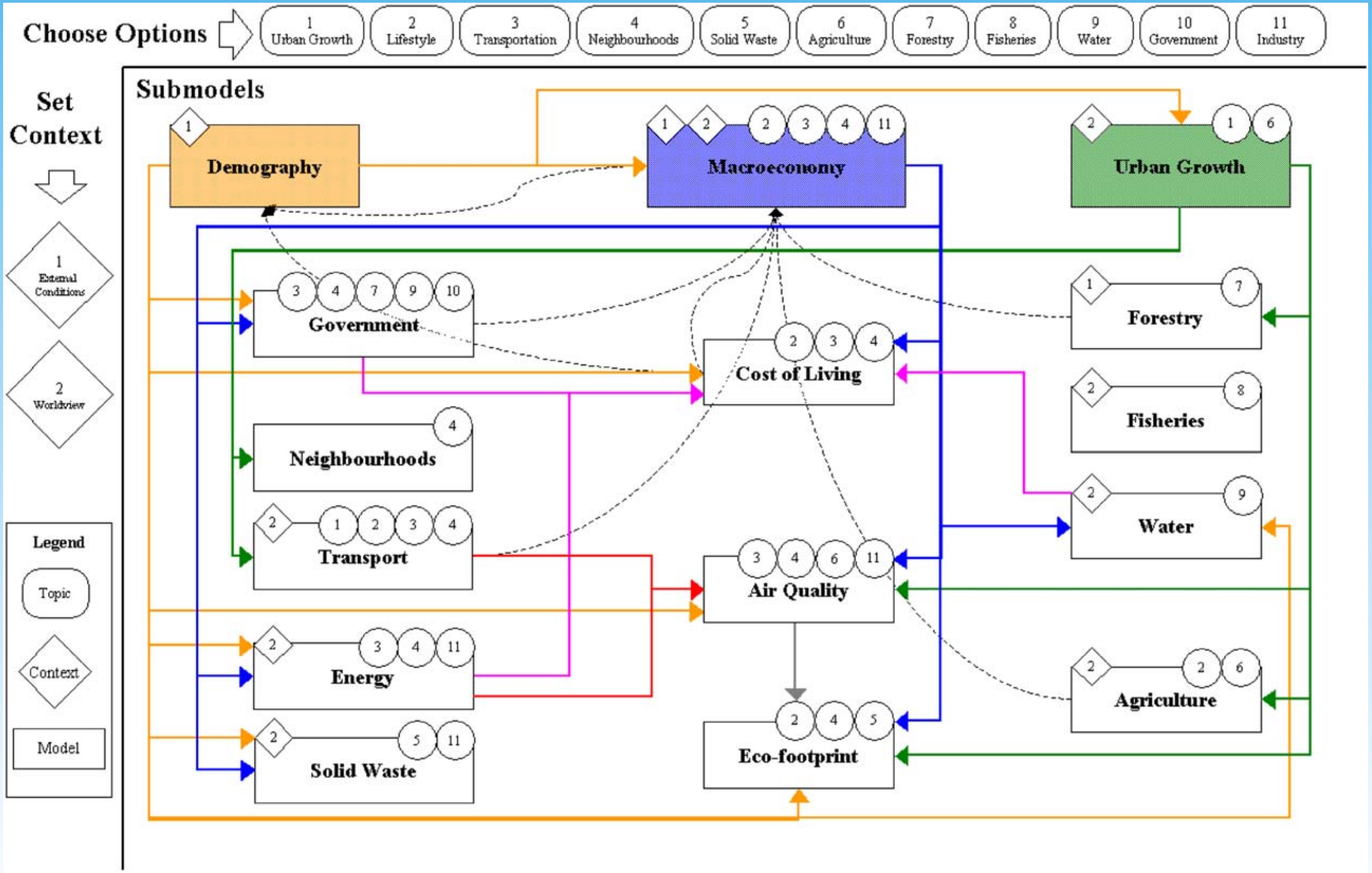
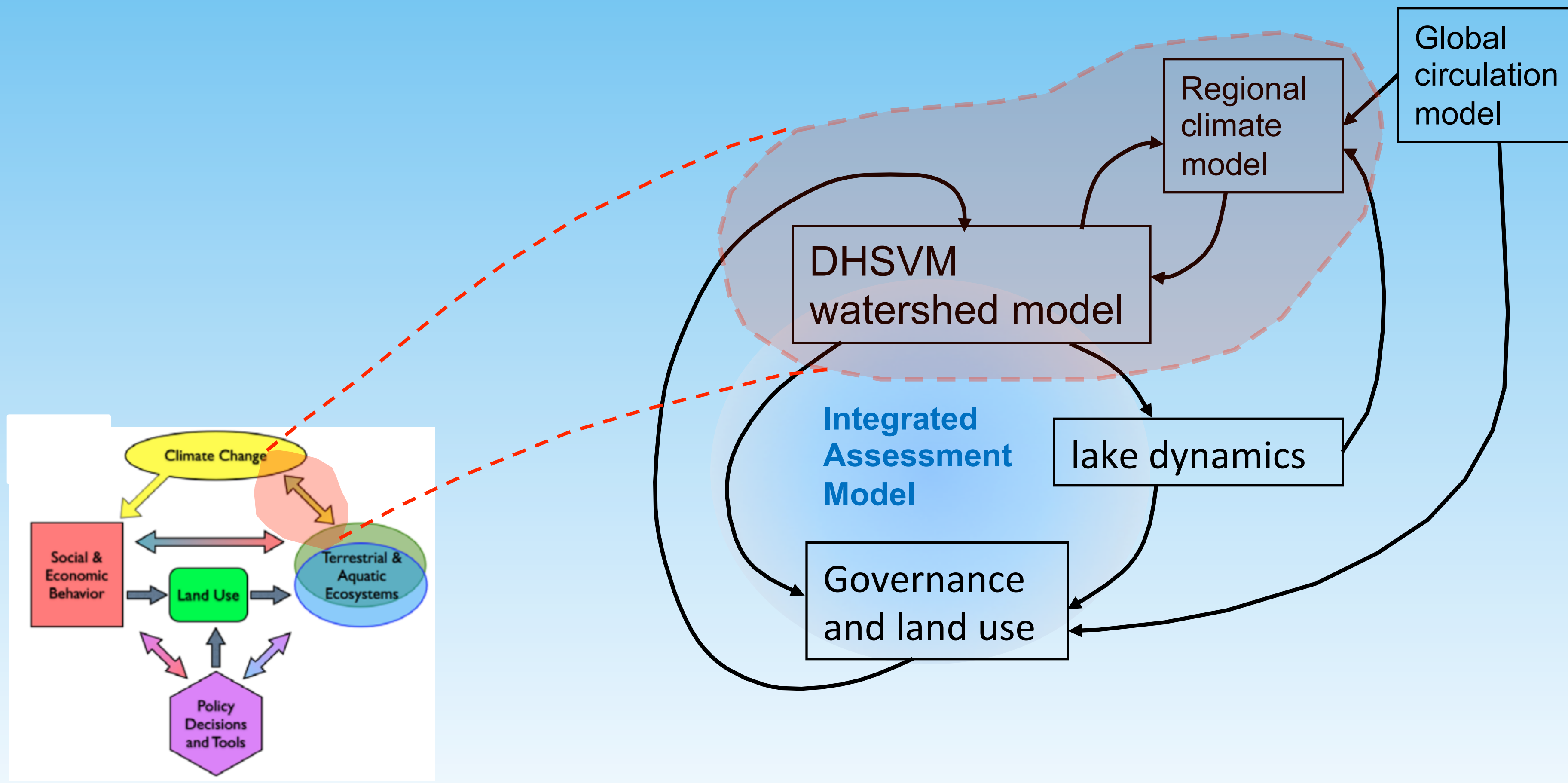


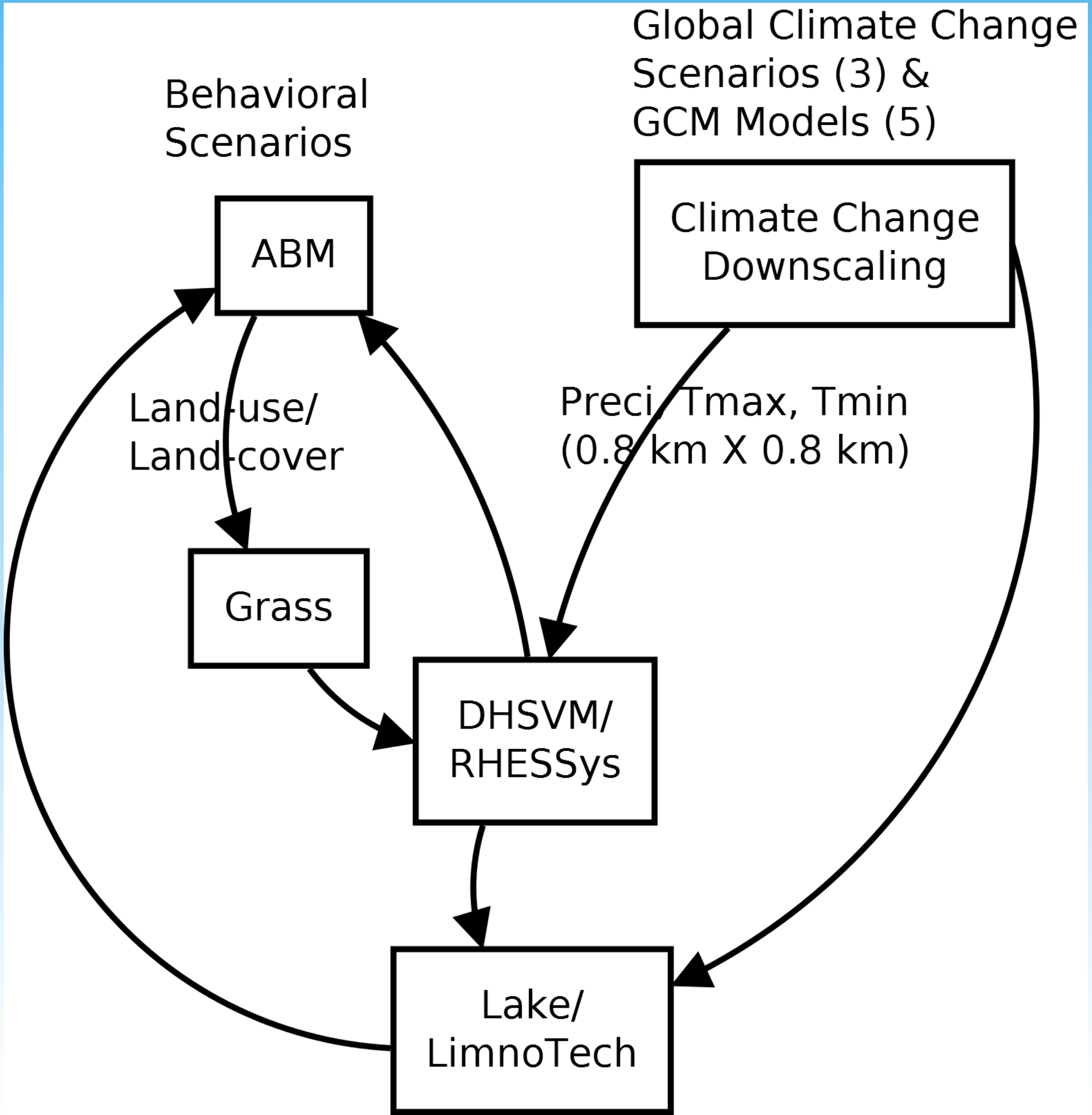
Fig. 2. GB-QUEST model structure.

Cascading Model Example: RACC's 2012 Version

RACC
Research on Adaptation to Climate Change



Current Architecture of RACC's Cascading IAM



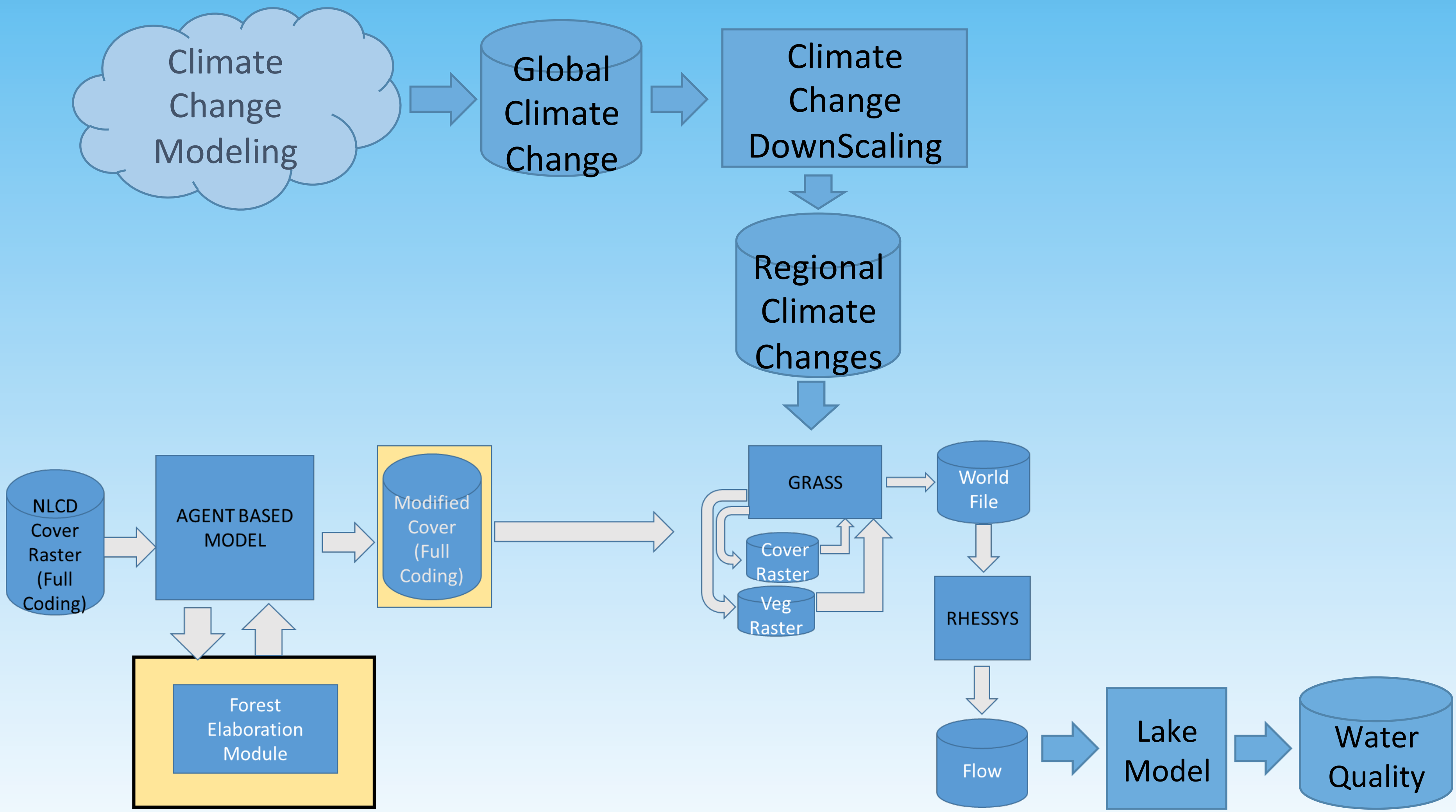
Cascading Model Integration

The making of an Integrated Assessment Model

May 2014

Scott Turnbull

Cascading IAM Overview



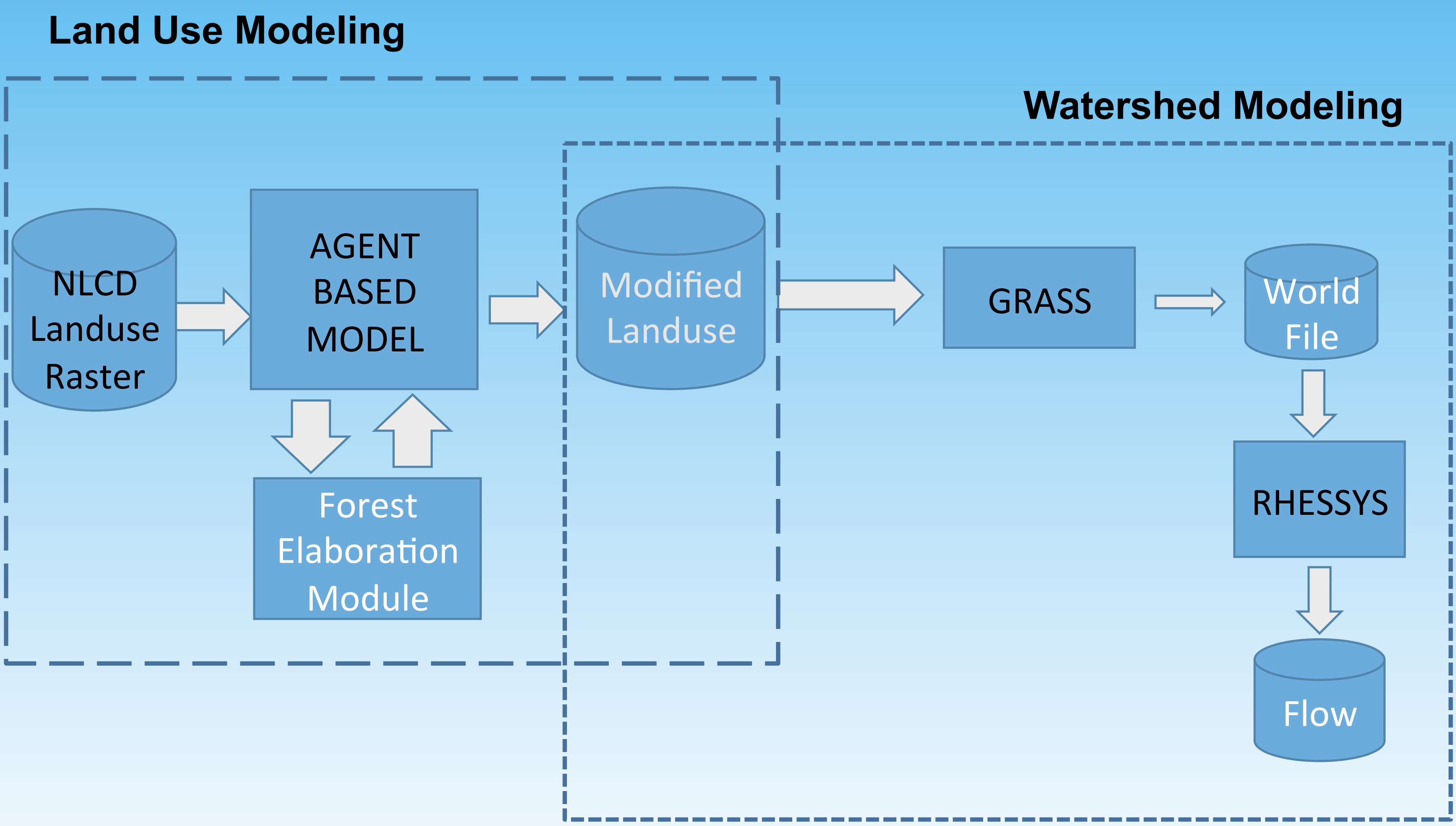
Multi-Discipline Modeling

RACC
Research on Adaptation to Climate Change

- Select the best practices for modeling each component of a complex system
  - Land Use Management and Prediction
  - Atmospheric/Weather/Climate Prediction
  - Watershed Hydrological Flow Analysis
  - Lake Water Quality

- Integrate by Building Connections between Dependent Models
  - Consistent land region of study
  - Isolate Parameters that Affect Other Models
  - Bridge Between Models with Necessary Data Manipulations
  - Create a Framework to House and Direct Data Between Models

Cascading Landuse to Flow



Forest Elaboration Case Study

RACC
Research on Adaptation to Climate Change

- Landuse Change Modeling was originally unconcerned with what species of trees reforest a section of field no longer being cultivated
- Watershed Model is Sensitive to Deciduous versus Evergreen Forestation
- A Method to Generate Re-Forestation Details Was Created
- Tracks Adjacent Land Cover to Influence Re-Foresting Details

DV	DV	RK	RK	RK
EF	EF	EF	EF	AG
EF	F?	EF	EF	EF
EF	EF	EF	F?	EF
AG	AG	DF	DF	EF

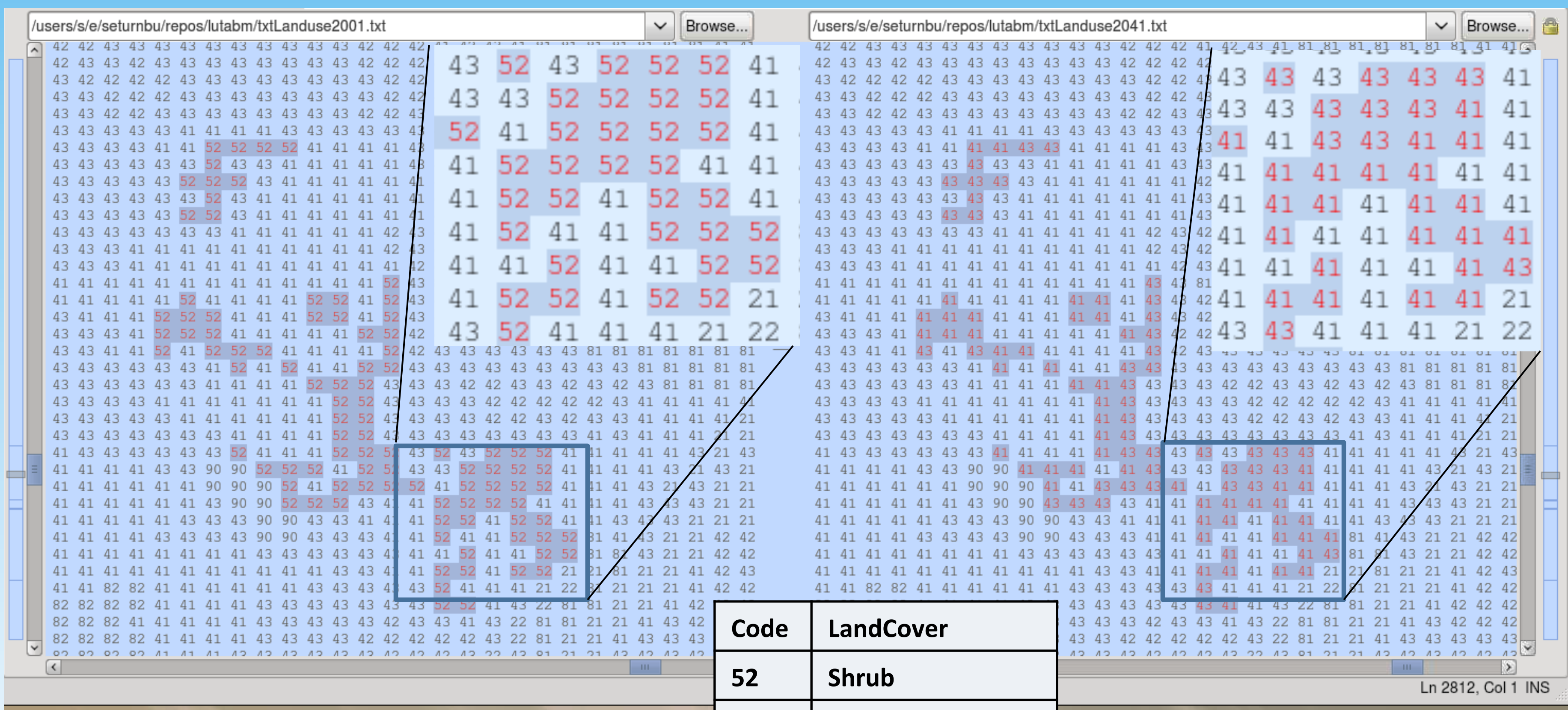
DV	DV	RK	RK	RK
EF	EF	EF	EF	AG
EF	EF	EF	EF	EF
EF	EF	EF	MF	EF
AG	AG	DF	DF	EF

KEY:
AG – Agricultural
DF – Deciduous Forest
DV - Developed
EF - Evergreen Forest
MF - Mixed Forest
RK - Rock

Sample Shrub to Tree Progression

RACC
Research on Adaptation to Climate Change

Actual data from 2001 to 2041 ABM Forecast



2001 Land Use

Code	LandCover
52	Shrub
41	Deciduous
42	Evergreen
43	Mixed Forest

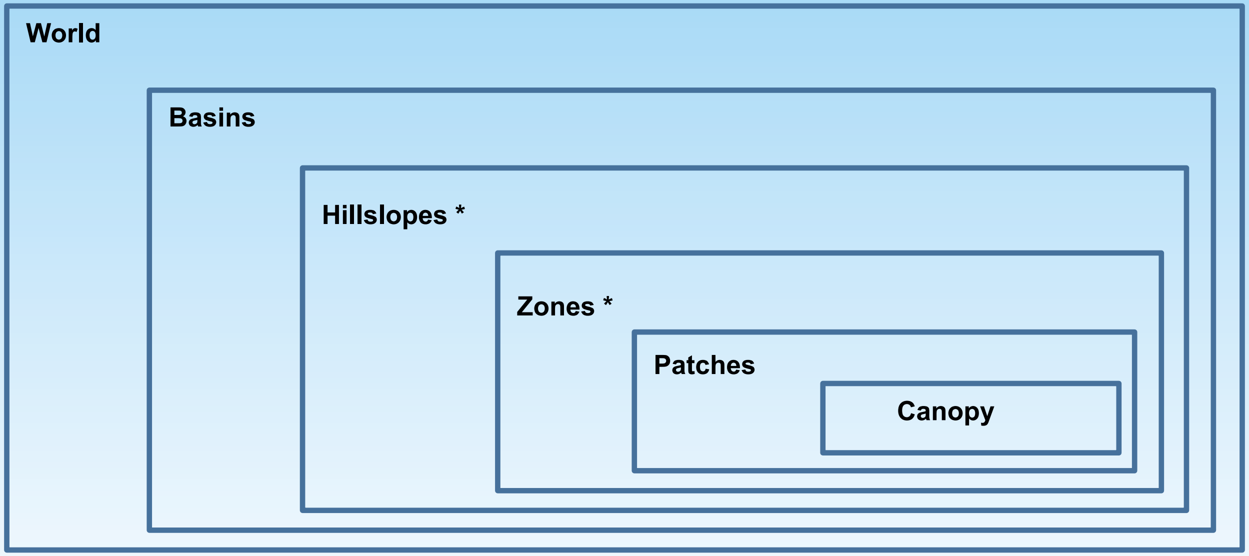
2041 Land Use

Steps taken to run RHESSys model with new land cover/use inputs

- GRASS
  - Converts LandUse by Cell to Hillslopes and Patches
  - Aggregates Changes into Larger Logical Structures
- WorldFile Merge Function
  - Merging trained *worldfile* (watershed parameters and variables information) with updated *worldfile* that has new watershed land cover/use information.
  - Preserves the model training of unmodified patches whenever possible

WorldFile LandUse Merge

- Selectively Merges ABM and Original WorldFiles
- Preserves 200 Simulated Years of Model Training
- Updates Patches or Canopies if ABM Changed LandUse
  - Patch's landuse_default_ID
  - Canopy's default_ID
- Java Object modeling of WorldFile structures

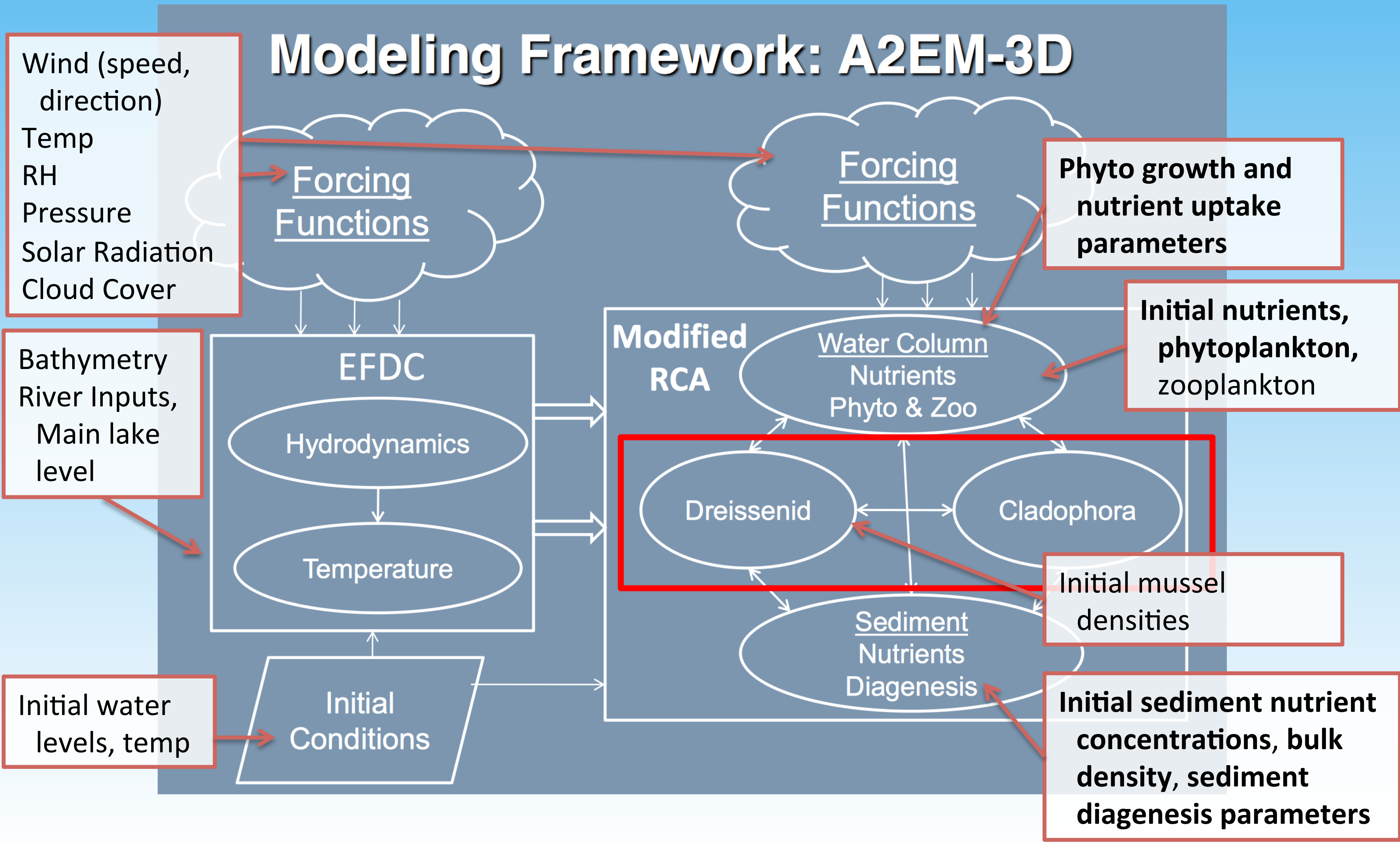


* Multiples in Missisquoi Data

Phase 2 (2014-15): Integration of DHVSM/RHESSYS with Lake Model (A2EM)

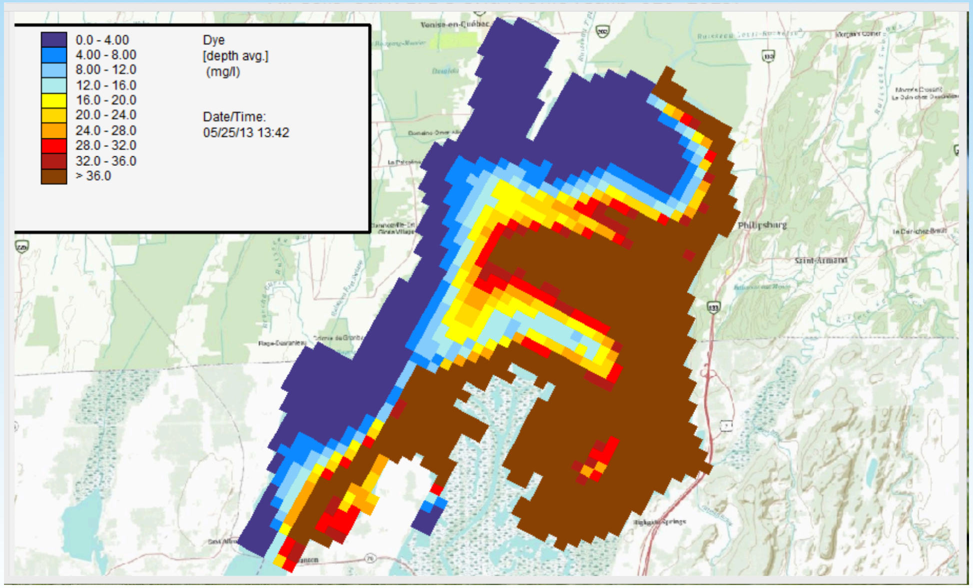
A2EM Architecture

Background: A2EM (Advanced Aquatic Ecosystem Model)



A2EM Steps for 2014

- Complete calibration of water quality model to 2012 & 2013
  - Many parameter estimates for Limnotech version of the model appear suspect
  - Integrate hydrodynamic model insights into mechanistic papers



Integrating A2EM with RHESSYS

- Anticipated steps to Integrate A2EM into the IAM framework
  - Develop preprocessor to translate RHESSYS/ DHSVM output into input file formats for EFDC and RCA (text-delimited files)
  - Develop script to automate EFDC→ RCA → EFDC… batch runs (integrating watershed model)
    - Current framework uses an Access database and a semi-proprietary interface, but that mostly facilitates the development of input files; that could be done manually.
  - Come up with a method of estimating meteorological variables not being downscaled (**solar radiation, cloud cover, wind**, RH, pressure)

RACC Hybrid IAM Architecture

System Dynamic/Hybrid Model Examples: Meals et al. (2008) P flow model

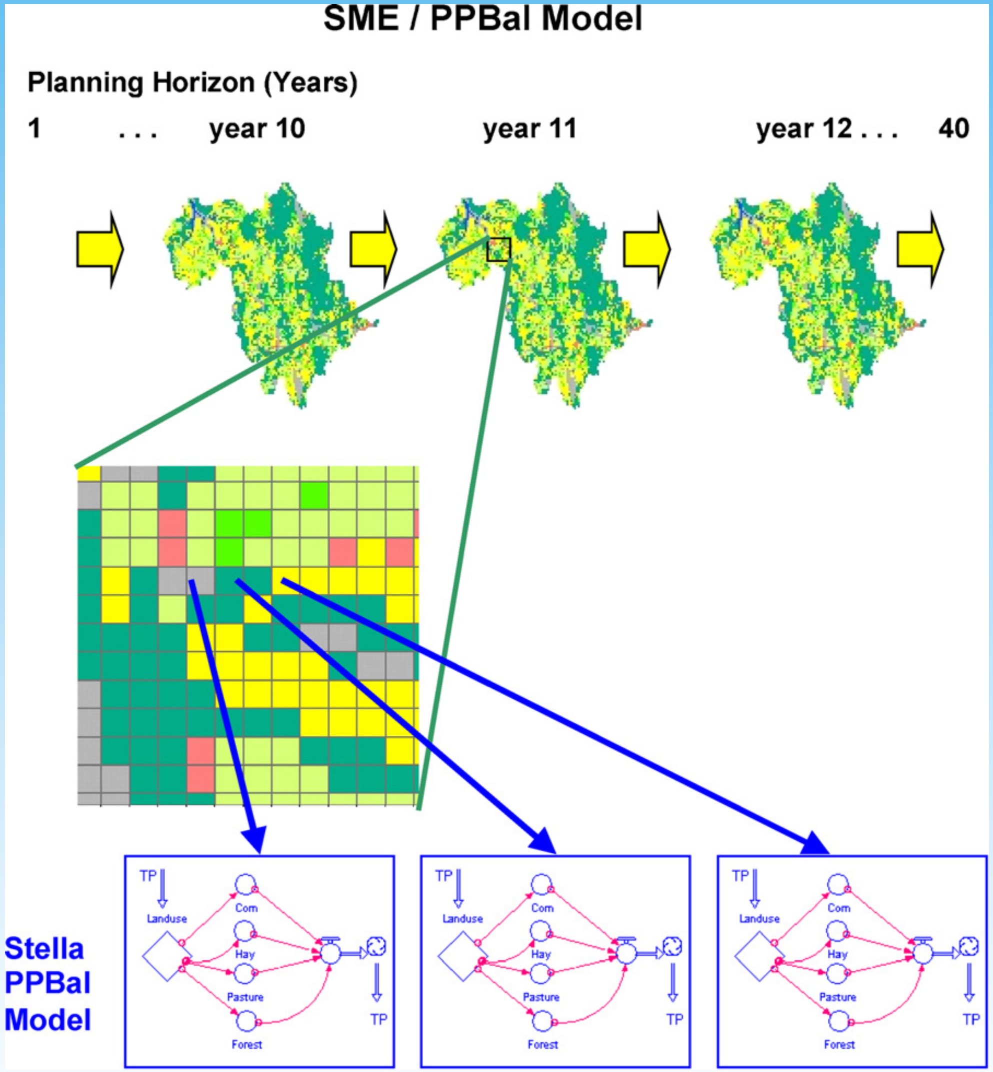
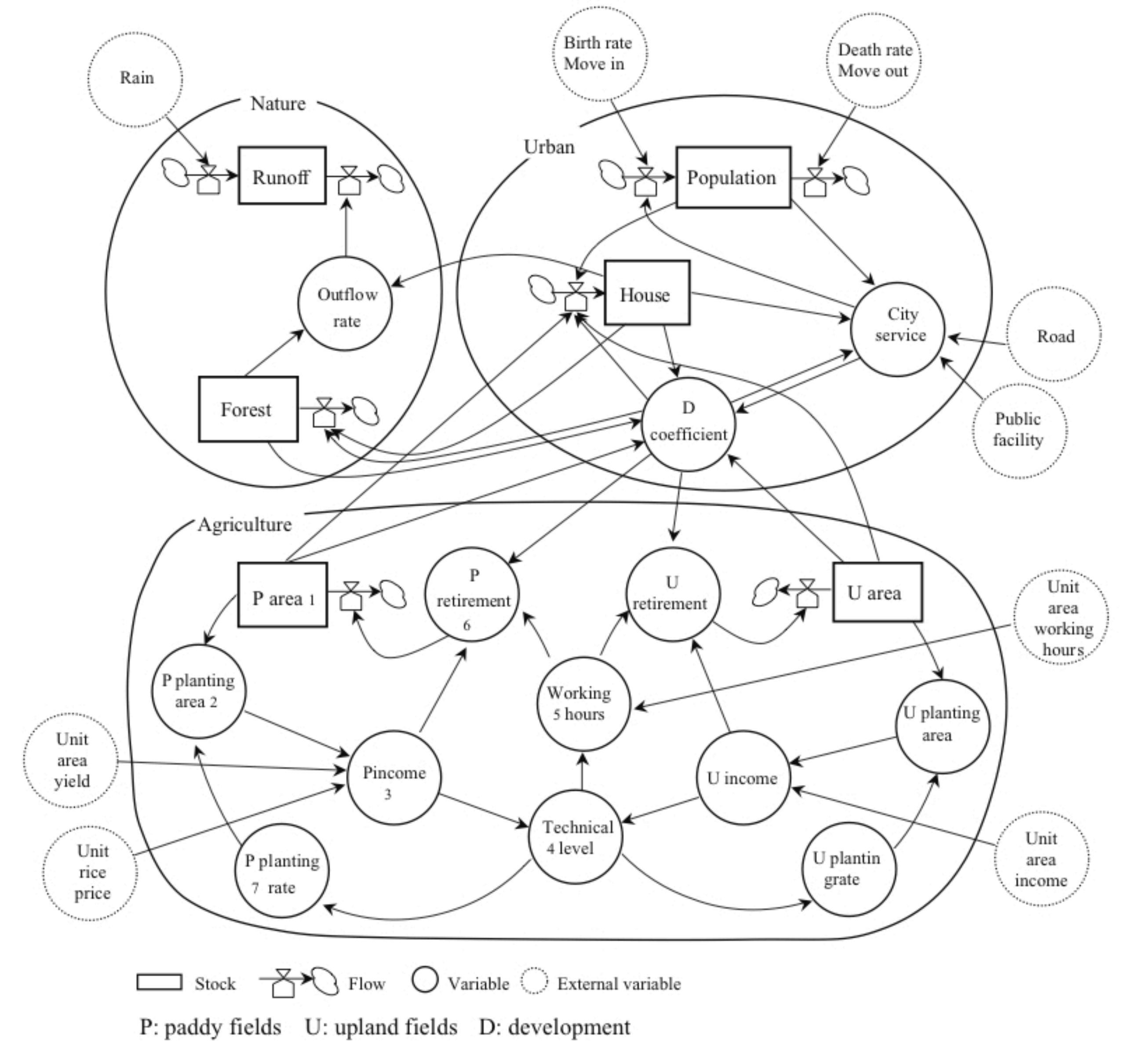
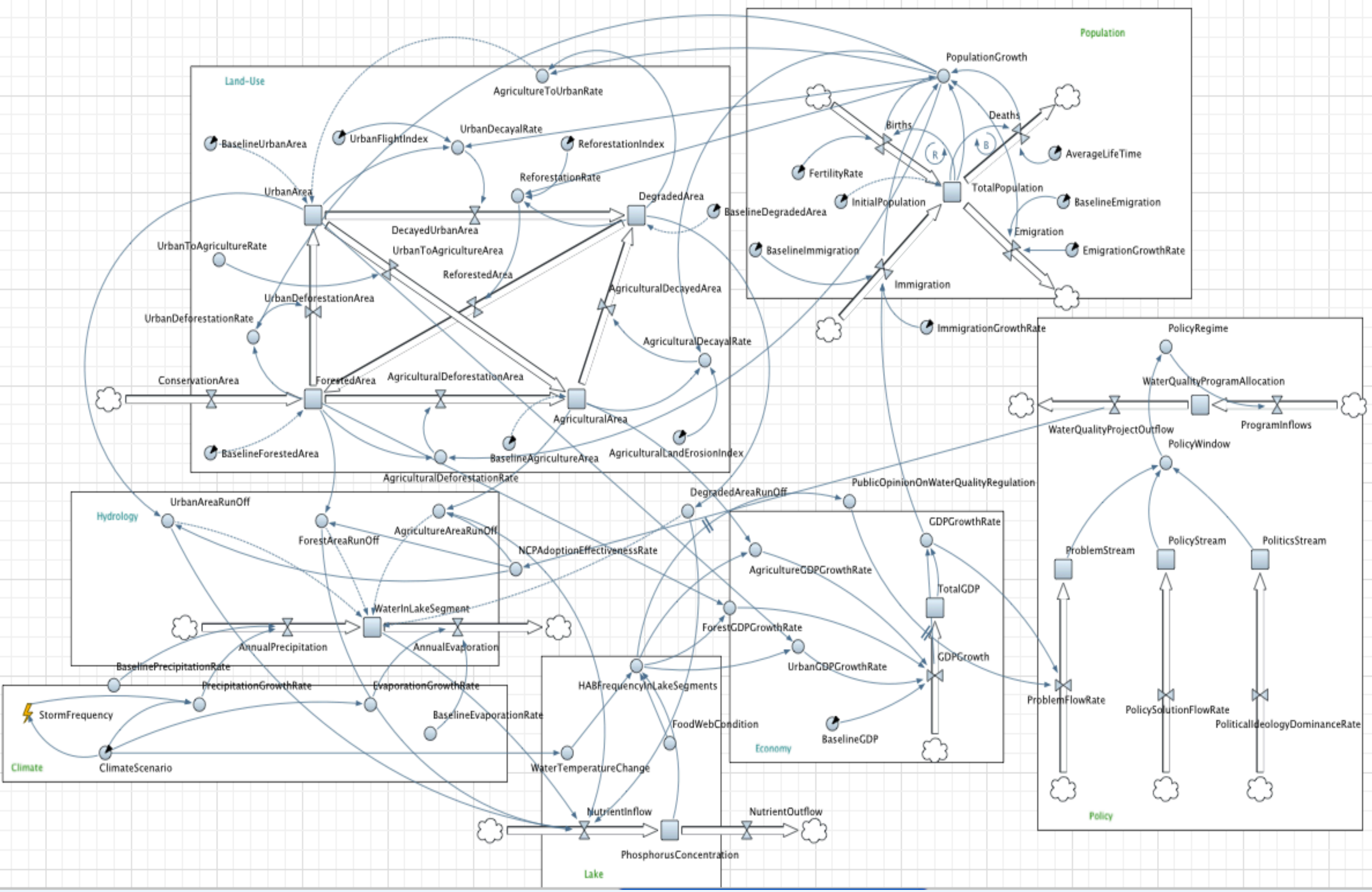


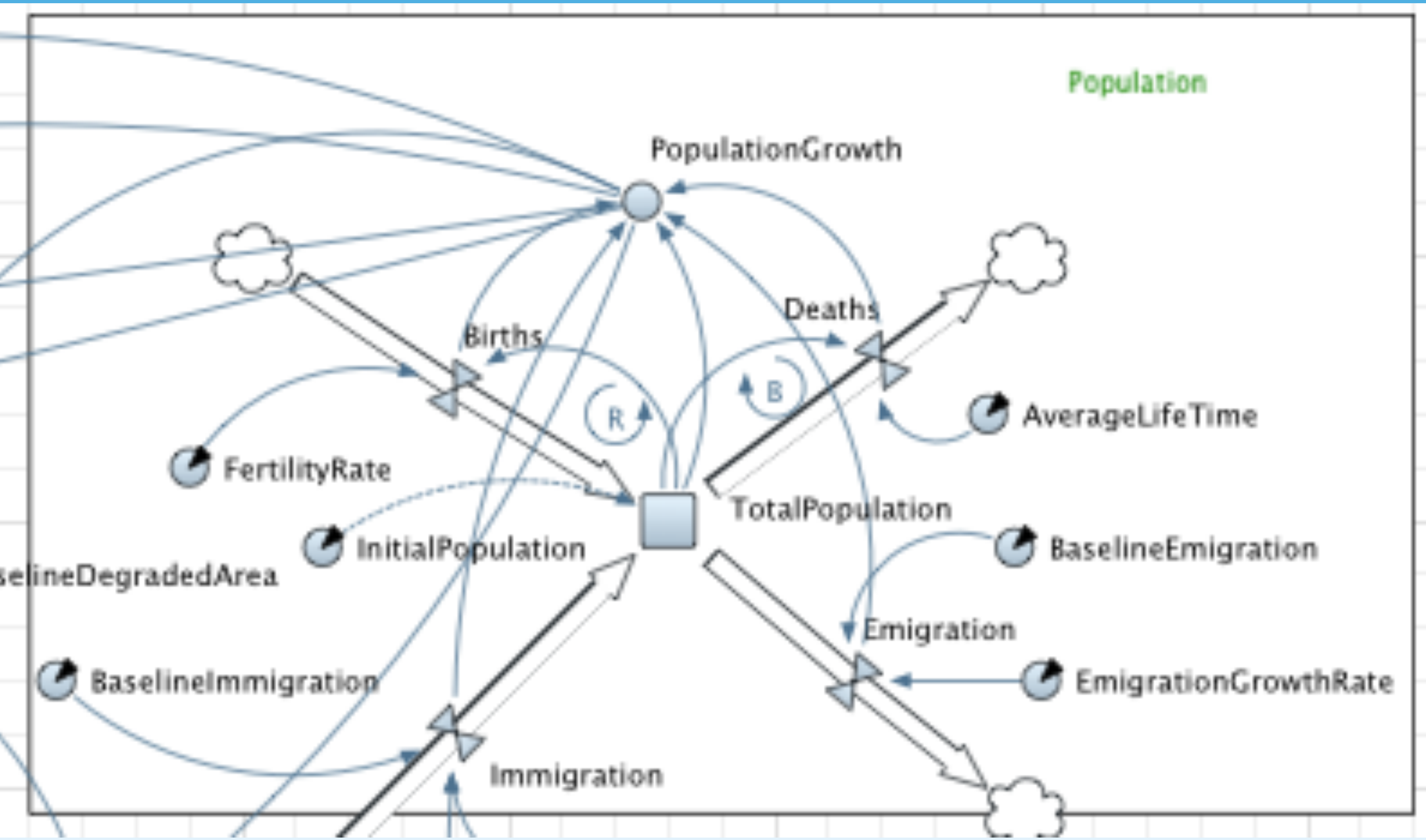
Fig. 2. Schematic diagram of the DISPLA approach based on the *Spatial Modeling Environment* (SME) and the *PPBalModel*.

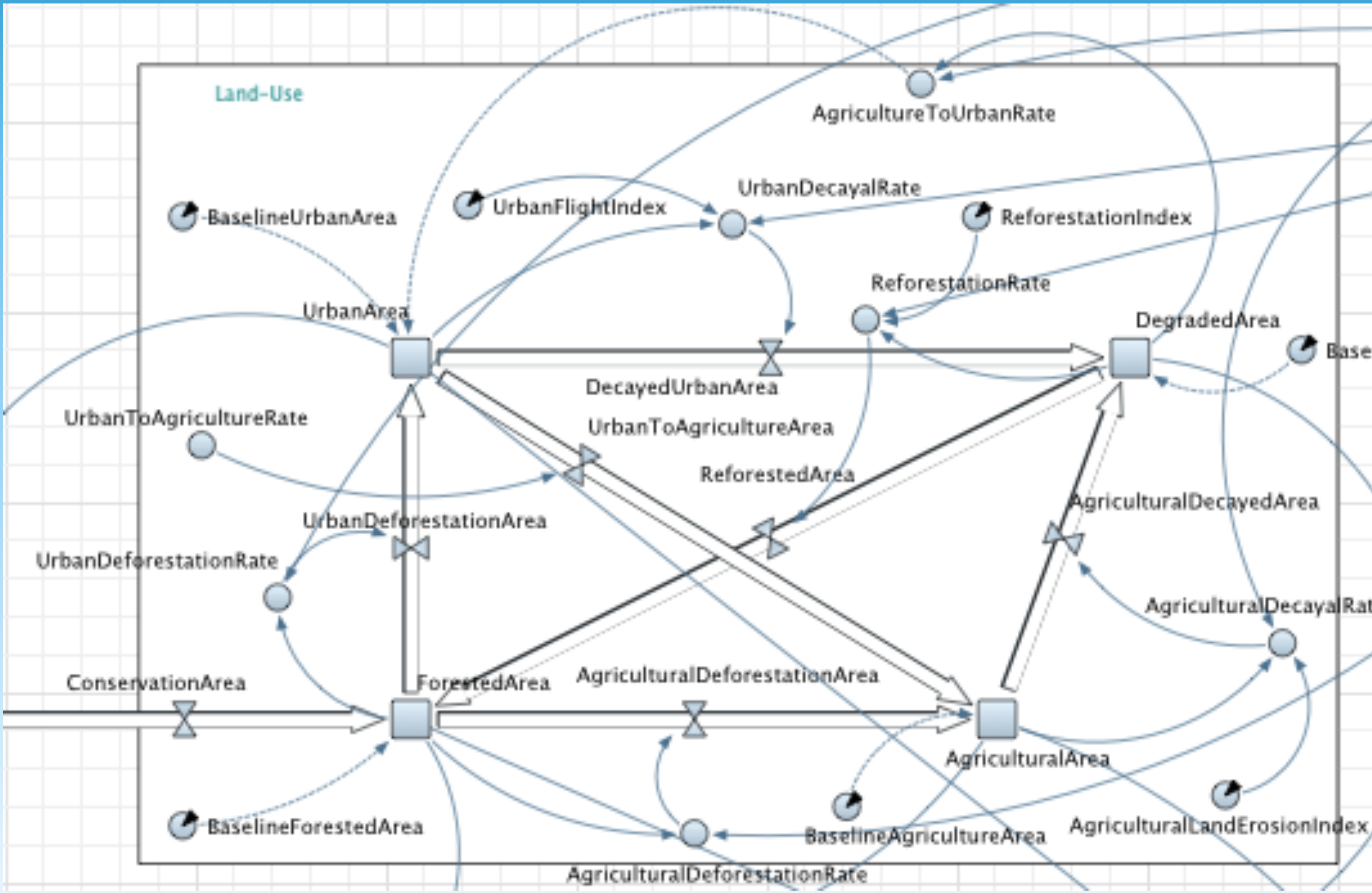
System Dynamic/Hybrid Model Examples: Kato (2005) Nutrient Flow Model



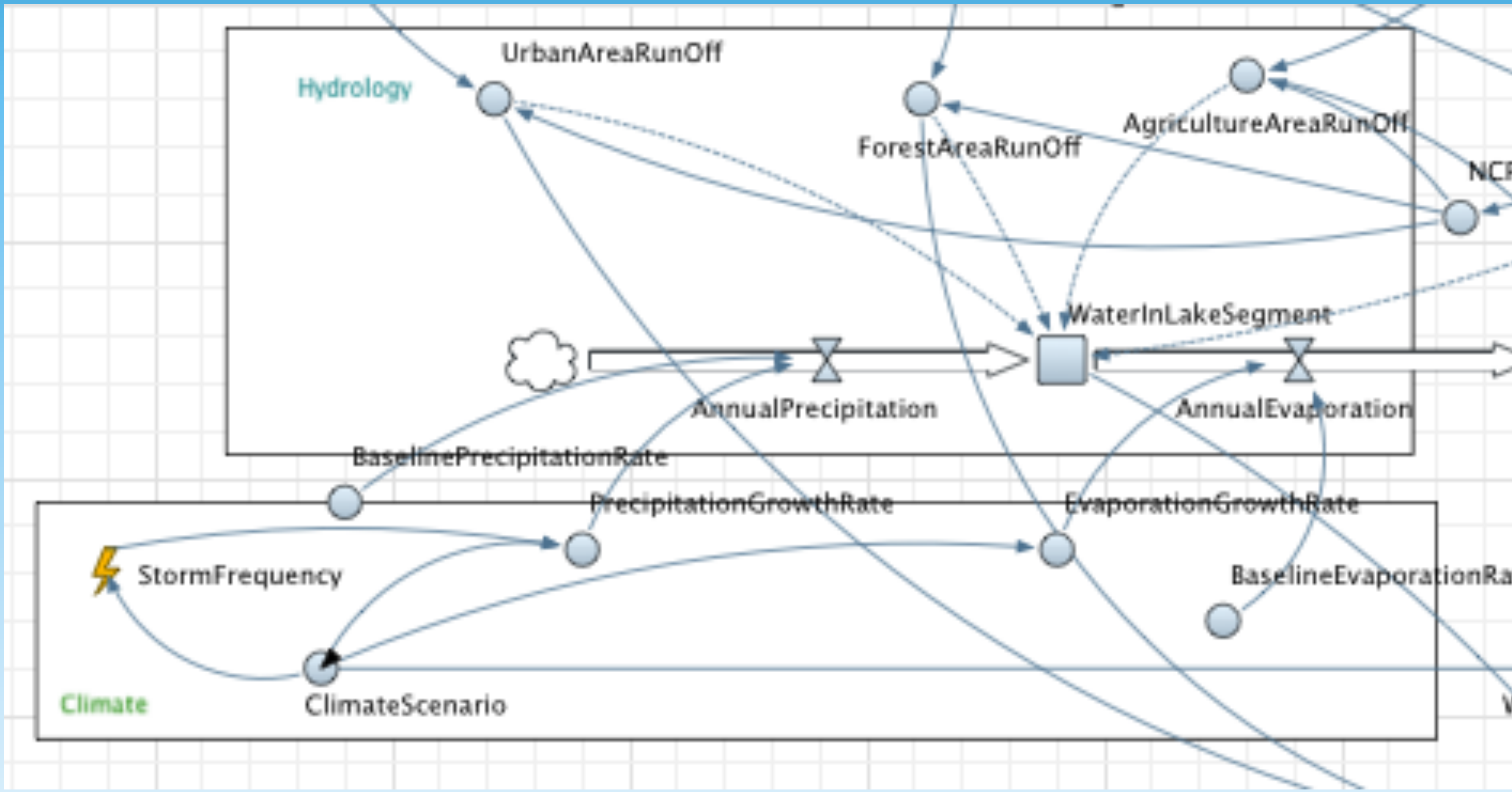


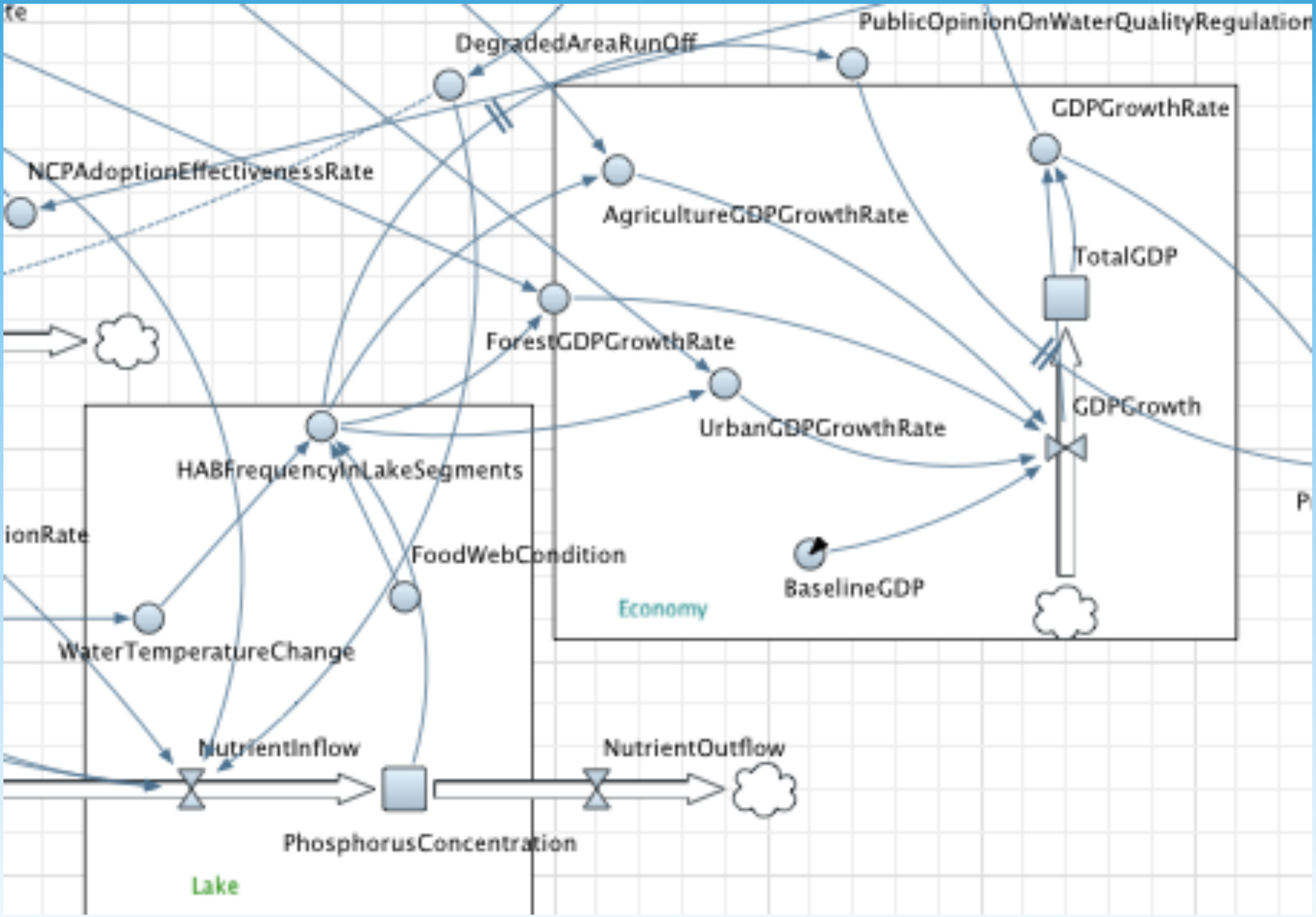
LCB Hybrid Model: A Coupled Natural and Human System


Population
PopulationGrowth
Births
Deaths
R
B
AverageLifeTime
FertilityRate
TotalPopulation
BaselineEmigration
InitialPopulation
elineDegradedArea
Emigration
BaselineImmigration
EmigrationGrowthRate
Immigration



Land-Use
AgricultureToUrbanRate
UrbanDecayalRate
BaselineUrbanArea
UrbanFlightIndex
ReforestationIndex
ReforestationRate
UrbanArea
DegradedArea
DecayedUrbanArea
UrbanToAgricultureRate
UrbanToAgricultureArea
ReforestedArea
AgriculturalDecayedArea
UrbanDeforestationArea
UrbanDeforestationRate
AgriculturalDecayalRate
ConservationArea
ForestedArea
AgriculturalDeforestationArea
AgriculturalArea
BaselineForestedArea
BaselineAgricultureArea
AgriculturalLandErosionIndex
AgriculturalDeforestationRate


Hydrology
UrbanAreaRunOff
ForestAreaRunOff
AgricultureAreaRunOff
WaterInLakeSegment
AnnualPrecipitation
AnnualEvaporation
BaselinePrecipitationRate
PrecipitationGrowthRate
EvaporationGrowthRate
StormFrequency
BaselineEvaporationRat
ClimateScenario
Climate


DegradedAreaRunOff
PublicOpinionOnWaterQualityRegulation
GDPGrowthRate
NCPAdoptionEffectivenessRate
AgricultureGDPGrowthRate
TotalGDP
ForestGDPGrowthRate
GDPGrowth
UrbanGDPGrowthRate
HABFrequencyInLakeSegments
FoodWebCondition
BaselineGDP
Economy
WaterTemperatureChange
NutrientInflow
NutrientOutflow
PhosphorusConcentration
Lake

Integrating Climate Change, Hydrology and Lake Dynamics

RACC
Research on Adaptation to Climate Change

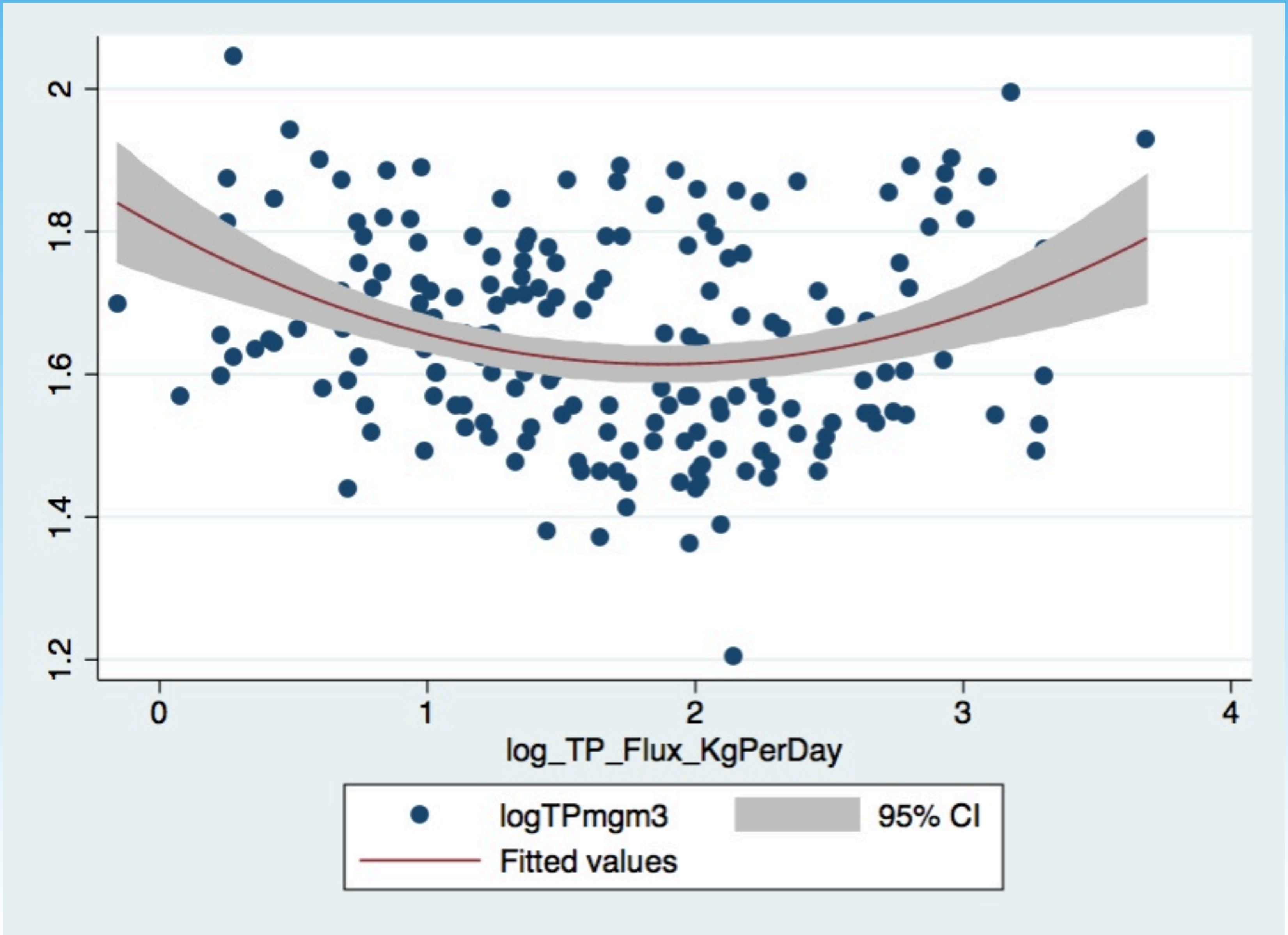
- Anthropogenic climate change could induce abrupt alternate stable states in the Lake Champlain segments from more frequent and more intense flooding events in Lake Champlain Basin as well as reduced ice cover internally in the lake system.
- The severity of algal blooms are subject to a variety of influences, ranging from N and P fluxes in the lake segments, water depth, formation and evolution of zooplankton species, and vertical and horizontal profiles of temperature gradients.

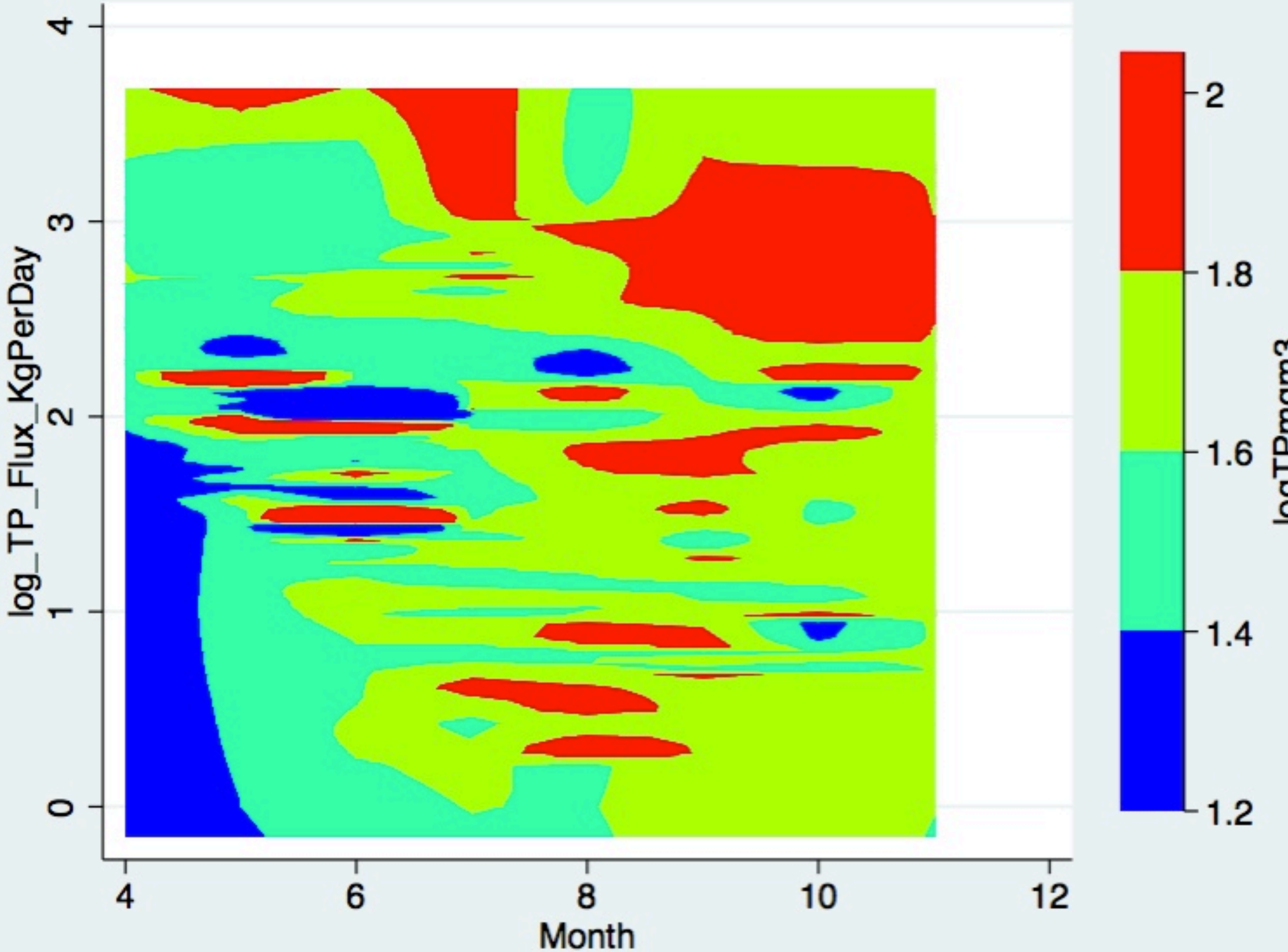
Assessment and Management of Uncertainty

- Understanding the impacts of anthropogenic climate change on water quality, such as formation and persistence of harmful algal blooms (HABs), requires **quantification of uncertainty** that is introduced in assuming future trajectories of N and P fluxes as well as water and atmospheric temperature gradients.

- Forecasting the location and timing of critical transitions in fresh water lake systems
  - Empirical Focus on Missisquoi Bay
  - LCBP and USGS monitoring data from 1992-2010 is aggregated at bi-weekly timescale to train the models

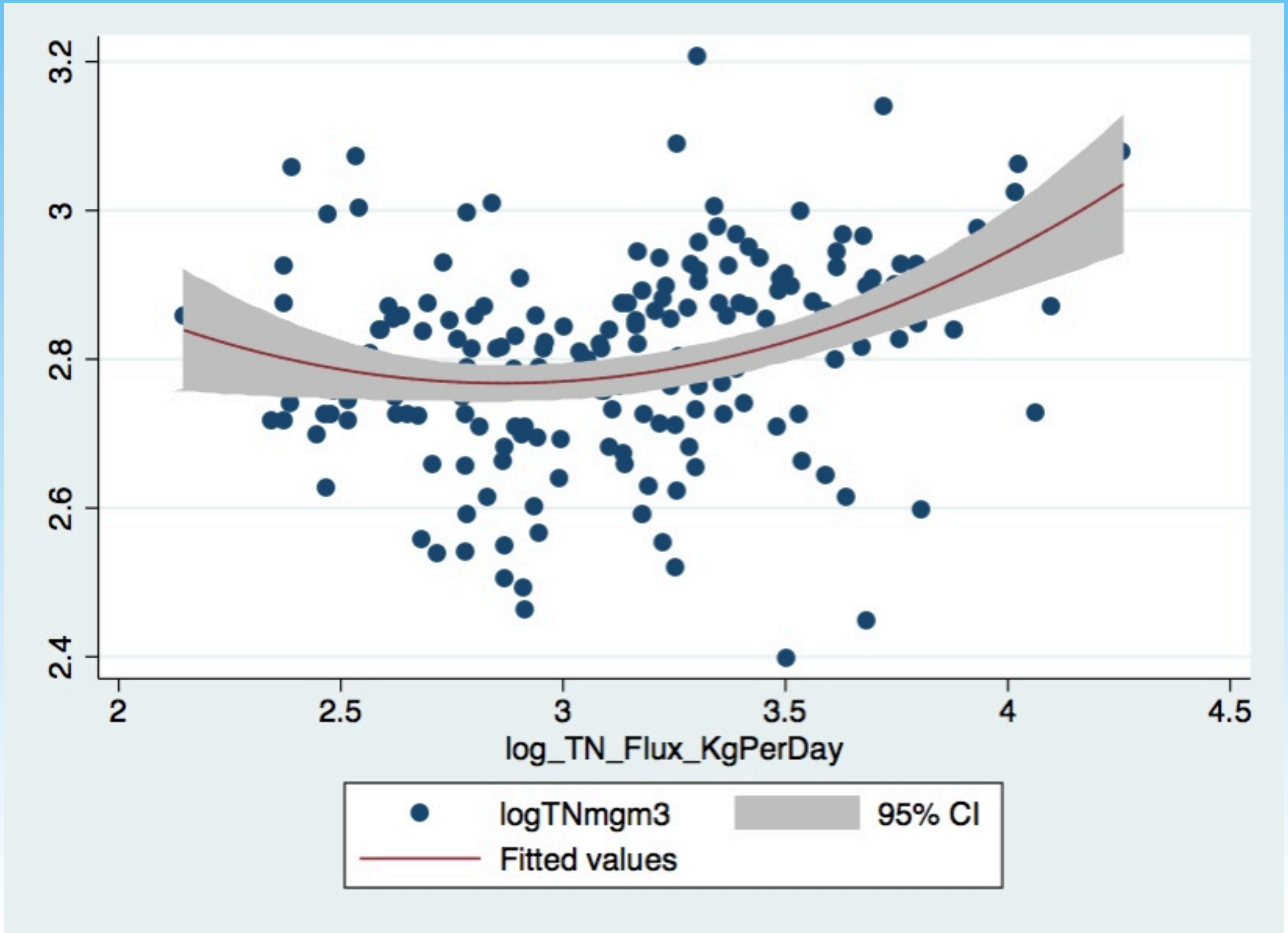
Phosphorus Flux Dynamics



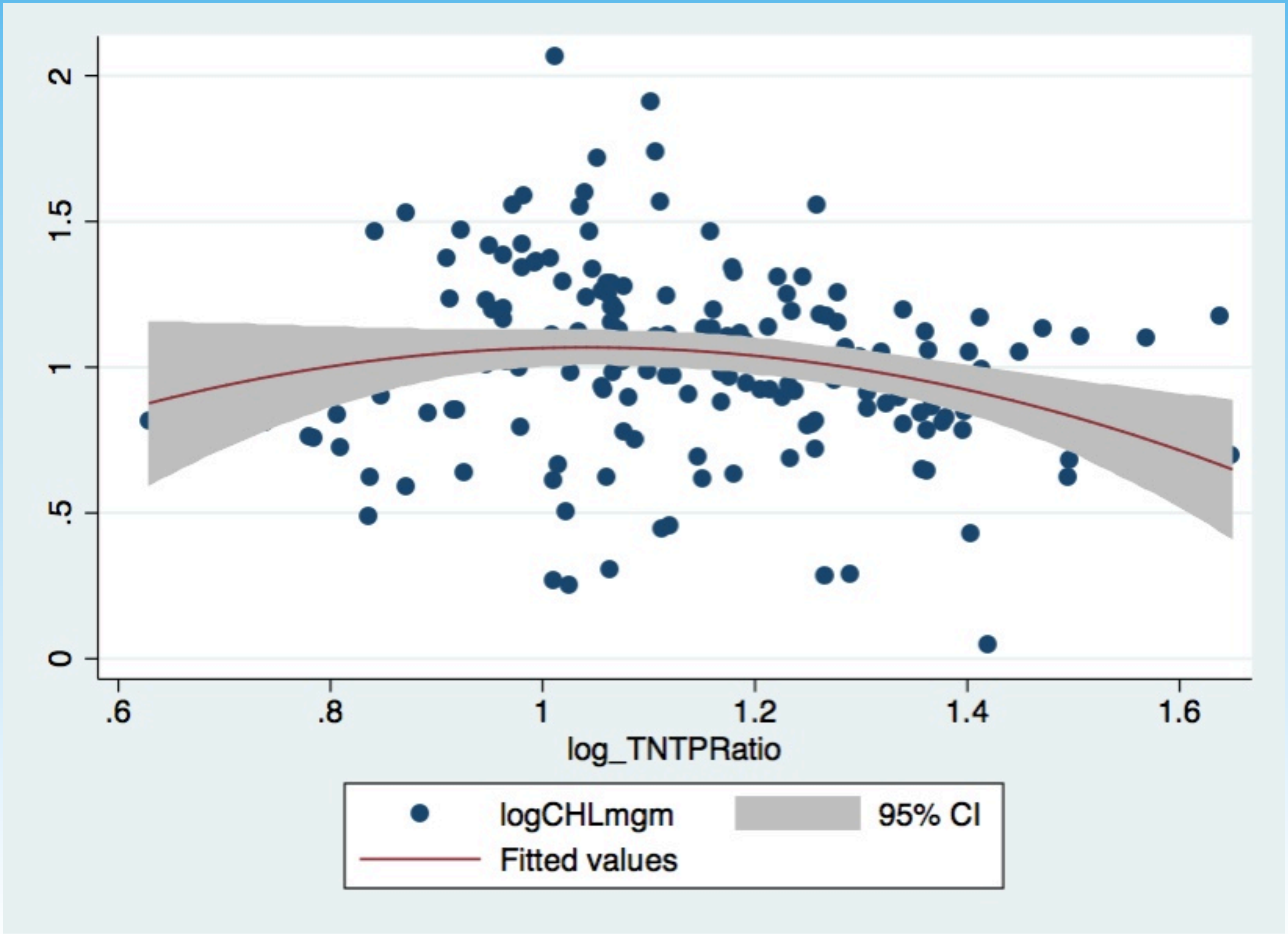


log_TP_Flux_KgPerDay
0
1
2
3
4
4
6
8
10
12
Month
logTPmgm3
1.2
1.4
1.6
1.8
2

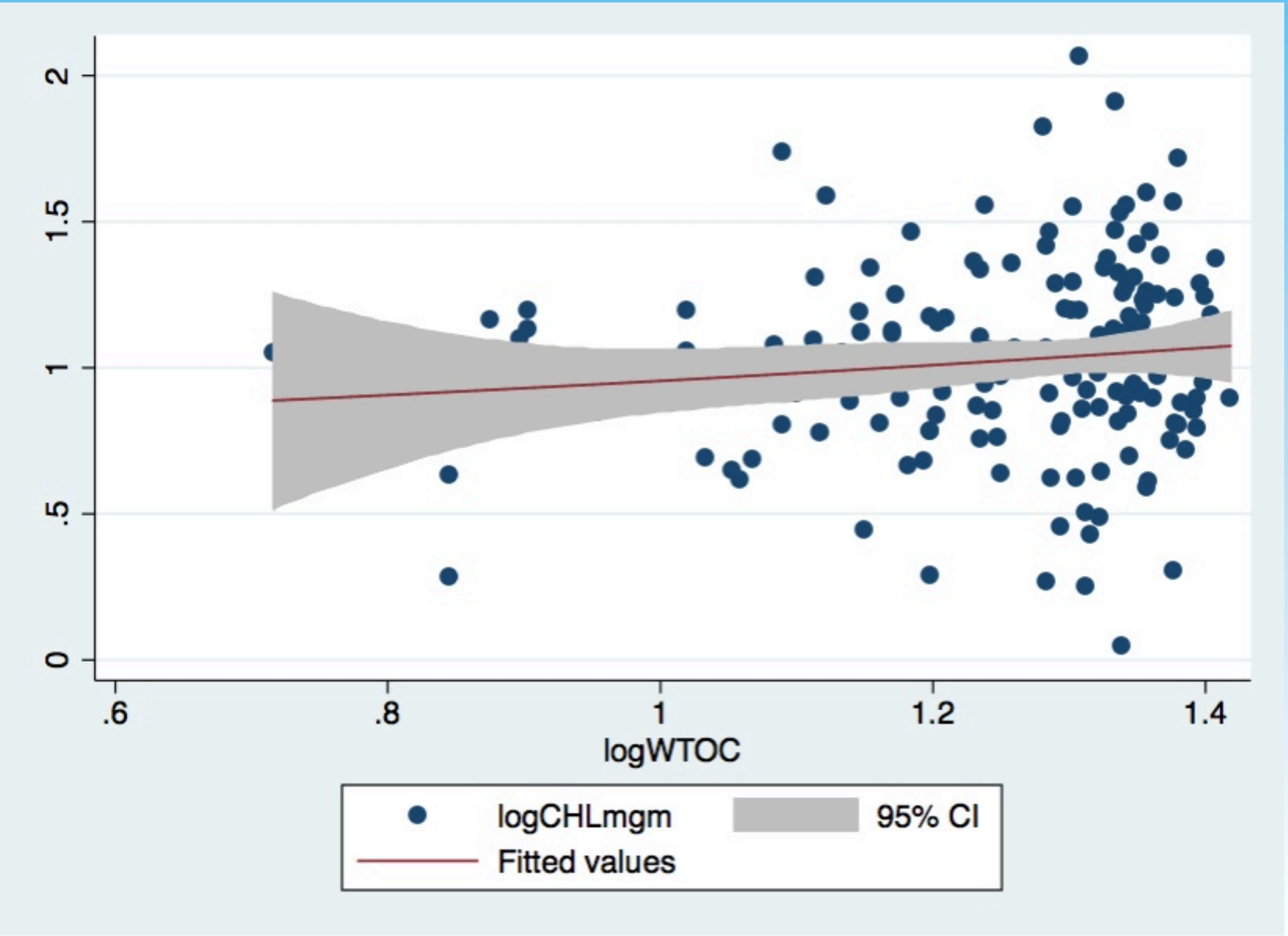
Nitrogen Flux Dynamics



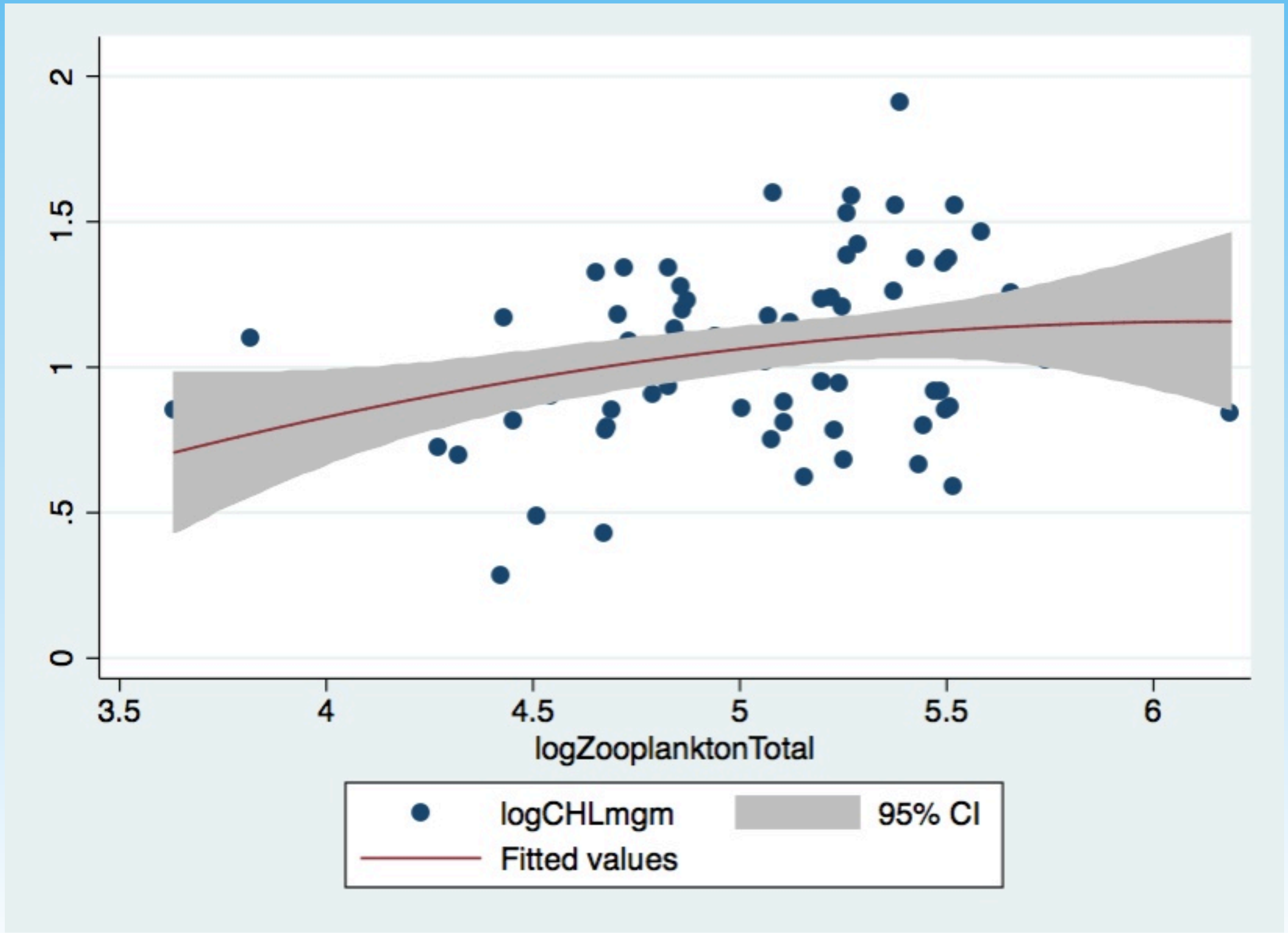
ChlA Dynamics: TN/TP



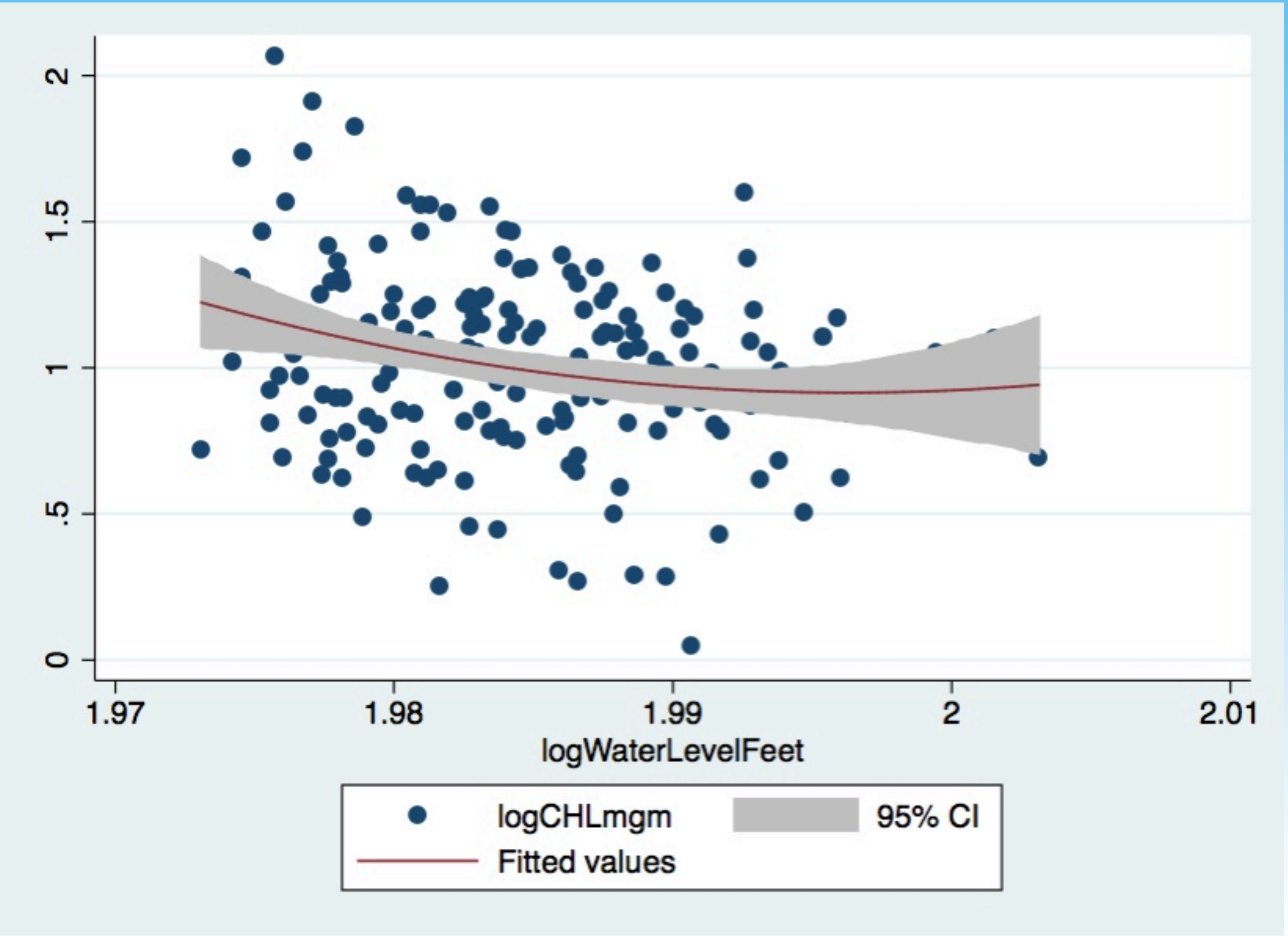
ChlA Dynamics: Temperature



ChlA Dynamics: Zooplankton



ChlA Dynamics: Waterlevel



Dynamic Forecasting of Critical Transitions
[Dakos et al. (2012) PLoS One (7)7: e41010]

Table 1. Early warning signals for critical transitions.

		Phenomenon		
	Method/Indicator	**Rising memory**	**Rising variability**	**Flickering**
metrics	Autocorrelation at-lag-1	x		
	Autoregressive coefficient of AR(1) model	x		
	Return rate (inverse of AR(1) coefficient)	x		
	Detrended fluctuation analysis indicator	x		
	Spectral density	x		
	Spectral ratio (of low to high frequencies)	x		
	Spectral exponent	x		
	Standard deviation		x	x
	Coefficient of variation		x	x
	Skewness		x	x
	Kurtosis		x	x
	Conditional heteroskedasticity		x	x
	BDS test		x	x
models	Time-varying AR(p) models	x	x	
	Nonparametric drift-diffusion-jump models	x	x	x
	Threshold AR(p) models			x
	Potential analysis (potential wells estimator)			x

Modeling Approach

- Focus on developing a "hybrid" integrated assessment model that integrates P and N fluxes from watersheds as well as climate change scenarios in predicting Harmful Algal Blooms (HABs) in the lake Segments.
- There are two concurrent modeling approaches that are being developed to integrate dynamic P and N fluxes at biweekly time-scale from Missisquoi river in predicting the likelihood of algal blooms in the bay:
  - Dynamic Forecasting approach, e.g. ARIMA, GARCH and state space models;
  - Bayesian Network Modeling approach

ARIMA Model

Consider a first-order autoregressive moving-average process. Then `arima` estimates all the parameters in the model

$$\begin{aligned} y_t &= \mathbf{x}_t\boldsymbol{\beta} + \mu_t && \textit{structural equation} \\ \mu_t &= \rho\mu_{t-1} + \theta\epsilon_{t-1} + \epsilon_t && \textit{disturbance}, \text{ ARMA}(1,1) \end{aligned}$$

where

ρ	is the first-order autocorrelation parameter
θ	is the first-order moving-average parameter
ϵ_t	$\sim$ *i.i.d.* $N(0,\sigma^2)$, meaning that ϵ_t is a white-noise disturbance

You can combine the two equations and write a general ARMA(p,q) in the disturbances process as

$$\begin{aligned} y_t = \mathbf{x}_t\boldsymbol{\beta} &+ \rho_1(y_{t-1} - \mathbf{x}_{t-1}\boldsymbol{\beta}) + \rho_2(y_{t-2} - \mathbf{x}_{t-2}\boldsymbol{\beta}) + \cdots + \rho_p(y_{t-p} - \mathbf{x}_{t-p}\boldsymbol{\beta}) \\ &+ \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \cdots + \theta_q\epsilon_{t-q} + \epsilon_t \end{aligned}$$

It is also common to write the general form of the ARMA model more succinctly using lag operator notation as

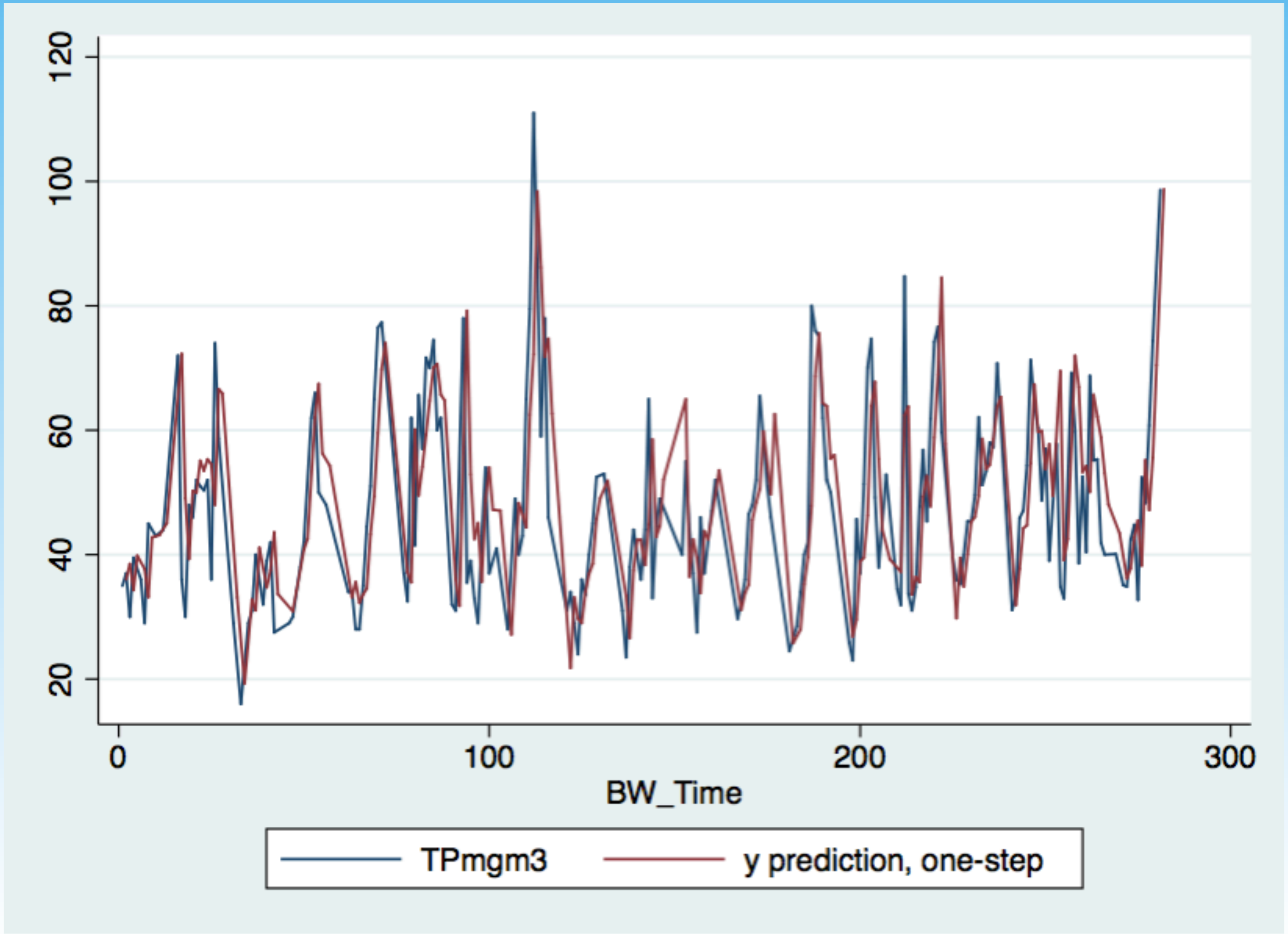
$$\boldsymbol{\rho}(L^p)(y_t - \mathbf{x}_t\boldsymbol{\beta}) = \boldsymbol{\theta}(L^q)\epsilon_t \qquad \text{ARMA}(p,q)$$

where

$$\begin{aligned} \boldsymbol{\rho}(L^p) &= 1 - \rho_1 L - \rho_2 L^2 - \cdots - \rho_p L^p \\ \boldsymbol{\theta}(L^q) &= 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q \end{aligned}$$

and $L^j y_t = y_{t-j}$.

Observed versus predicted TP (ARIMA Model 1)



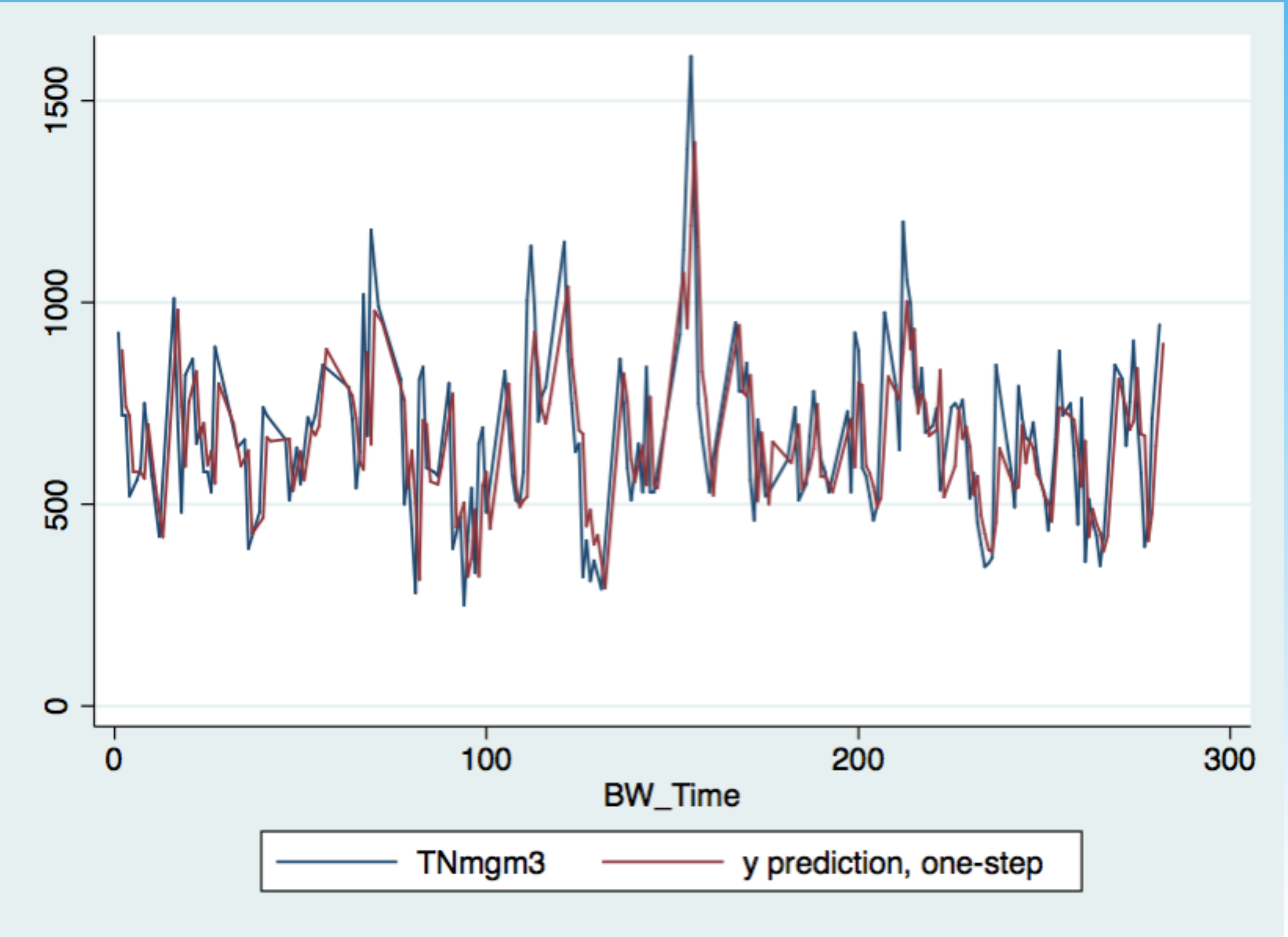
ARIMA Model (1) Predicting TP

```
ARIMA regression

Sample:  2 - 279, but with gaps                 Number of obs      =       163
                                                Wald chi2(7)       =   2534.89
Log likelihood = -649.1978                      Prob > chi2        =    0.0000

------------------------------------------------------------------------------
---
             |                 OPG
    D.TPmgm3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interv
> al]
-------------+----------------------------------------------------------------
---
TPmgm3       |
TP_Flux_KgPerDay |
          D1. |   .0060248   .0012448     4.84   0.000      .003585    .0084
> 645
             |
       _cons |   1.715991   .6359509     2.70   0.007     .4695499    2.962
> 432
-------------+----------------------------------------------------------------
---
ARMA         |
          ar |
         L1. |  -.5265149   2.374632    -0.22   0.825    -5.180708    4.127
> 678
         L2. |   .5497295   1.157792     0.47   0.635    -1.719502    2.818
> 961
         L3. |   .1052658   1.136078     0.09   0.926    -2.121405    2.331
> 937
             |
          ma |
         L1. |    13.4402   386.4365     0.03   0.972    -743.9614    770.8
> 418
         L2. |   .1448429   25.82107     0.01   0.996    -50.46352     50.7
> 532
         L3. |  -11.28013   328.0176    -0.03   0.973    -654.1828    631.6
> 226
```

Observed versus predicted TN (ARIMA Model 2)



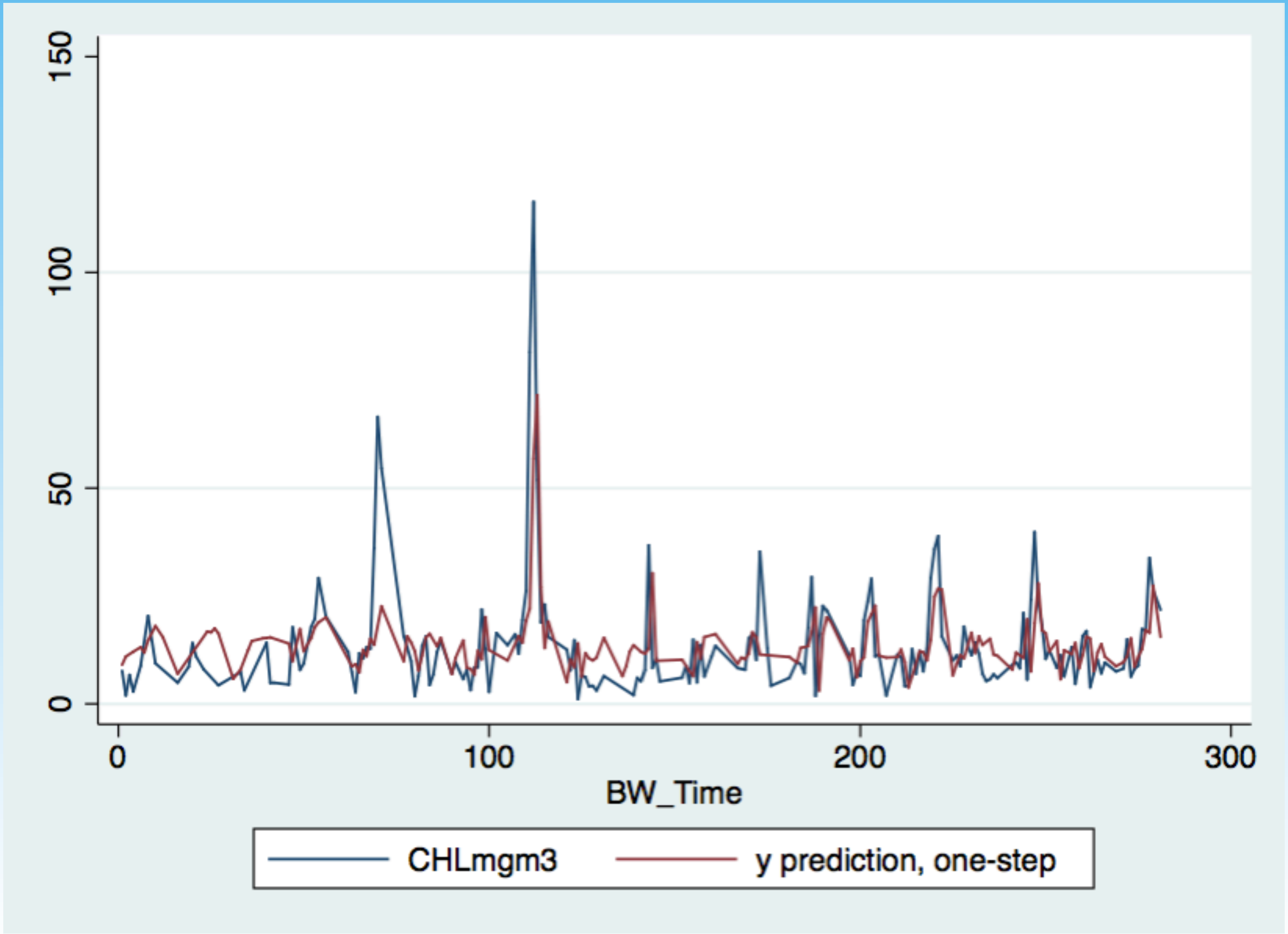
ARIMA Model (2) Predicting TN

```
ARIMA regression

Sample:  2 - 279, but with gaps                 Number of obs      =       149
                                                Wald chi2(3)       =     83.19
Log likelihood = -985.844                       Prob > chi2        =    0.0000

--------------------------------------------------------------------------------
---
             |                 OPG
    D.TNmgm3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interv
> al]
-------------+------------------------------------------------------------------
---
TNmgm3       |
TN_Flux_KgPerDay |
         D1. |   .0140862   .0039098     3.60   0.000     .0064231     .0217
> 494
             |
       _cons |  -17.77988   8.647686    -2.06   0.040    -34.72904    -.8307
> 297
-------------+------------------------------------------------------------------
---
ARMA         |
          ar |
         L1. |   .5487558    .101667     5.40   0.000     .3494921     .7480
> 195
             |
          ma |
         L1. |  -.9999903    .119112    -8.40   0.000    -1.233446    -.7665
> 351
```

Observed versus predicted ChlA (ARIMA Model 3)



ARIMA Model (3) Predicting ChlA

```
ARIMA regression

Sample:  1 - 281, but with gaps                 Number of obs      =       164
                                                Wald chi2(5)       =    381.80
Log likelihood = -622.4949                      Prob > chi2        =    0.0000

--------------------------------------------------------------------------------
-
             |                 OPG
     CHLmgm3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval
> ]
-------------+------------------------------------------------------------------
-
CHLmgm3      |
   TNTPRatio |  -.1095068     .250728    -0.44   0.662    -.6009246     .381910
> 9
WaterLevelFeet |  -1.639719   1.364225    -1.20   0.229    -4.313552     1.03411
> 3
        WToC |  -.0042319    .3038048    -0.01   0.989    -.5996785     .591214
> 7
       _cons |    173.697    131.0826     1.33   0.185    -83.22004     430.614
> 1
-------------+------------------------------------------------------------------
-
ARMA         |
          ar |
         L1. |   .6259218    .0435882    14.36   0.000     .5404905     .711353
> 1
         L2. |  -.1248174    .0801543    -1.56   0.119    -.2819169      .03228
> 2
-------------+------------------------------------------------------------------
-
      /sigma |   10.24293    .3662327    27.97   0.000     9.525122     10.9607
> 3
```

Next Steps: Hybrid IAM Development

- Missisquoi Basin (1992-2010) Long-term monitoring and USGS dataset as training dataset for model development
- In addition, three downscaled GCM scenarios for temperature, precipitation and solar radiation
- **ARIMA Models (1, 2 and 3) presented above are being used to connect P and N fluxes with climatic scenarios, predict TN/TP ratios, and in turn predict HABs [Focus on critical transitions and alternate stable states]**
- Calibrated model will be used to predict TN/TP ratios and ChlA (2011-2050) under different climate change, land-use change and policy scenarios
- Bi-weekly time scale
- Focus on Missisquoi, then expanding to South Lake, and rest of the VT's Lake Segments

Summary: Comparing Cascading and Hybrid IAMs

Cascading IAM

- High spatial resolution (30m x 30m)
- High temporal resolution (nested from hourly to daily and annual)
- Limited scope (only Missisquoi and Winooski watershed)
- Highly process-based
- Difficult to adjust and re-calibrate
- May take many days and perhaps weeks to run a scenario!

Hybrid IAM

- Low spatial Resolution (watershed scale)
- Low temporal resolution (nested from weekly to annual and decadal)
- Broader scope (all VT-LCB watersheds)
- Dynamic but less emphasis on process
- Flexible adjustments and easier re-calibration
- May take minutes to run a scenario!