A *Complex Systems* Approach towards a *Better* Understanding of Healthcare

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(@ BHI'13, Maebashi)

NATIONAL ACADEMY OF ENGINEERING
OF THE NATIONAL ACADEMIES

CHALLENGES
GIVE US YOUR THOUGHTS

IDEAS
WORLD NEEDS

NEXT STEPS
TECHNOLOGIES, IDEAS AND RESEARCH

COMMITTEE
ROLE AND BIOGRAPHIES

GRAND CHALLENGES FOR ENGINEERING

Find information about the Summit on the NAE's Grand Challenges, March 2-3, 2009, in Durham, NC, organized by Duke University; the Viterbi School of Engineering at the University of Southern California; and Olin College.

Get a PDF of the Grand Challenges booklet here.

With input from people around the world -- much of it on this website -- an international group of leading technological thinkers were asked to

SHARE YOUR COMMENTS ON

One of these grand challenges:

- **Prevent nuclear terror**
- **Engineer better medicines**

COMMITTEE MEMBER SPOTLIGHT

WILLIAM PERRY

MICHAEL AND BARBARA BERBERIAN PROFESSOR, PROFESSOR OF ENGINEERING, AND FORMER U.S. SECRETARY OF DEFENSE

William J. Perry (chair), former U.S. secretary of defense (1994-1997), is Michael and Barbara Berberian Professor, a senior fellow at the Freeman Spogli Institute for International Studies (FSI), and a member of the ...


Make solar energy economical


Provide energy from fusion


Develop carbon sequestration methods


Manage the nitrogen cycle


Provide access to clean water


Restore and improve urban infrastructure

AMT


Advance health informatics

BHI


Engineer better medicines


Reverse-engineer the brain

BHI


Prevent nuclear terror


Secure cyberspace

AMT


Enhance virtual reality


Advance personalized learning

AMT


Engineer the tools of scientific discovery

BHI

- US National Academy of Engineering

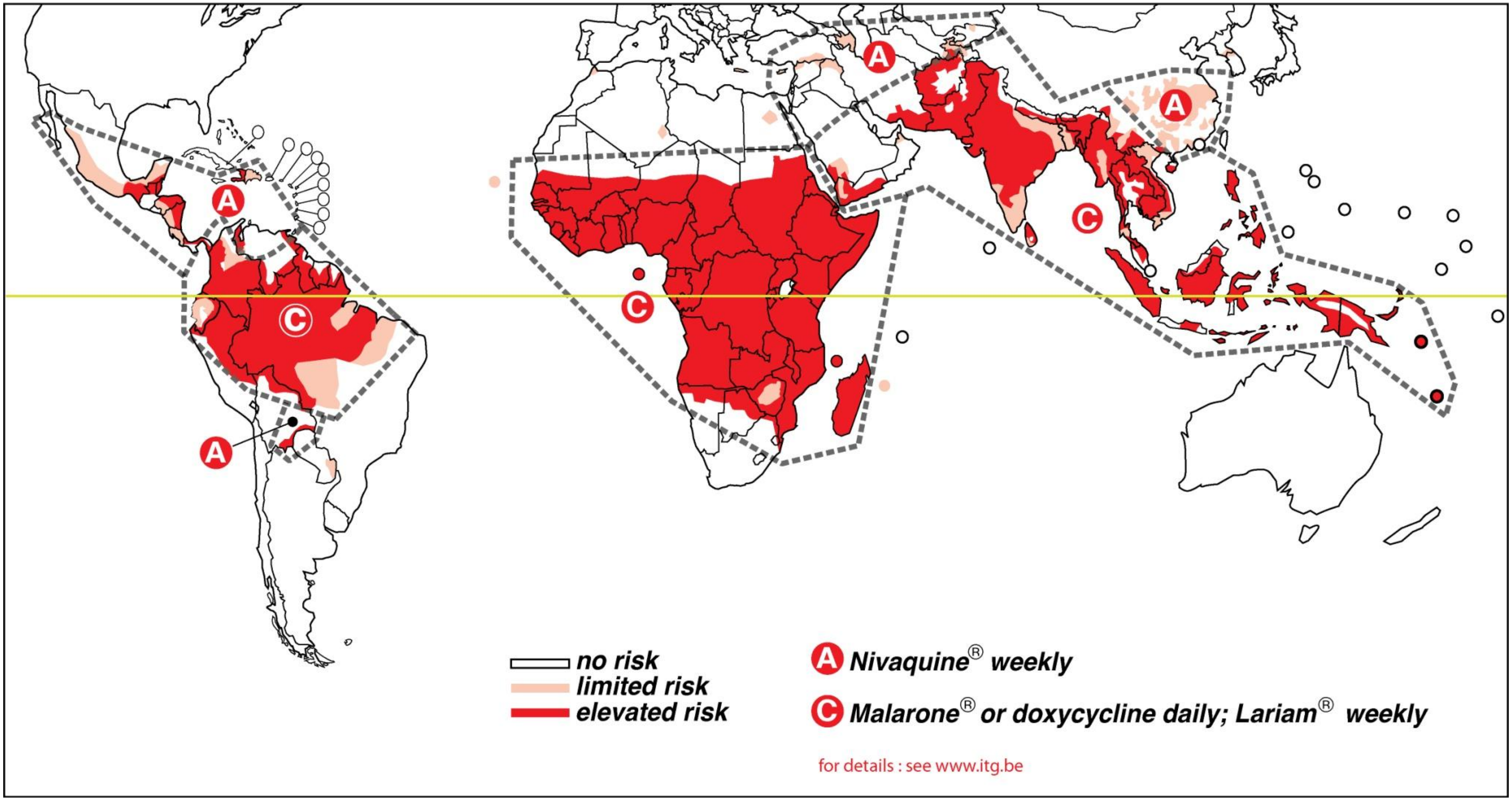
Global Healthcare Challenge 1
Disease Surveillance/Control

Millennium Development Goals

- Eight goals are to be achieved by 2015, agreed by all 191 UN member states:
  1. Eradicate extreme poverty and hunger
  2. Achieve universal primary education
  3. Promote gender equality and empower women
  4. Reduce child mortality rates
  5. Improve maternal health
  6. Combat HIV/AIDS, malaria, and other diseases
  7. Ensure environmental sustainability
  8. Develop a global partnership for development

6. Combat HIV/AIDS, **malaria**, and other diseases

Malaria 2012-2013 *(source WHO 2009)*



Malaria Endemic in China

I. Epidemiological profile

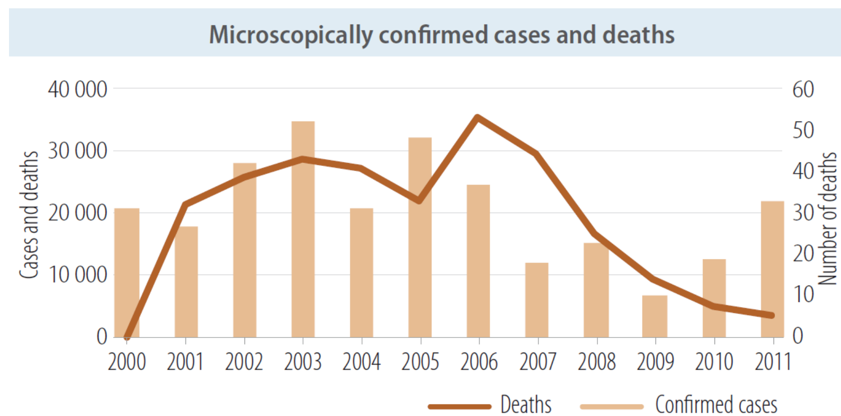
Population (UN Population Division)	2011	%
High transmission (≥1 case per 1000 population)	13 500 000	1
Low transmission (0-1 cases per 1000 population)	674 000 000	50
Malaria-free (0 cases)	660 000 000	49
Total	1 347 500 000	

Parasites and vectors

Major plasmodium species:	*P. falciparum* (43%), *P. vivax* (57%)
Major anopheles species:	*An. minimus, sinensis, anthropophagus, dirus*

II. Intervention policies and strategies

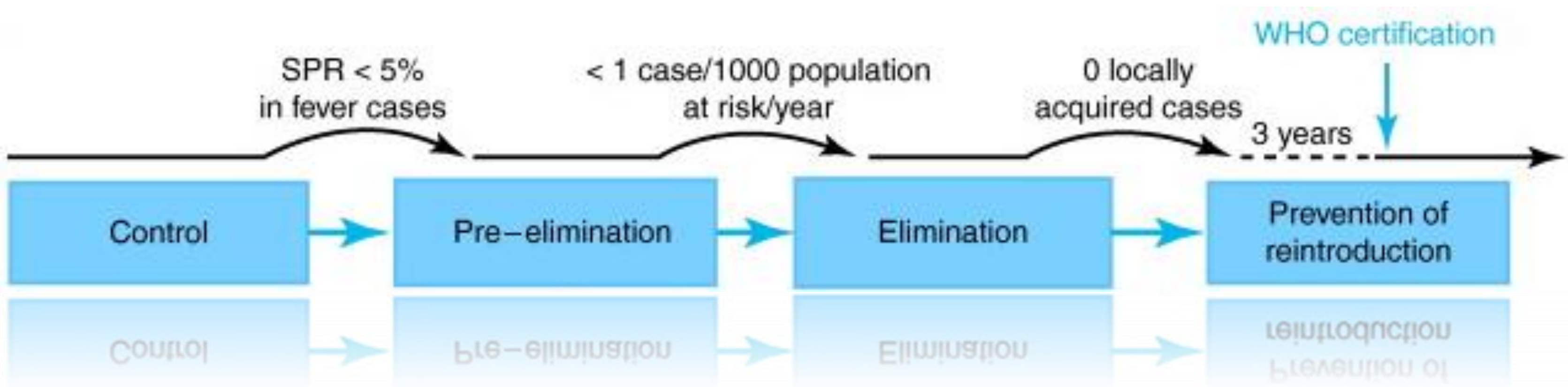
Intervention	WHO-recommended policies/strategies	Yes/ No	Year adopted
ITN/LLIN	ITNs/LLINs distributed free of charge	Yes	2003
	ITNs/LLINs distributed to all age groups	Yes	2000
IRS	IRS is recommended	Yes	2000
	DDT is used for IRS	No	–
IPT	IPT used to prevent malaria during pregnancy	NA	–
Case management	Patients of all ages should receive diagnostic test	Yes	2000
	RDTs used at community level	No	–
	ACT is free for all ages in public sector	Yes	2006
	Pre-referral treatment with recommended medicines	No	–
	Oral artemisinin-based monotherapies are not registered	Yes	2006



ITN: Insecticide-treated mosquito net; **LLIN**: Long-lasting insecticidal net; **IPT**: Intermittent preventive treatment; **IRS**: Indoor residual spraying; **DDT**: Dichloro-diphenyl-trichloroethane; **RDT**: Rapid diagnostic test; **ACT**: Artemisinin-based combination therapy.

Public Health Indicators

- **Transmission Patterns**
  - Temporal distribution of malaria cases (When)
  - Spatial distribution of malaria cases (Where)
  - Demographical distribution (Who)
- **Risk Measures**
  - Under control
  - Elimination
  - Eradication



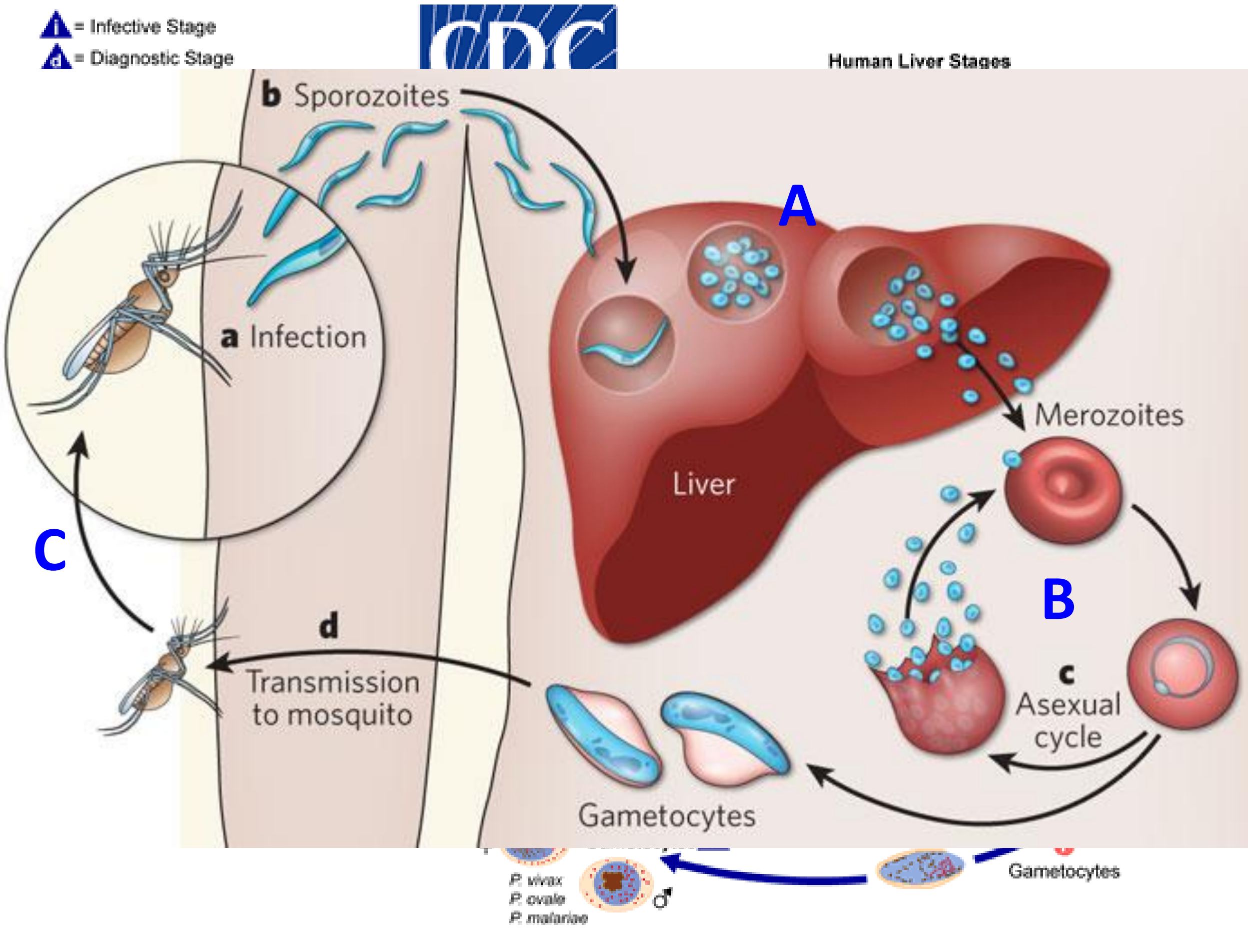
Malaria Transmission

Three Stages

- A. Exo-crythrocytic Cycle
- B. Erythrocytic Cycle
- C. Sporogonic Cycle

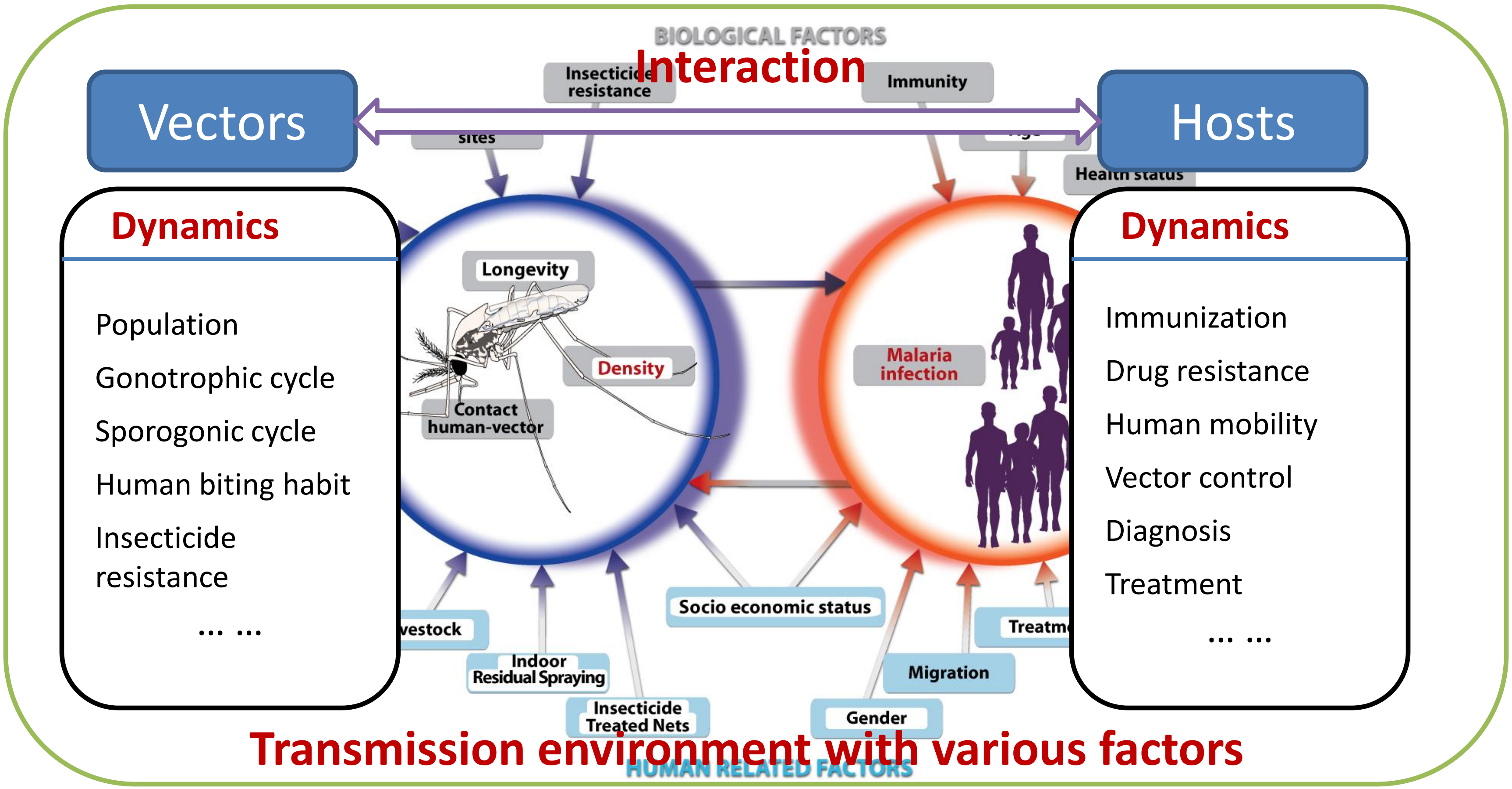
Within human body (A, B)

Within mosquito (C)



Multi-scale Impact Factors

- *Malaria transmission between human beings and vectors may be impacted by various factors* ***at different scales.***



[3] Protopopoff N, Van Bortel W, Speybroeck N, Van Geertruyden J-P, Baza D, et al. (2009) Ranking Malaria Risk Factors to Guide Malaria Control Efforts in African Highlands. PLoS ONE 4(11): e8022.

Multi-level Transmission Dynamics

Macroscopic

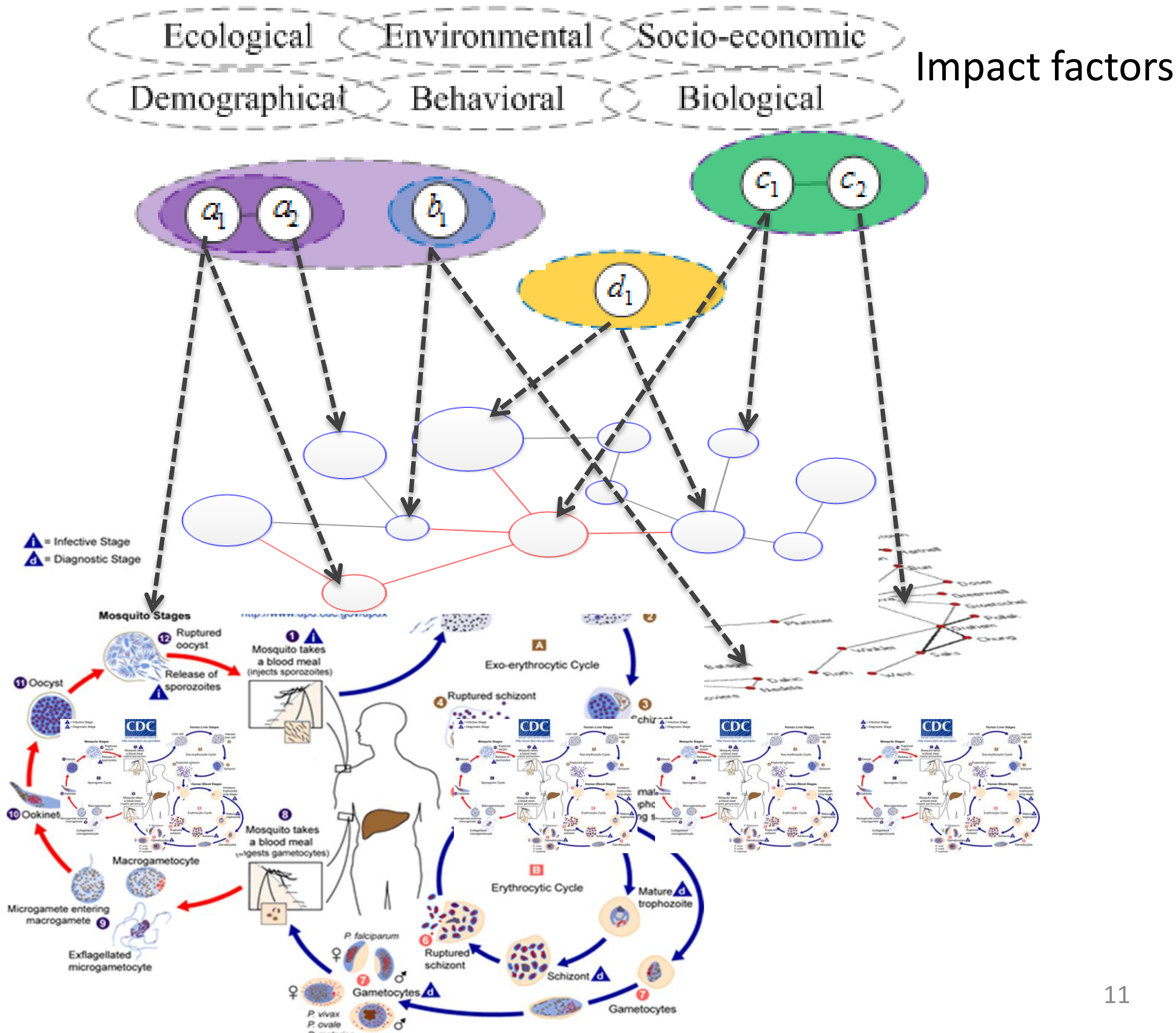
Multi-scale

Microscopic

Metapopulation

Multi-level

Individual



A Complex Systems Perspective

- **Coupling Relationships and Interactions**
  - Epidemiological entities: the host, the disease, and the transmission agent (e.g., mosquitos)
- **Multi-scale impact factors**
  - Ecological, Physiological, environmental, demographical, behavioral factors, and so on.
- **Multi-level Transmission Dynamics**
  - Agent-based models at the individual level
  - Homogeneous mixing models at the metapopulation level
- **Externality**
  - For example, **human response (e.g., social awareness)**, public policies, environment (e.g., abnormal weather), etc.

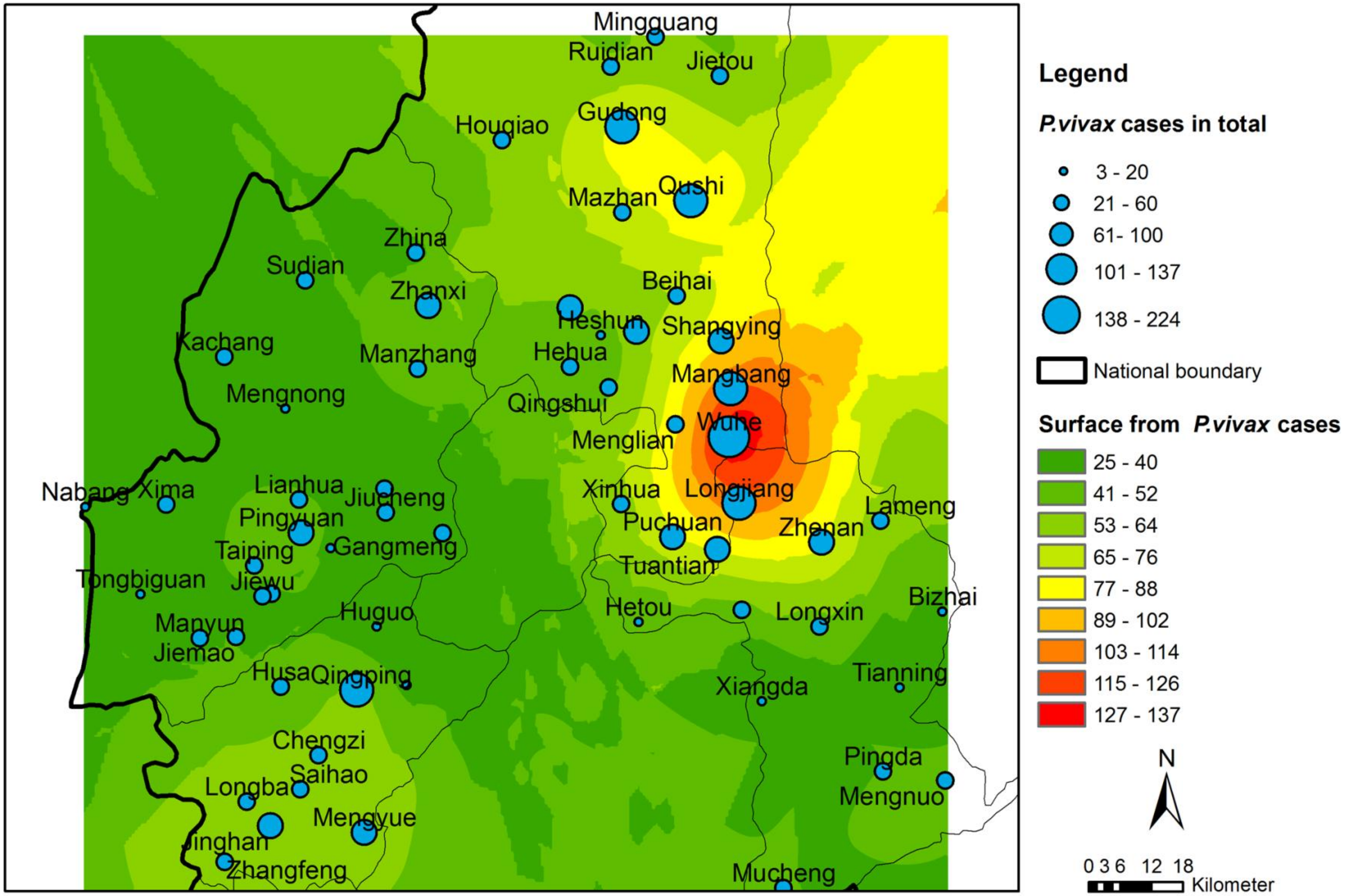
What’s the Role of Computing? (e.g., computational intelligence)

1. **Complex Systems Modeling**
   - Discovering (and predicting) tempo-spatial transmission patterns
   - Identifying underlying interactions

2. **Policy-level Decision Making**
   - Active surveillance
   - Strategy planning
   - Resource deployment
   - Policy assessment

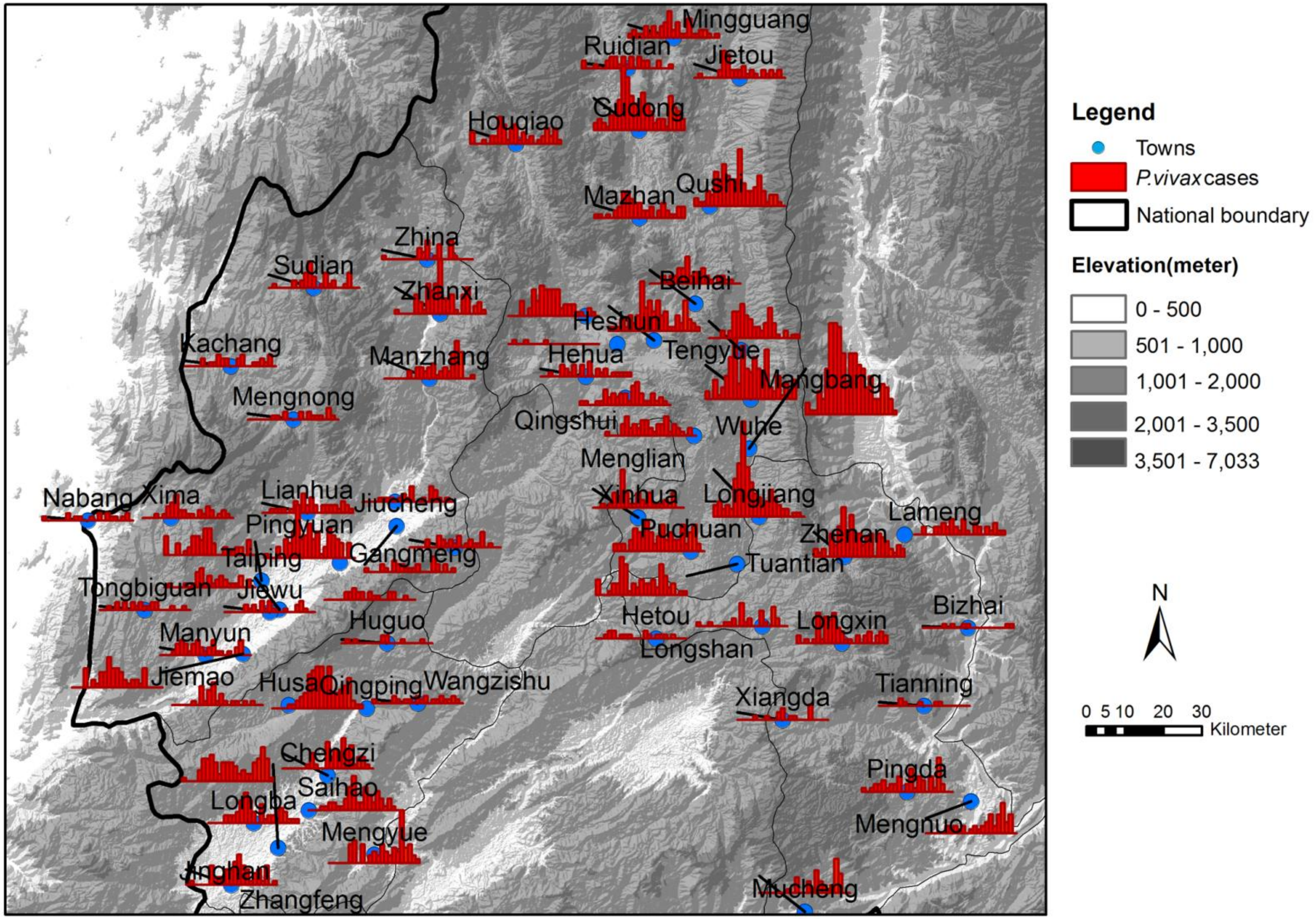
Wikipedia.com

Malaria Endemic in Yunnan, China



[1] Shi B, Liu J, Zhou XN, and Yang GJ: Inferring P. vivax Transmission Networks from Tempo-spatial Surveillance Data. *PLoS NTD*.

Tempo-spatial Distribution of Malaria Cases

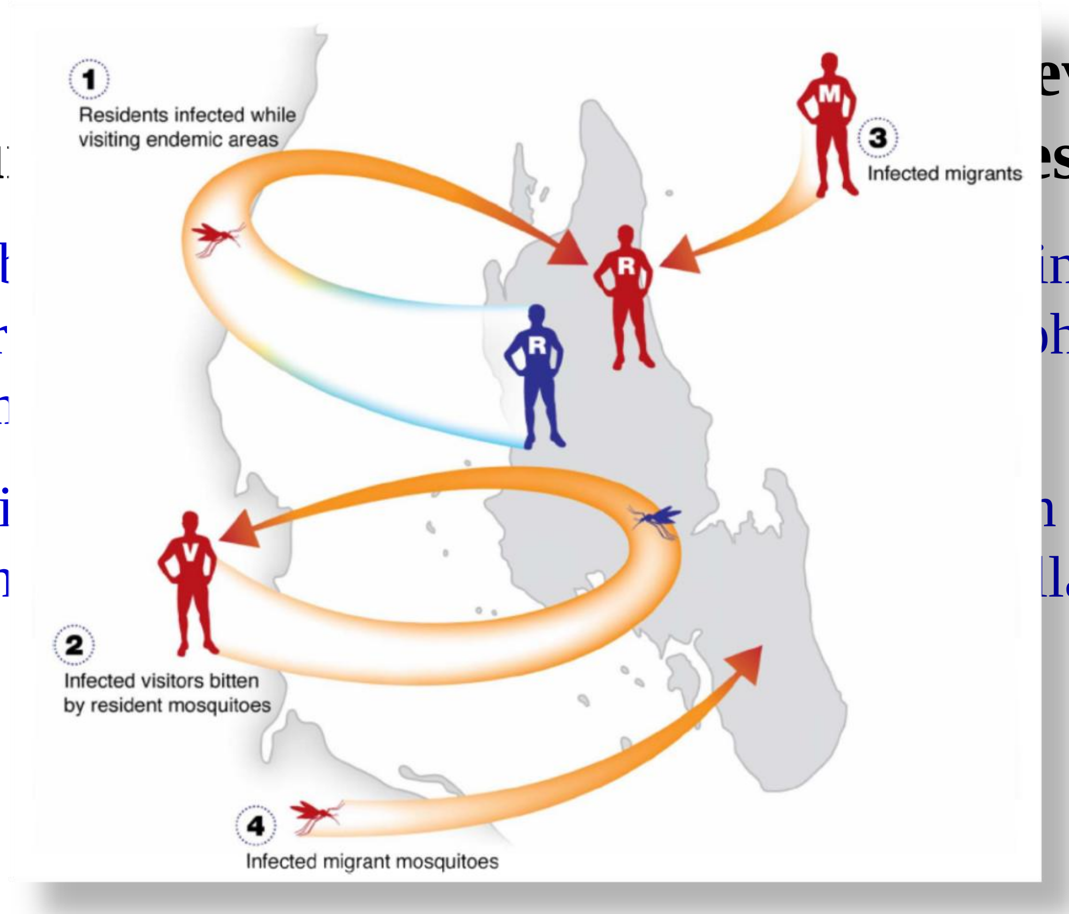


The number of *P. vivax* incidences of 62 towns in Yunnan, China, in 2005.

What is the underlying malaria transmission network?

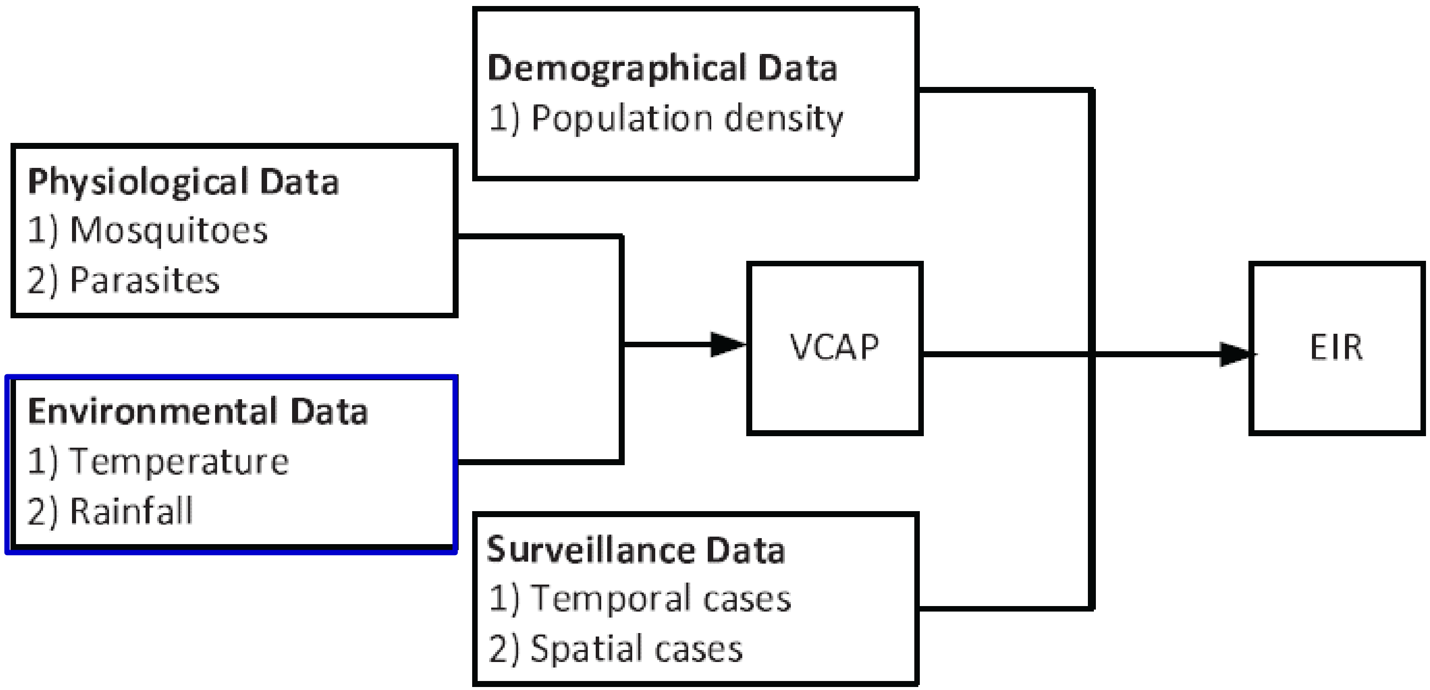
Malaria Endemic in Yunnan

- **Malaria Transmission Networks**
  - How to characterize malaria transmissions from one location to another due to **human movement**?
- **Based on** ... **evalence, we can fu** ... **estions:**
  - How to ... into consider ... physiological, environ...
  - How to i ... **networks** based on ... llance data?



A Spatial Malaria Transmission Model

- **Evaluating malaria risk for each individual town**

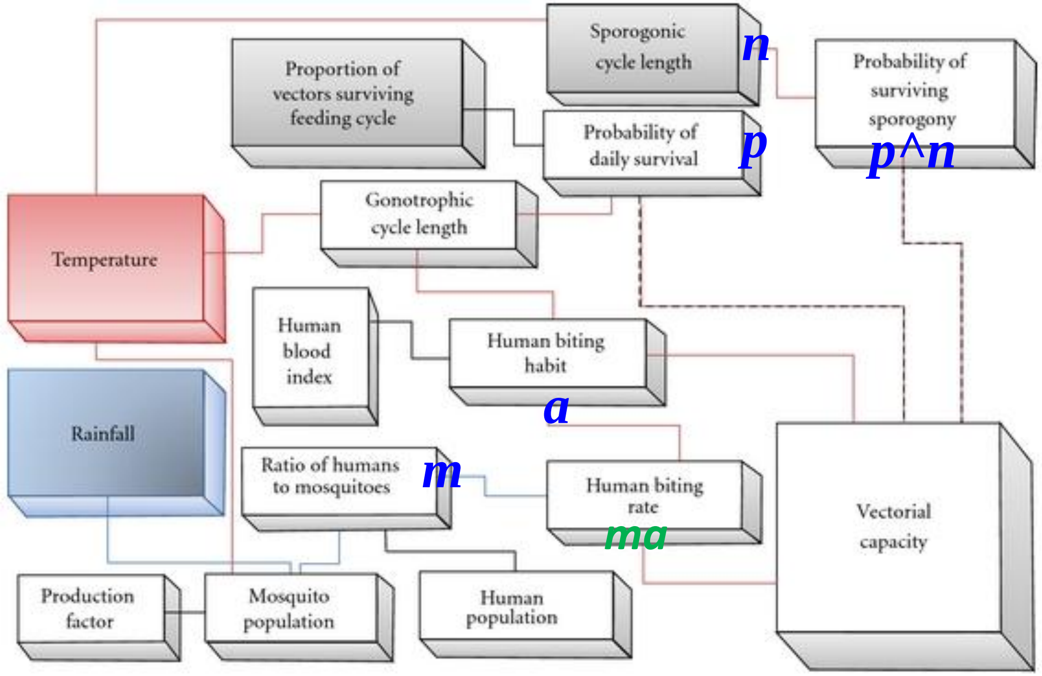


VCAP: the number of **potentially infective contacts** an individual person makes, through vector population, per unit time.

EIR: the number of **infectious bites** received per day by a person.

[4] P. Ceccato, C. Vancutsem, R. Klaver, J. Rowland, and S. J. Connor: A vectorial capacity product to monitor changing malaria transmission potential in epidemic regions of Africa. Journal of Tropical Medicine, 2012, e595948.

VCAP and EIR



- $VCAP = \dfrac{ma^2p^n}{-ln(p)}$

  a – human biting habit

  m – ratio of humans to mosquitoes

  n – Sporogonic cycle length

  p – probability of daily survival

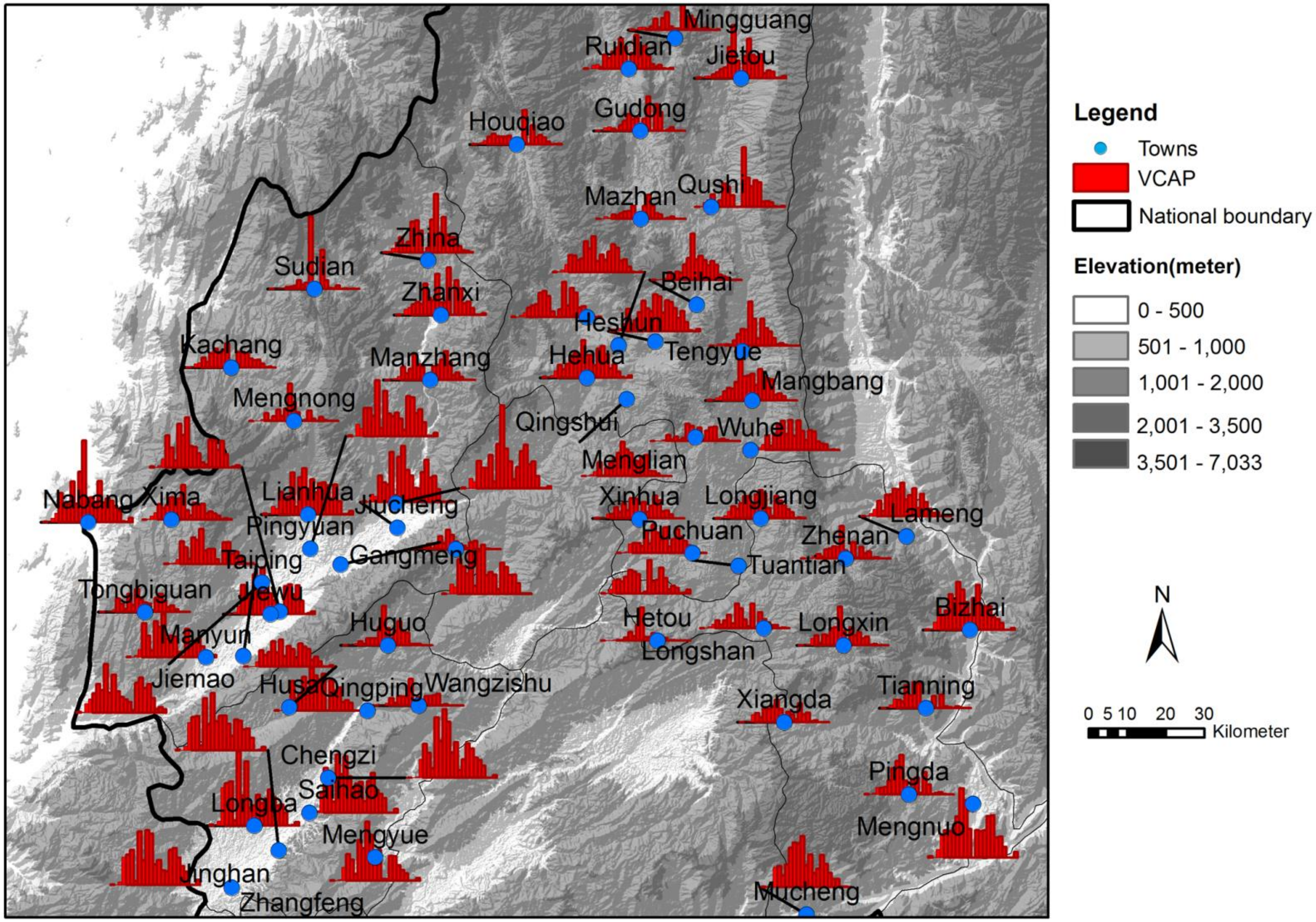
- $EIR(t) = \dfrac{c{\cdot}VCAP{\cdot}x(t)}{1-ca{\cdot}x(t)/\ln(p)}$

  x(t) -- the proportion of infectious person at time t

  c -- the transmission efficiency from an infectious person to an uninfected mosquito

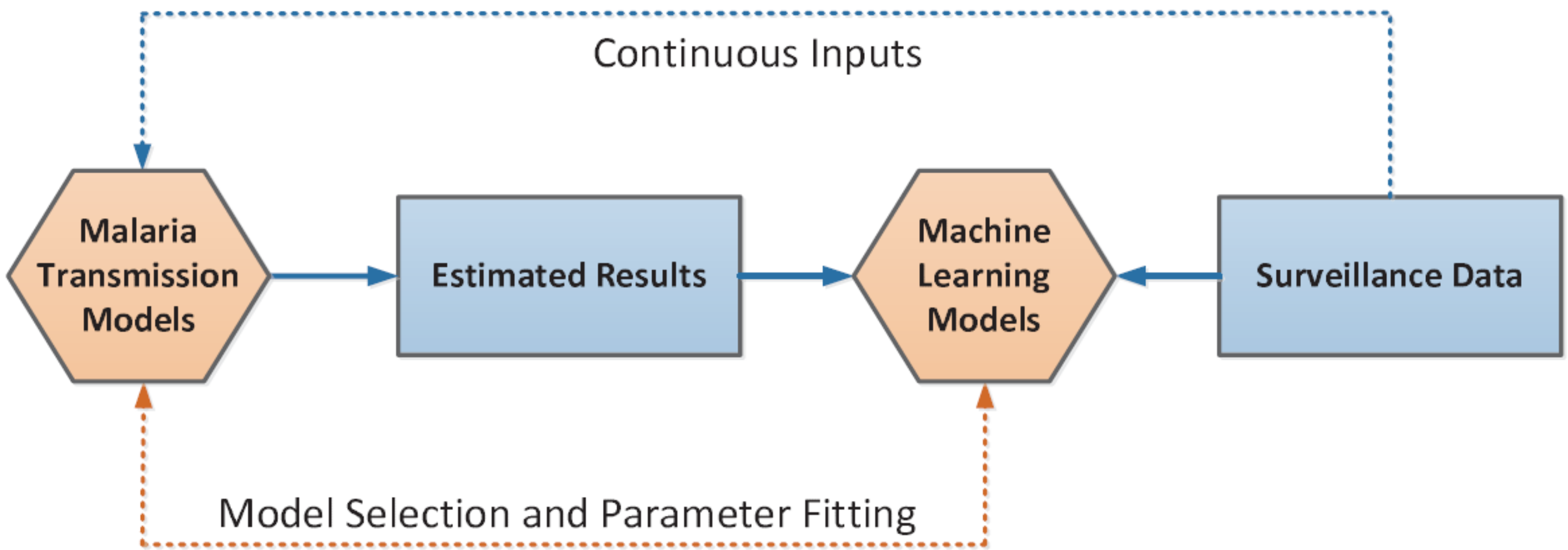
[2] P. Ceccato, C. Vancutsem, R. Klaver, J. Rowland, and S. J. Connor, “A vectorial capacity product to monitor changing malaria transmission potential in epidemic regions of Africa,” *Journal of Tropical Medicine*, p. e595948, October 2012.

VCAP of 62 Malaria Endemic Towns in Yunnan



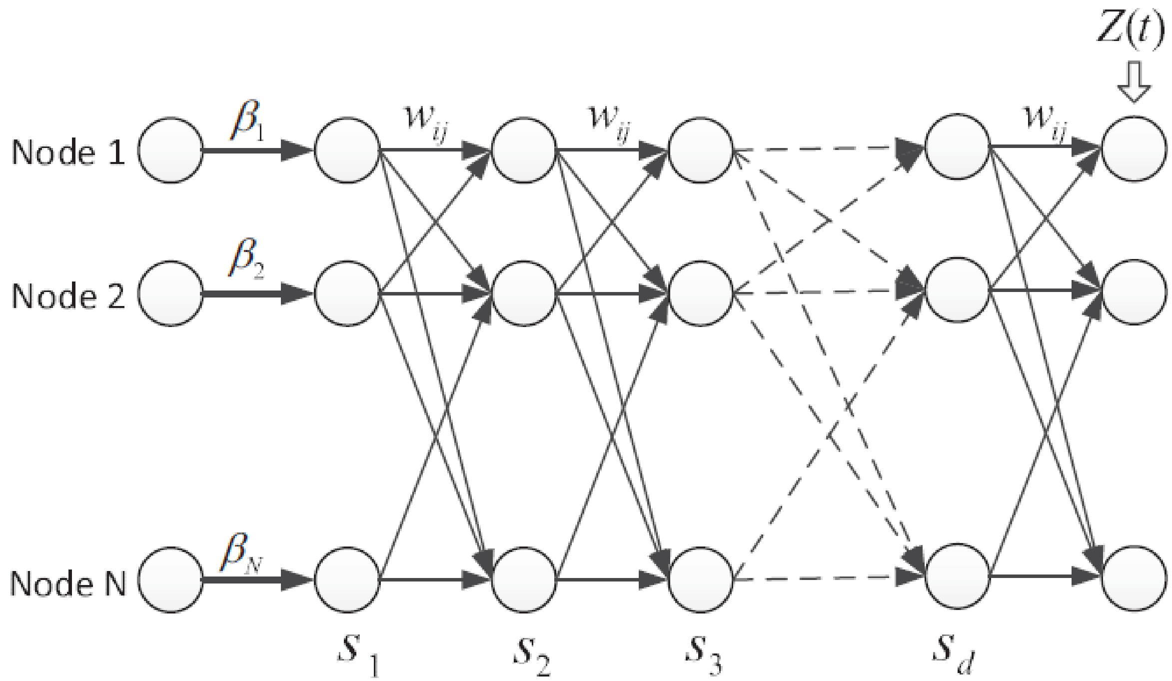
The values of vectorial capacity of the 62 towns in Yunnan province in 2005. The values are calculated using time window size 16 days.

A Machine Learning Approach



- The **tempo-spatial surveillance data** about malaria infections can perform as *continuous inputs* to *an appropriate malaria transmission model*. Accordingly, the model will output some results, which will be treated as inputs to *a learning method.*
- The surveillance data can also perform as *a training set* to the learning method. Based on the learning results, certain *parameters in the malaria transmission model* will be adjusted.

A Learning Method: Recurrent Neural Network



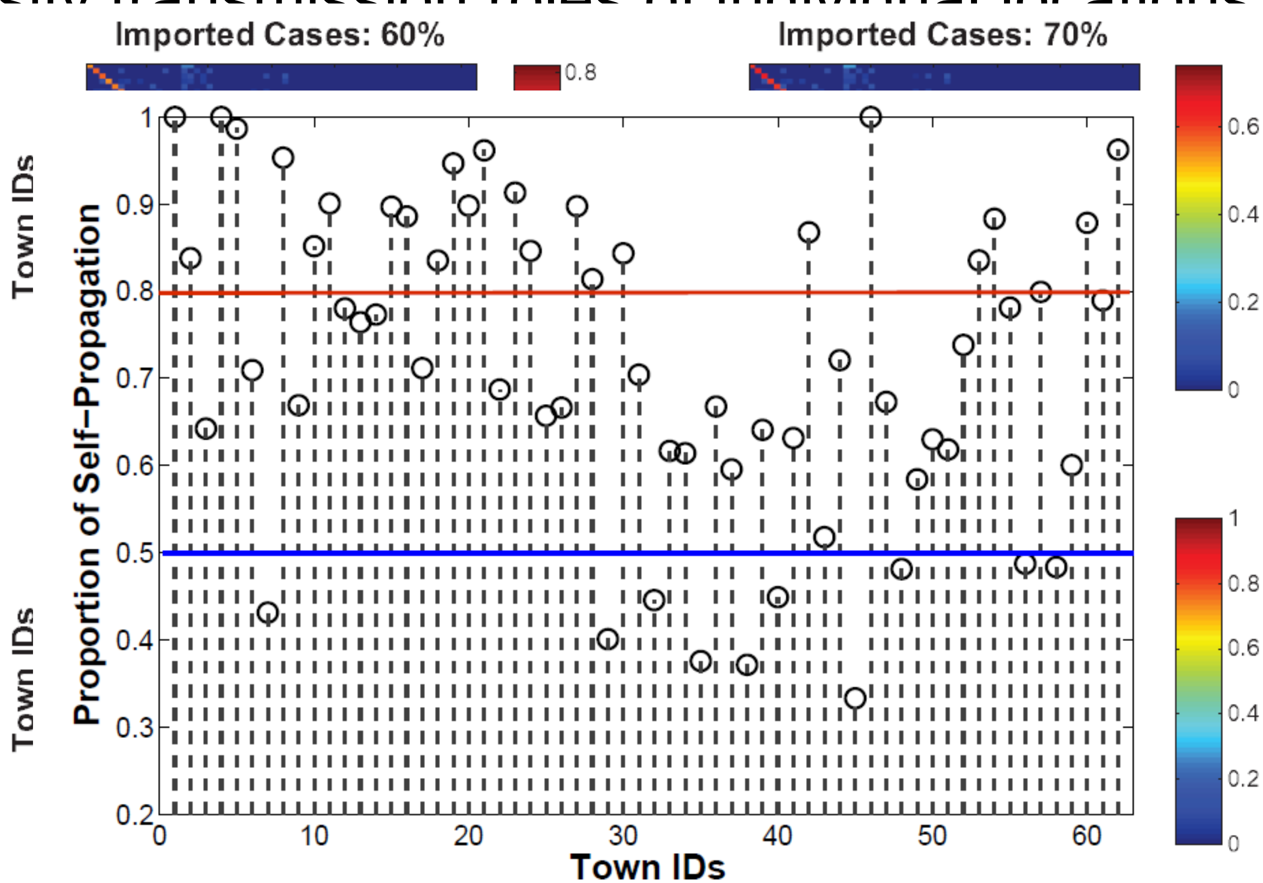
- Each node represents a town.
- β_i represents the control effort of each node.
- Z represents imported cases.
- d is the diameter of the transportation network among 62 towns.

Objective: Inferring malaria transmission networks, i.e., w_{ij}.

Method: The backpropagation algorithm.

Our Results

- Using *a machine learning method* to infer underlying malaria transmission networks under different scenarios
- Classify transmission roles of individual locations



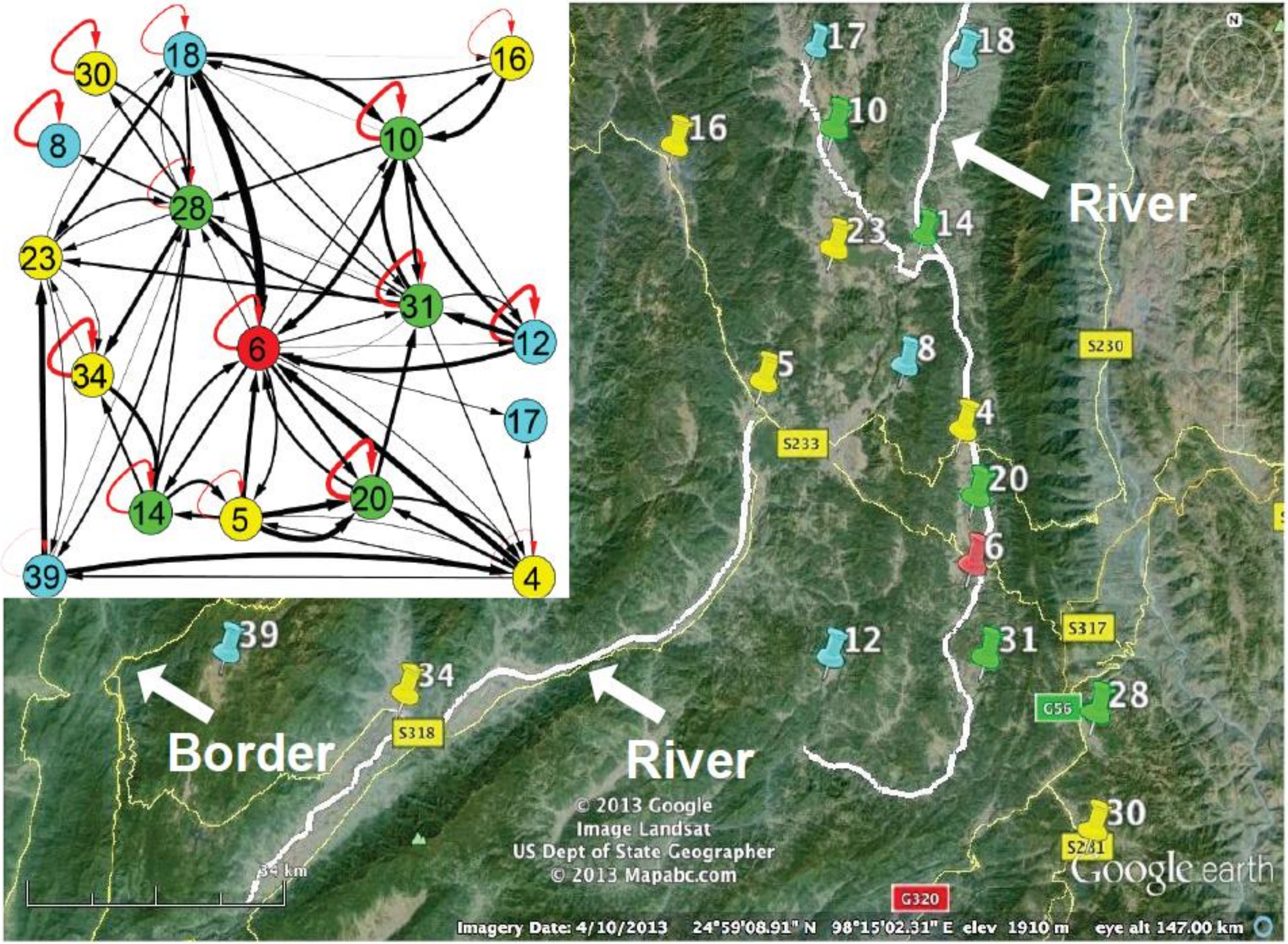
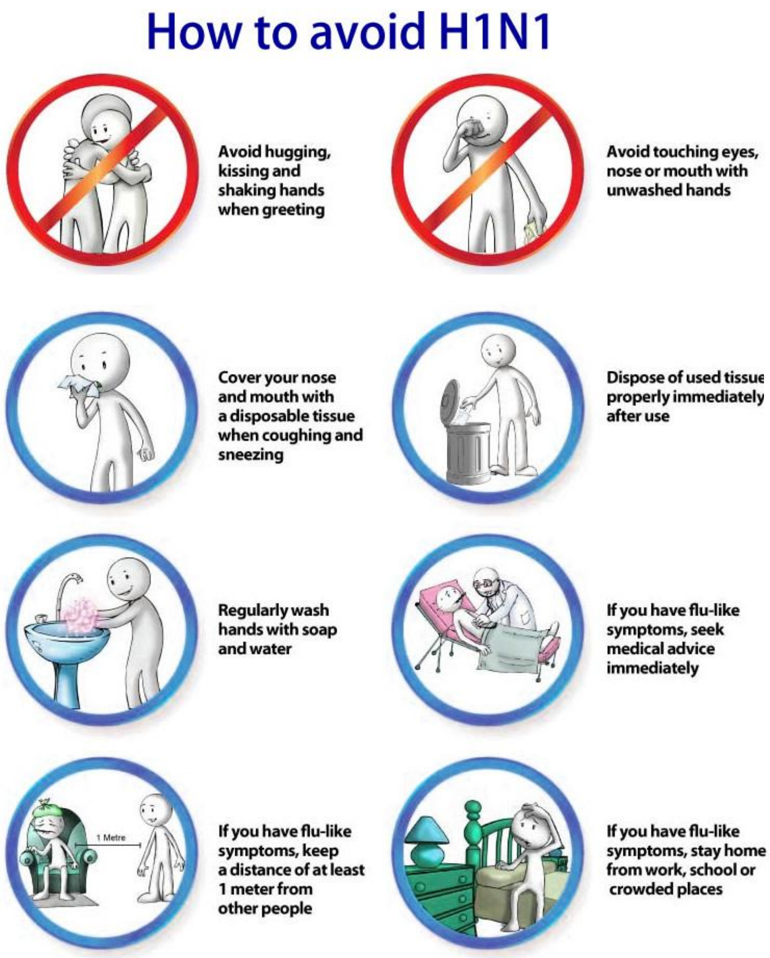
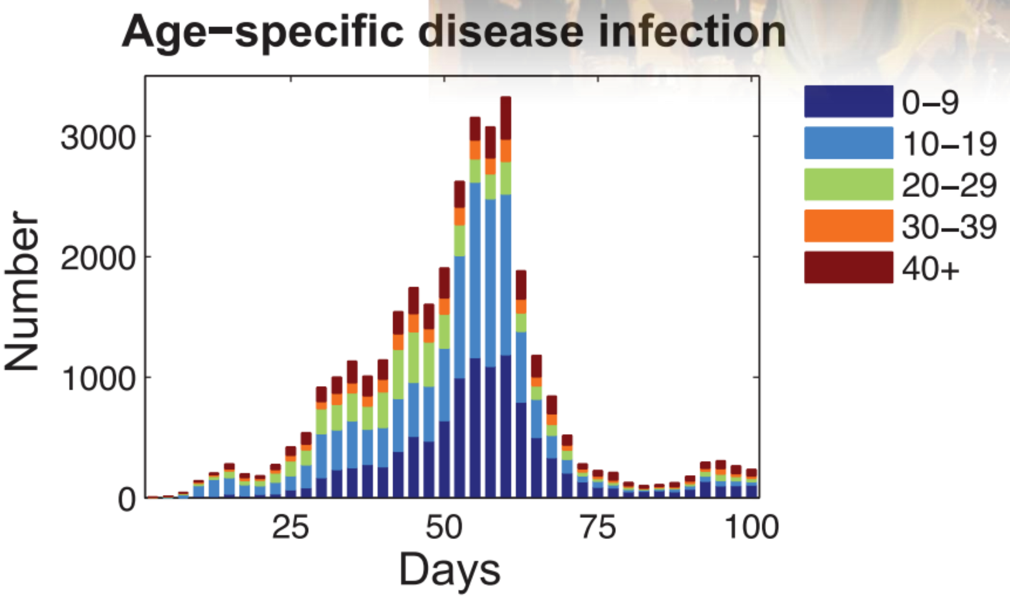


Fig. 4. Townships that form a community in the inferred malaria transmission network.

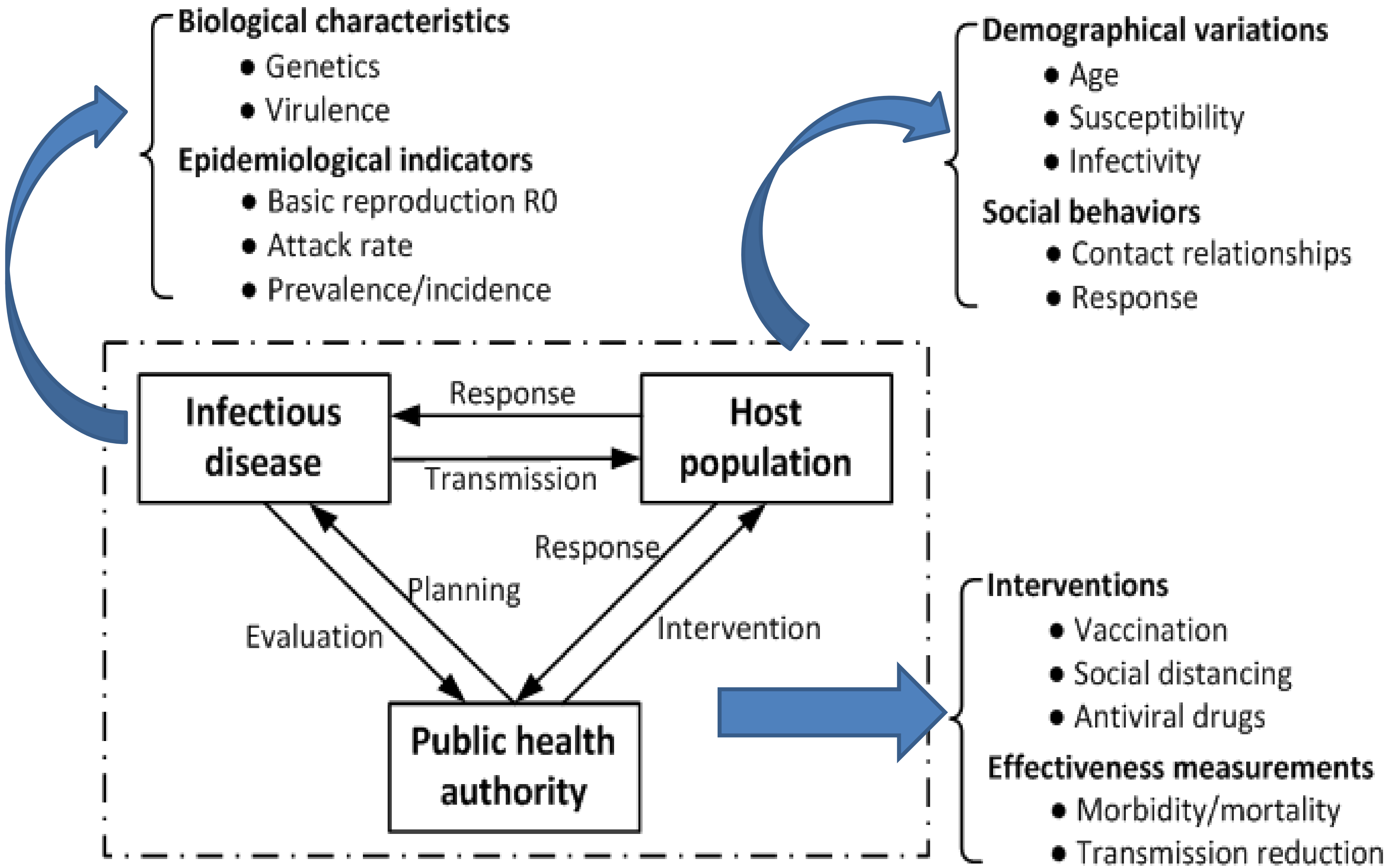
H1N1 Epidemic





Spread of H1N1 influenza in Hong Kong [2].

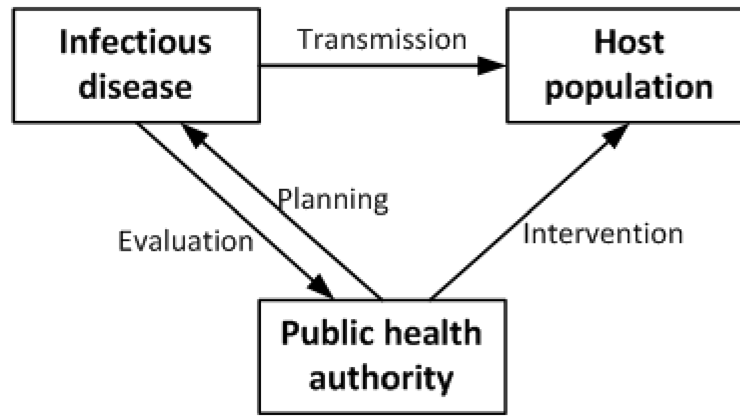
[2] Xia S, Liu J, Cheung W (2013) Identifying the Relative Priorities of Subpopulations for Containing Infectious Disease Spread. PLoS ONE 8(6): e65271.


Biological characteristics
Genetics
Virulence
Epidemiological indicators
Basic reproduction R0
Attack rate
Prevalence/incidence
Demographical variations
Age
Susceptibility
Infectivity
Social behaviors
Contact relationships
Response
Infectious disease
Host population
Response
Transmission
Response
Planning
Evaluation
Intervention
Public health authority
Interventions
Vaccination
Social distancing
Antiviral drugs
Effectiveness measurements
Morbidity/mortality
Transmission reduction

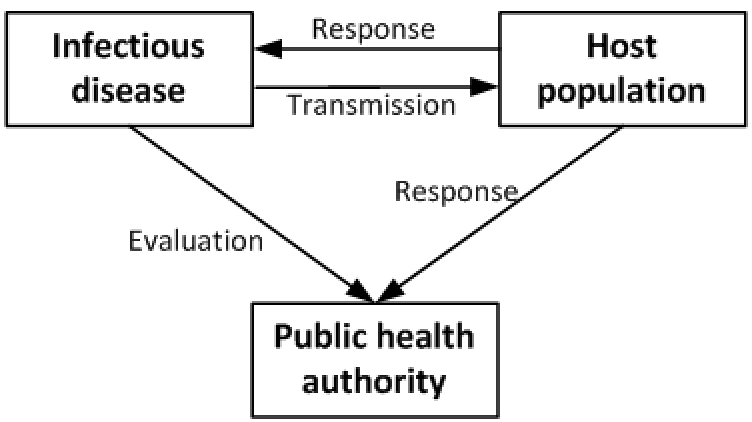
Motivation

1. Characterizing disease dynamics in a host population
2. Strategic planning for effective disease control
3. Characterizing and evaluating human responsive behaviors

1



2



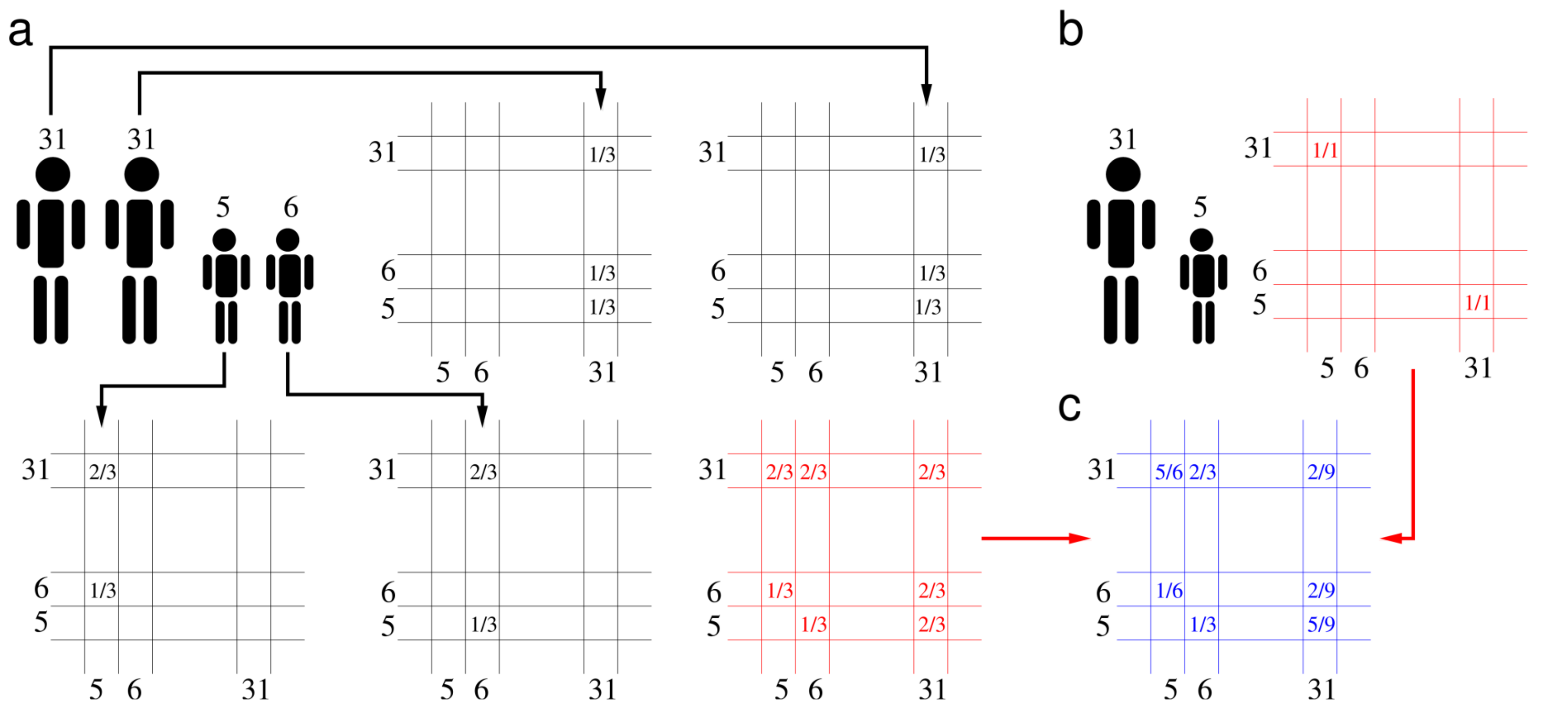
3

1. **Vaccination**
2. **Influenza-like disease**
3. **Computational approach**

H1N1 Epidemic

- **Age-Specific Contact Patterns**
  - Disease transmissions are subject to the structure of individuals social contacts, which plays a key role in the assessment of an infection outbreak
- **We aim to investigate H1N1transmission in Hong Kong by addressing the following two specific issues:**
  - How to characterize **age-specific contact patterns** by exploiting the demographical information of a host population (i.e., census data)?
  - How to use **a computational model to predict** the disease transmission patterns, at the metapopulation level?

Age-Specific Contact Patterns



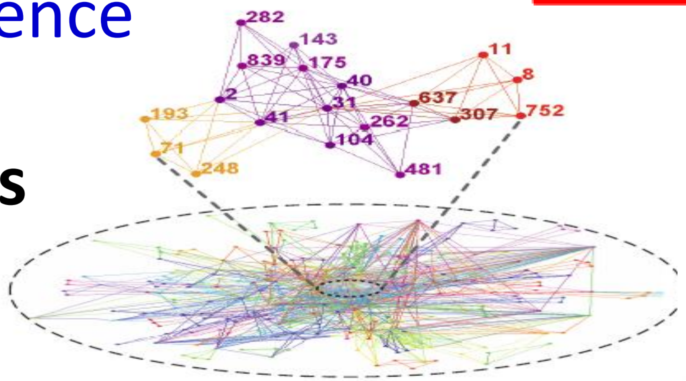
a Computation of contact frequencies for every member of a household composed by two adults aged 31 and two children of 5 and 6 years old. The sum of the four contributions gives contact frequencies within this household (in red).

b Contact frequencies within a household composed of an adult aged 31 and a child aged 5.

c Assuming that these two households constitute the whole population, the frequency of household contacts that individuals of age have with individuals aged is given by the sum of the contributions from each household, divided by the number of individuals aged having at least one household contact.

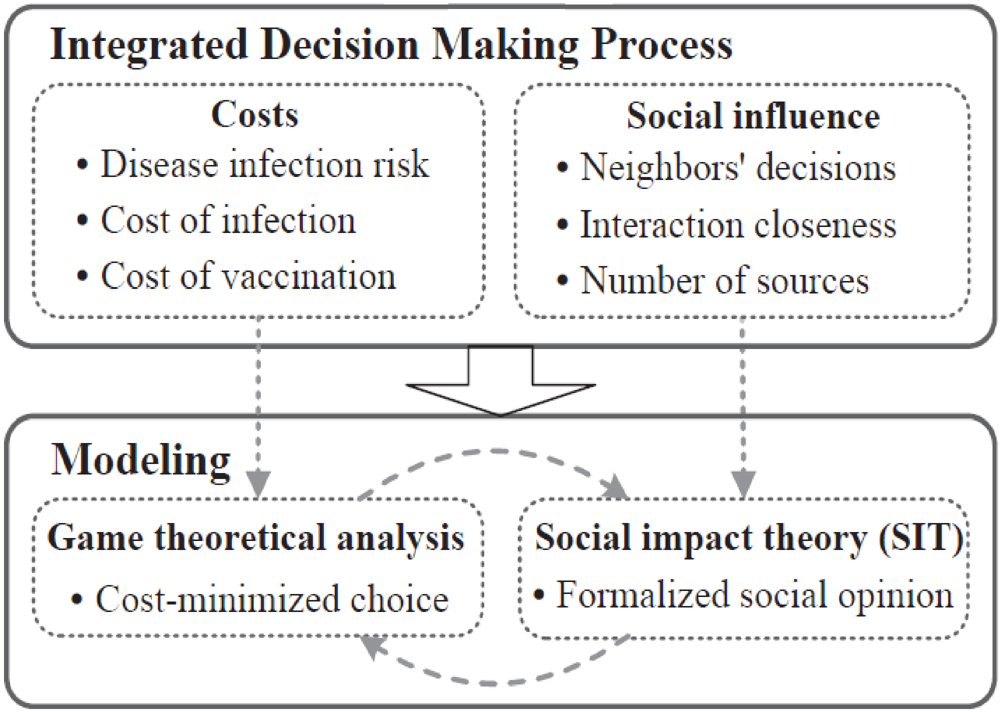
[5] Fumanelli L, Ajelli M, Manfredi P, Vespignani A, Merler S (2012) Inferring the Structure of Social Contacts from Demographic Data in the Analysis of Infectious Diseases Spread. PLoS Comput Biol 8(9): e1002673.

Individuals' vaccination decision making -- Social Influence

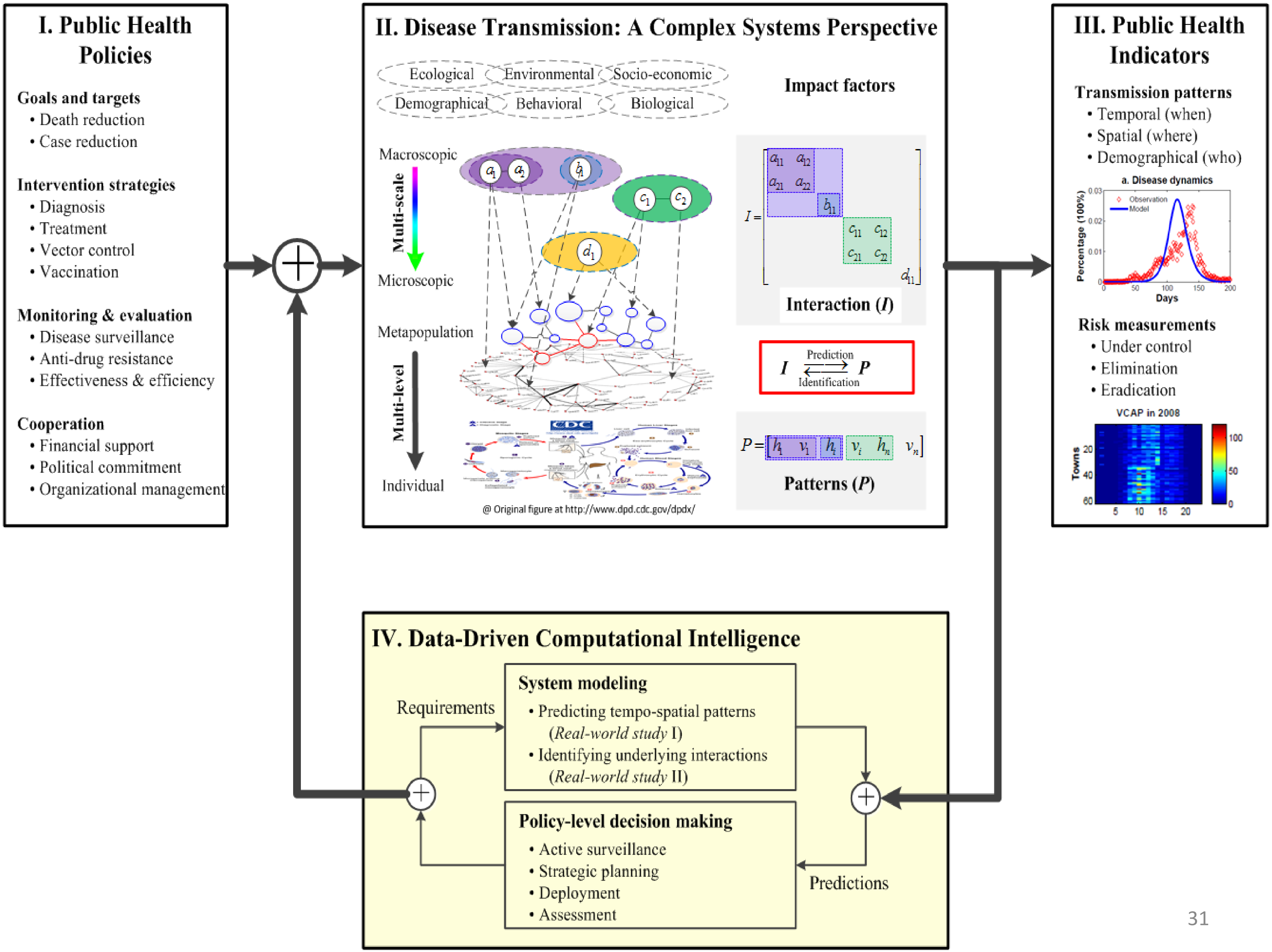


- **Majority followers**
  - Social neighbors' choices
  - Interaction relationships
  - Strength of social influence

- **Duel-perspective view**
  - Cost-benefit analysis
  - Social influence
  - Balance between them

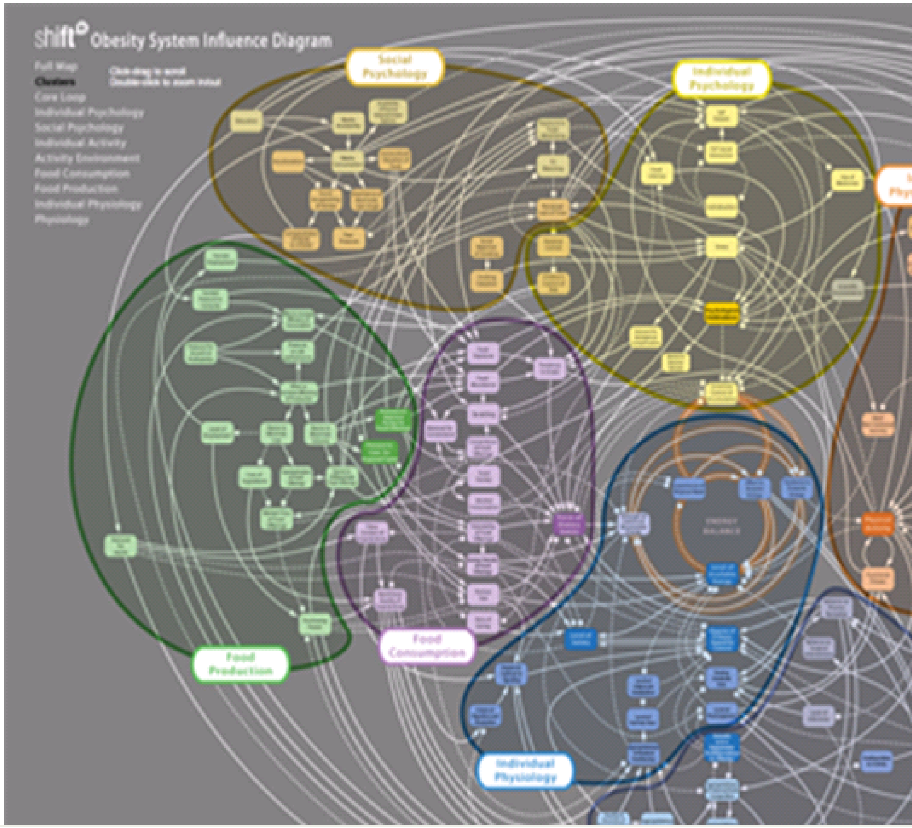


How to measure social influence?



I. Public Health Policies
Goals and targets
• Death reduction
• Case reduction
Intervention strategies
• Diagnosis
• Treatment
• Vector control
• Vaccination
Monitoring & evaluation
• Disease surveillance
• Anti-drug resistance
• Effectiveness & efficiency
Cooperation
• Financial support
• Political commitment
• Organizational management
II. Disease Transmission: A Complex Systems Perspective
Ecological
Environmental
Socio-economic
Demographical
Behavioral
Biological
Impact factors
Macroscopic
Multi-scale
Microscopic
Metapopulation
Multi-level
Individual
a_1 a_2 b_1 c_1 c_2 d_1
$I =$ a_{11} a_{12} a_{21} a_{22} b_{11} c_{11} c_{12} c_{21} c_{22} d_{11}
Interaction (I)
I Prediction Identification P
$P = [h_1 \; v_1 \; h_i \; v_i \; h_n \; v_n]$
Patterns (P)
@ Original figure at http://www.dpd.cdc.gov/dpdx/
III. Public Health Indicators
Transmission patterns
• Temporal (when)
• Spatial (where)
• Demographical (who)
a. Disease dynamics
Observation
Model
Percentage (100%)
0.03
0.02
0.01
0
0
50
100
150
200
Days
Risk measurements
• Under control
• Elimination
• Eradication
VCAP in 2008
Towns
20
40
60
5
10
15
20
100
50
0
IV. Data-Driven Computational Intelligence
Requirements
System modeling
• Predicting tempo-spatial patterns (*Real-world study* I)
• Identifying underlying interactions (*Real-world study* II)
Policy-level decision making
• Active surveillance
• Strategic planning
• Deployment
• Assessment
Predictions

Breaking Down Complex Systems in Public Health



In an effort to gain a more comprehensive understanding of public health issues, Columbia's Mailman School of Public Health has recently partnered with Columbia Engineering to create a new program that will give public health students the tools to analyze the complex systems tied to important health matters. The goal of this new program is to give the public health researchers the ability to tackle public health issues the way an engineer would.

The Columbia University Systems Science Program (CUSSP) is a new curriculum-based program led by the Mailman School of Public Health's Dean Linda Fried and Professors Sandro Galea and Roger Vaughan with the Engineering School's Professor [Garud Iyengar] of the Department of Industrial Engineering and

Global Healthcare Challenge 2

Service Performance


HealthData.gov
AHRQ
CDC
HRSA
CMS
IHS
ONC
NIH
FDA
ACF
Home
Data
Blog
Q & A
Ideas
Developers
Search entire site...
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Health Data Initiative Strategy & Execution Plan Released and Ready for Feedback
The new Health Data Initiative Strategy & Execution Plan has been released! Check it out as it will guide and measure the open data strategy for the Department. Provide your feedback! Read more »
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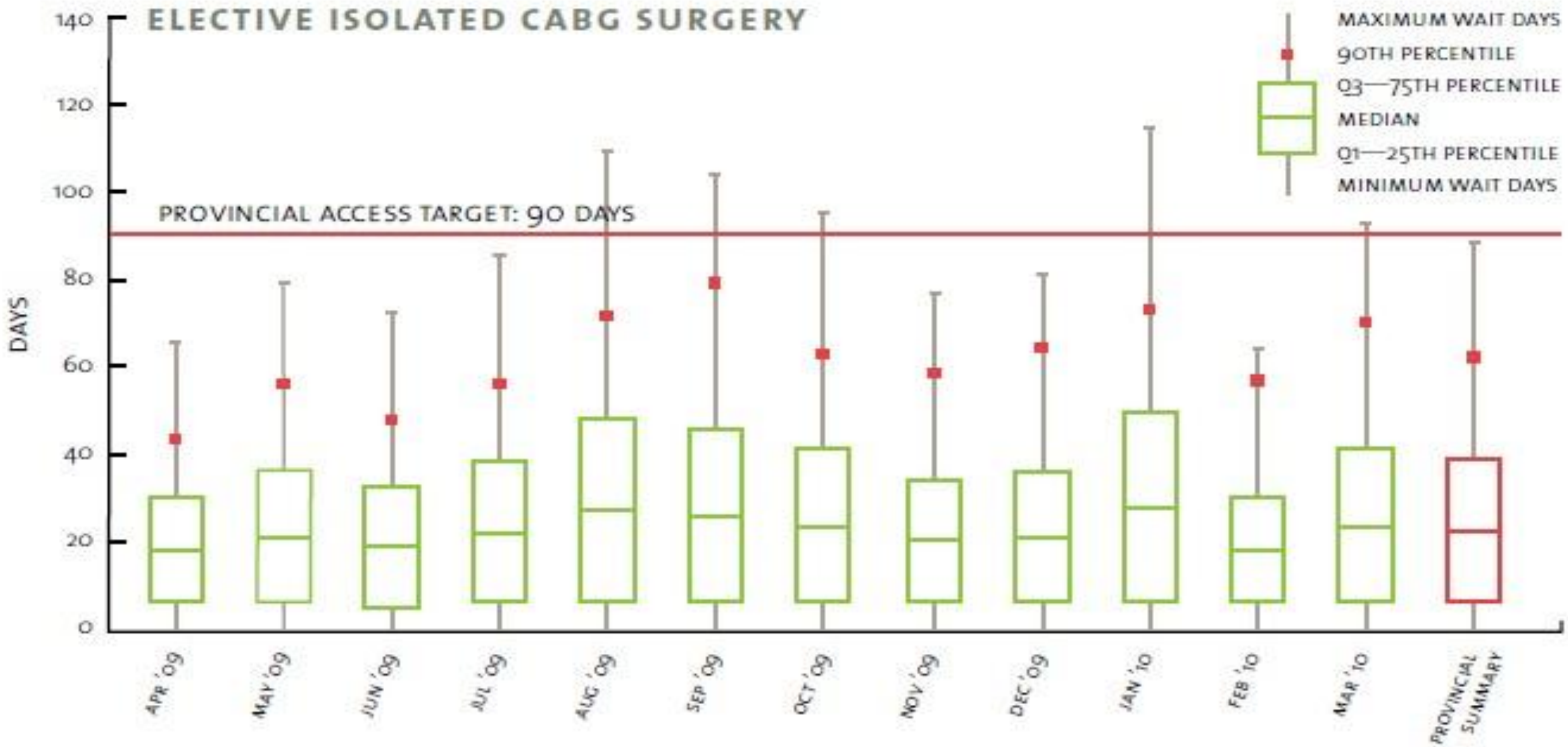
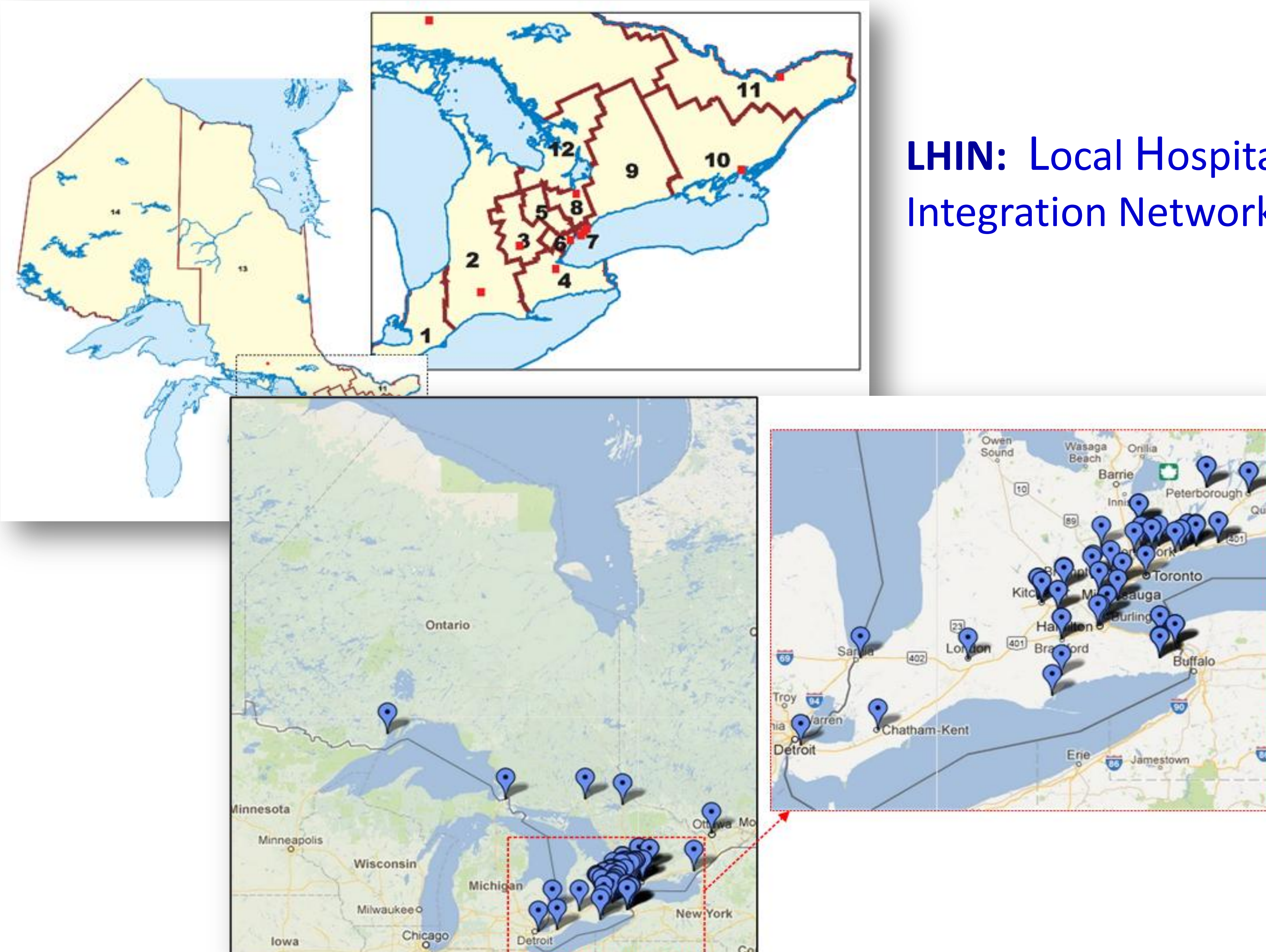
Provincial Wait Times by Month 2009–2010

www.ccn.on.ca





LHIN: Local Hospital Integration Networks

Research Context

- Local Health Integration Network (LHIN) in Ontario, Canada

LHIN ID	LHIN name	Area (km^2)	PD (per km^2)	Boundary (Major cities/towns/counties)
1	Erie St. Clair	7323.7	86.1	Windsor, Lambton, Chatham-Kent, and Essex
2	South West	20903.5	43.1	London, Stratford, Elgin, Middlesex, Oxford, Perth, Huron, Bruce, and part of Grey
3	Waterloo Wellington	4746.6	144.6	Wellington, Waterloo, Guelph, and part of Grey
4	Hamilton Niagara Haldimand Brant	6473.0	203.3	Hamilton, Niagara, Haldimand, Brant, and parts of Halton and Norfolk
5	Central West	2590.0	285.7	Dufferin, parts of Peel, York, and Toronto
6	Mississauga Halton	1053.7	956.7	Mississauga, parts of Toronto, Peel, and Halton
7	Toronto Central	192.0	5678.9	A large part of Toronto
8	Central	2730.5	561.3	Parts of Toronto, York, and Simcoe
9	Central East	15274.1	93.8	Durham, Kawartha Lakes, Haliburton Highlands, Heterborough, parts of Northumberland, and Toronto
10	South East	17887.2	26.1	Kingston, Hastings, Lennox and Addington, Prince Edward, and Frontenac
11	Champlain	1763.1	65.1	Ottawa, Renfrew, Prescott and Russell, Stormont, and Dundas and Glengarry
12	North Simcoe Muskoka	8372.3	50.5	Muskoka, parts of Simcoe and Grey
13	North East	395576.7	1.4	Nipissing, Parry Sound, Sudbury, Algoma, Cochrane, and part of Kenora
14	North West	406819.6	0.6	Thunder Bay, Rainy River, and most of Kenora

PD: population density.

- About Our LHIN
  - Aboriginal Communities
  - **About Our LHIN - Overview**
  - Disclosure of Expenses
  - Erie St. Clair LHIN Values
  - Health Professionals Advisory Committee
  - LHIN Legal, Governance and Ministerial Resources
  - Our Area Profile Information
  - Our Communities List
  - Our Mandate
  - Our Staff
  - Our Vision
  - Provincial and ESC LHIN Alignm & Priorities
  - Strategic Plan – 2012 – 2015
  - Why LHINs are Good for Health Care
- Board & Governance
- Calendar of Events
- Health Service Providers
- Engaging our Communities

About our LHIN

What is a LHIN

The Erie St. Clair Local Health Integration Network is one of 14 Local Health Integration Networks (LHINs) that have been established and launched in Ontario.

LHINs are community-based, non-profit organizations funded by the Ministry of Health and Long-Term Care to plan, fund and coordinate services delivered by:

- Hospitals
- Long-Term Care Homes
- Community Care Access Centre (CCAC)
- Community Support Service Agencies
- Mental Health and Addiction Agencies
- Community Health Centres (CHCs)

Erie St. Clair LHIN services the regions of Chatham-Kent, Sarnia/Lambton and Windsor/Essex which includes over 649,000 people and supports an annual budget of over $900 million for our local health care services.

Sector	Budget (Million)
Hospitals	$672.7
Long-Term Care	$179.9
Community Care Access Centre	$121.4
Mental Health Agencies	$31.2
Community Health Centres	$24.1
Community Support Services	$17.3

Data

- A summary of data and abbreviations

Characteristics	Measures	Abb. of surgery	Profile of surgery (per month)
Demand	Average number of Arrivals, monthly*	SA	82
Capacity	Number of physicians, yearly†	SC	7
Throughput	Average number of completed cases, monthly *	ST	83
Wait time	Median wait for urgent/semi-urgent /elective patient*	SUM/SSM/SEM	3/6/19
	90th percentile wait for urgent/semi-urgent/elective patient*	SUN/SSN/SEN	11/31/49
	Queue length*	SQ	58

Data source:
* Cardiac care network of Ontario,
† Ontario physician human resources data centre. https://www.ophrdc.org/Home.aspx
The college of physicians and surgeons of Ontario. http://www.cpso.on.ca/docsearch/default.aspx?id=2048

Data

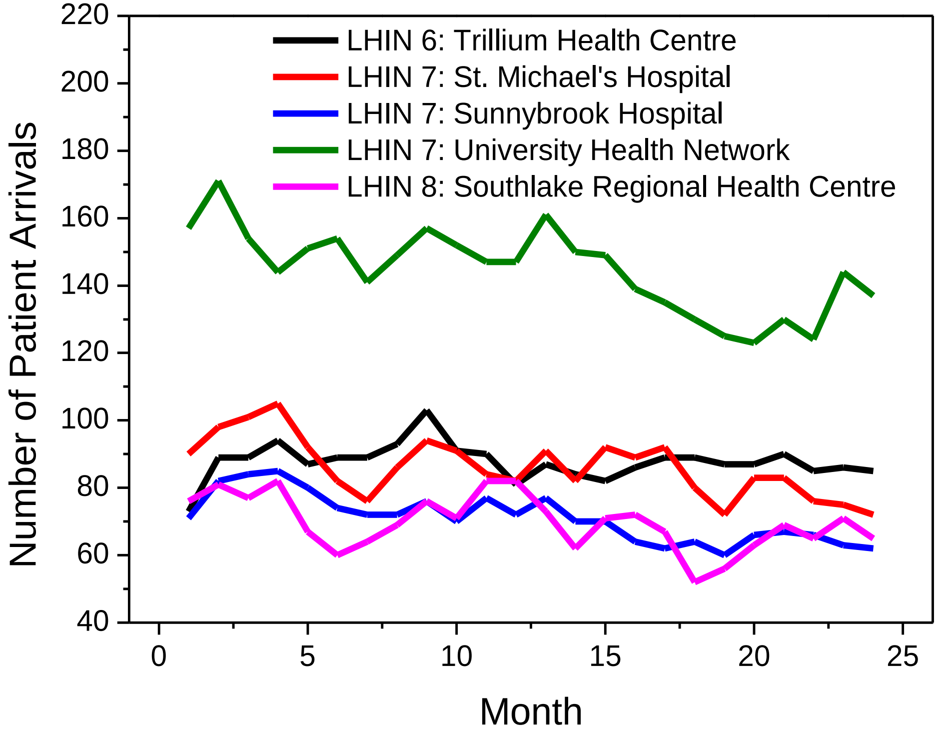
- A summary of data from individual hospitals

Hospital	SA	SC	ST	SUM	SUN	SSM	SSN	SEM	SEN	SQ
London HSC	115	8	120	2	7	6	29	15	49	76
St. Mary's General Hospital, Kitchener	111	8	113	2	8	6	29	15	50	71
Hamilton HSC	105	8	107	2	8	5	29	14	49	65
Trillium HC, Mississauga	100	8	101	2	7	5	29	14	48	61
St. Michael's Hospital, Toronto	91	7	94	1	7	5	30	13	48	55
Sunnybrook Health Sciences Centre	87	7	88	1	10	5	31	15	50	51
University Health Network, Toronto	81	7	82	1	10	5	32	15	51	48
Southlake Regional HC, Newmarket	73	7	74	1	10	5	31	16	51	43
Kingston General Hospital	64	7	67	1	9	4	30	17	49	37
University of Ottawa Heart Institute	59	6	60	1	10	4	29	16	48	32
Hôpital Régional de Sudbury	52	6	53	1	10	4	31	17	48	28

Self-Organized Regularities in the Cardiac Care System?

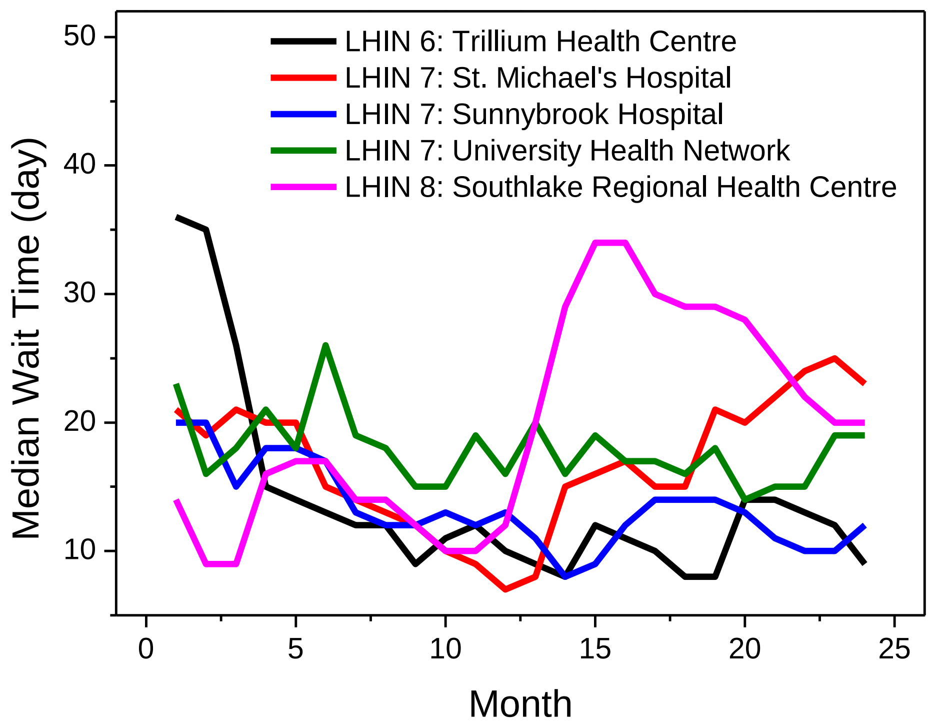
- Dynamically-changing **arrivals**

  (Jan. 2005~Dec. 2006)



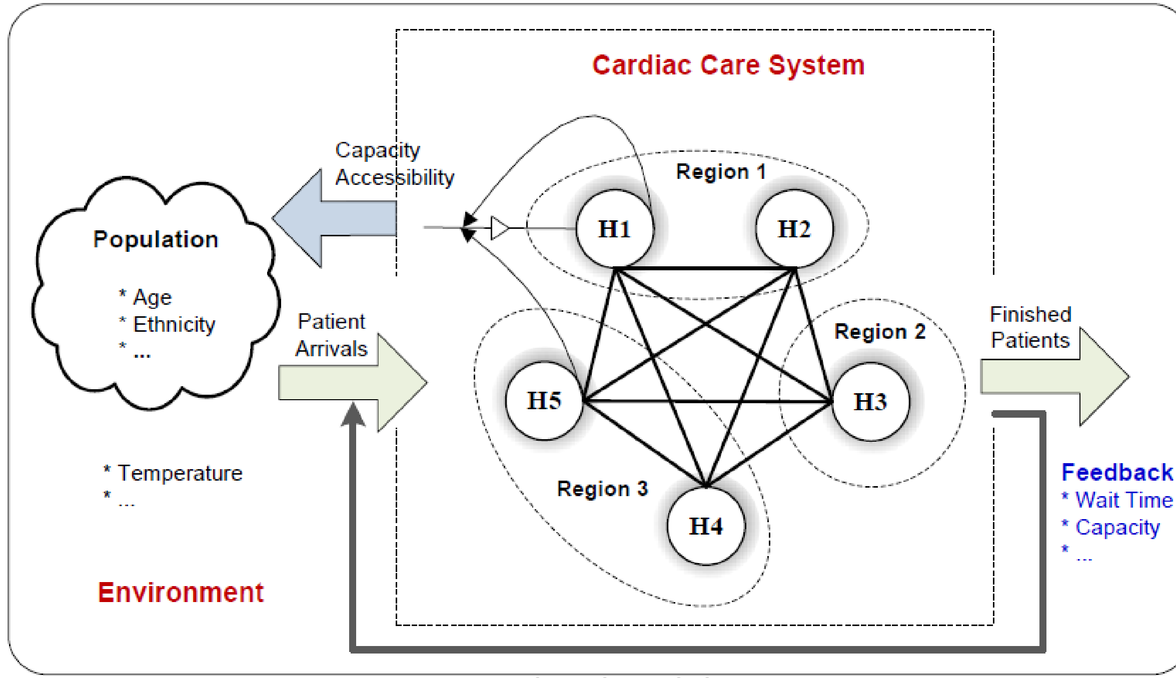
- Dynamically-changing **median wait time**

  (Jan. 2005~Dec. 2006)



Data source: Cardiac Care Network of Ontario (accessed these data in February 2011)

A Complex Systems Perspective



An open, complex health care system

Important Issues

❖Wait Time Dynamics

✓Capacity

✓Management (scheduler) strategies

✓Cross-unit wait time cascade effects

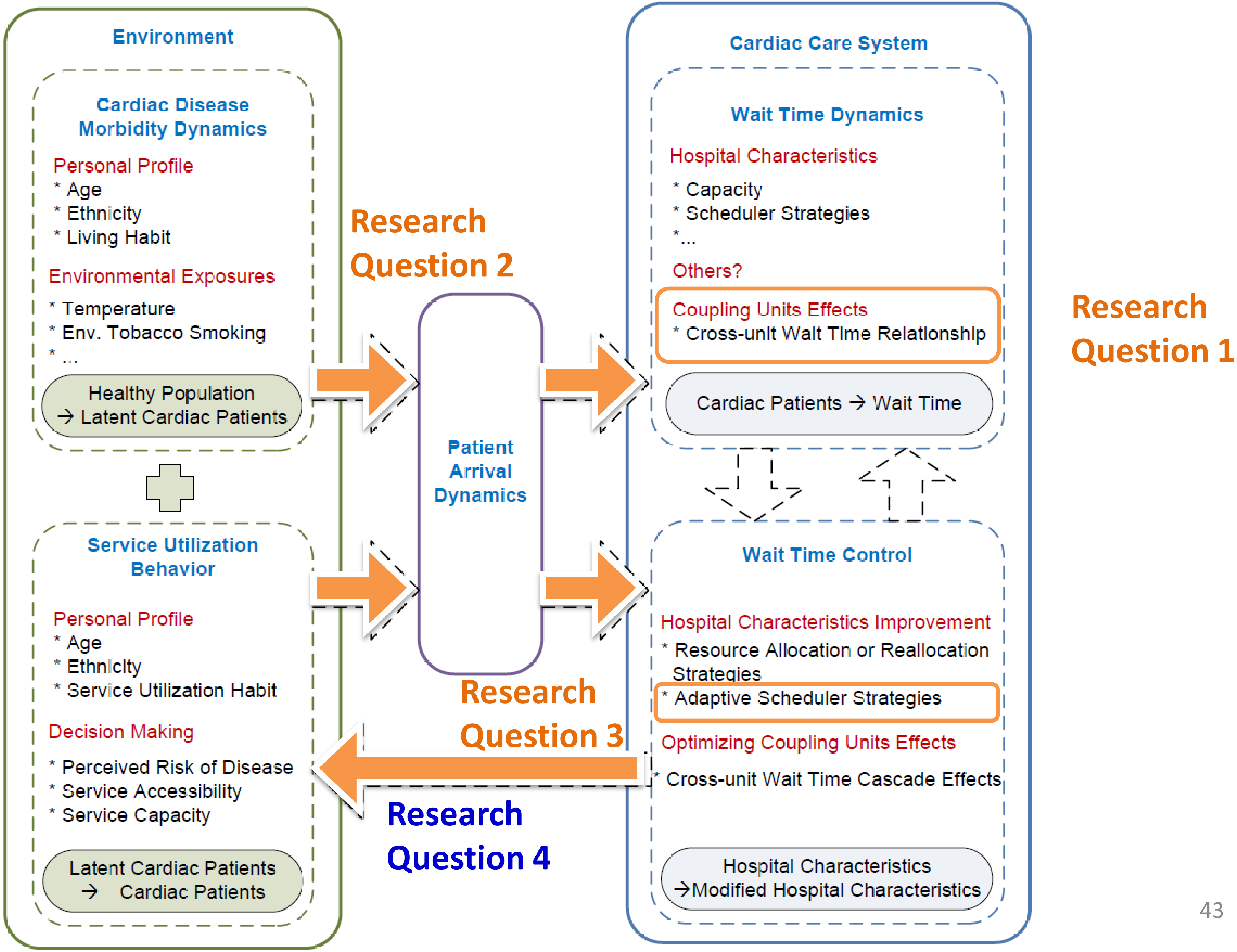
❖Patient Arrival Dynamics

✓Population profiles → "Latent" patients

✓Environmental factors → "Latent" patients

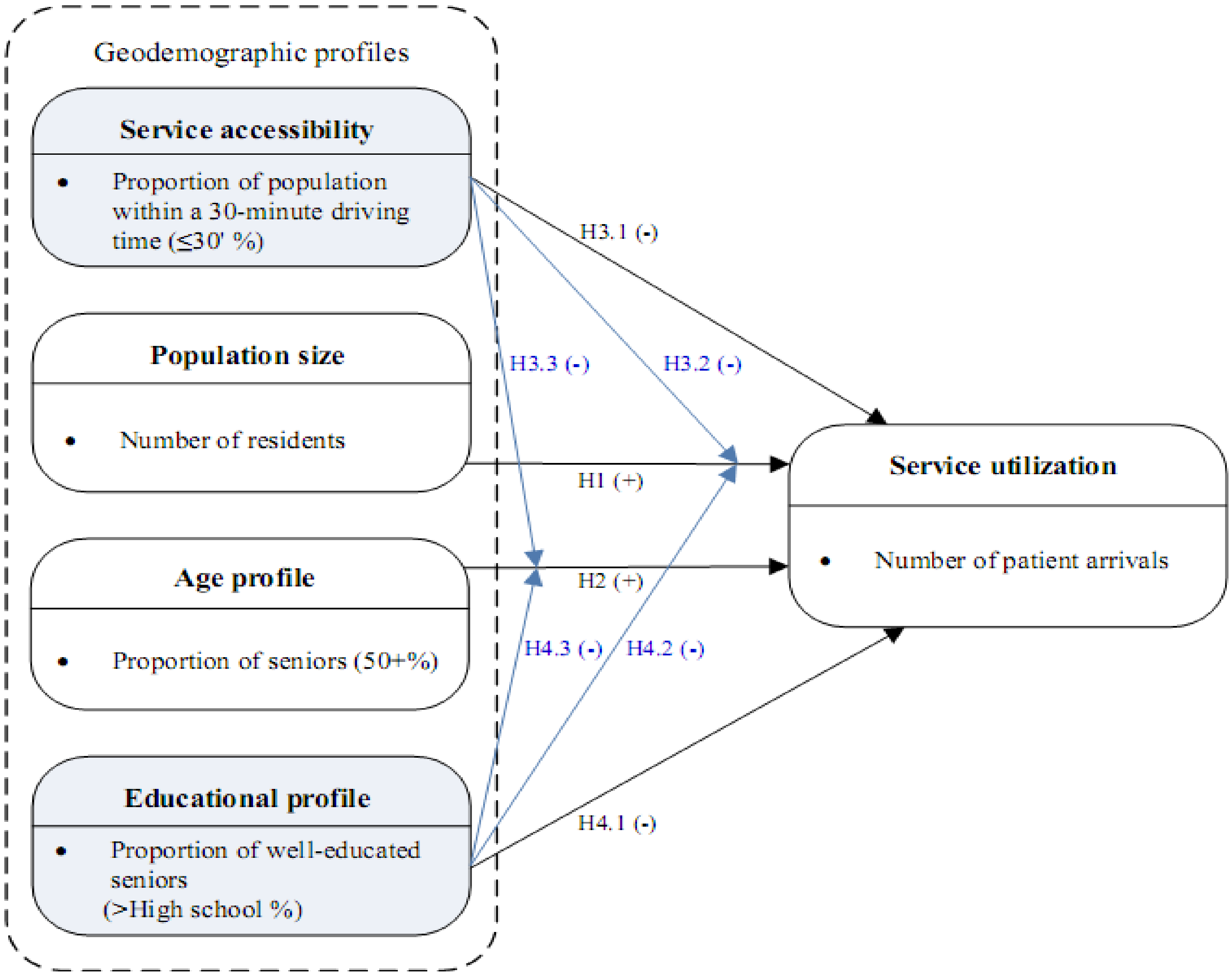
✓ Patient decision making (profile, environmental factors) → Patient arrivals

The Complexity of Wait Time Management



Question: **Can we observe any *direct* and *moderating* effects of geodemographic profiles on *service utilization* *(patient arrivals)*?**

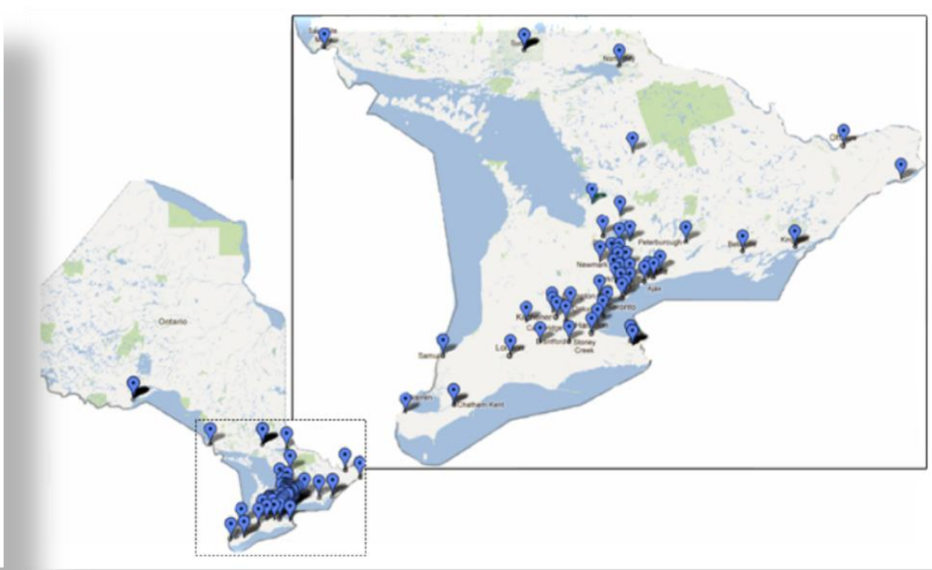
❖ Research hypotheses



Data

- Data Source
  - 11 CCN hospitals (2004-07): Cardiac Care Network of Ontario
  - Geodemography data for LHINs: 2006 Census of Canada
    - 47 cities/towns (no. population>40,000)

Sample hospitals in Ontario, Canada



Sample cities in Ontario, Canada

Method

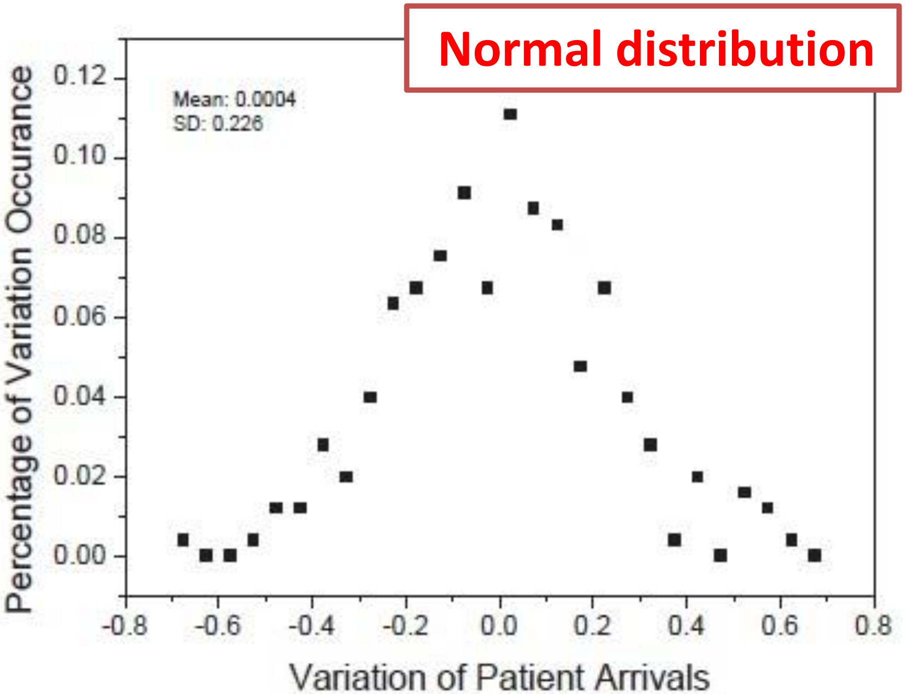
- Structural Equation Modeling (SEM)[Byrne, 09]
  - A second-generation statistic technique
- Features of SEM[Gefen,00]
  - Structural: To validate the assumed causation among a set of dependent and independent constructs
  - Measurement: To evaluate the loadings of observed items on their expected latent variables
- Partial-least-squares based SEM[Gefen,00] vs. Covariance based SEM
  - Efficient to examine the significance of the relationships of constructs
  - More suited for predictive applications and theory building

[Byrne, 09] B. M. Byrne. *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming (2nd).* Routledge, 2009.
[Gefen, 00]D. Gefen. Structural Equation Modeling and Regression: Guidelines for Research Practice. Communications of the Association for Information Systems, 4(7), 2000.

Self-Organized Regularities in the Cardiac Care System (1)

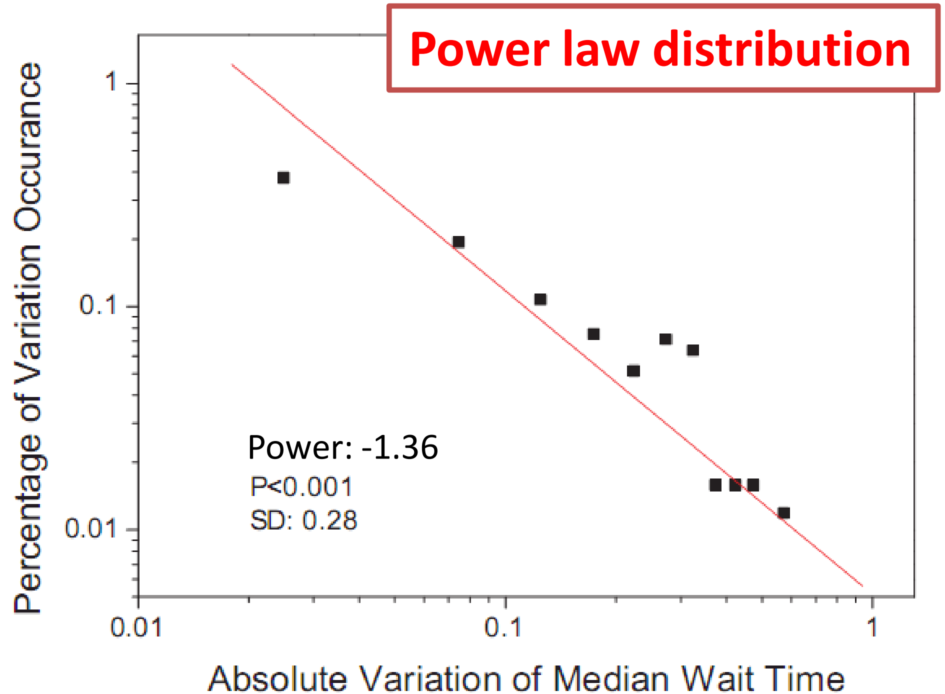
(Statistical regularities?)

- month-to-month **arrival variations**



$$v_{t+1} = \frac{x_{t+1} - x_{min}}{x_{max} - x_{min}} - \frac{x_t - x_{min}}{x_{max} - x_{min}}$$

- month-to-month **absolute variations** for median **wait time**



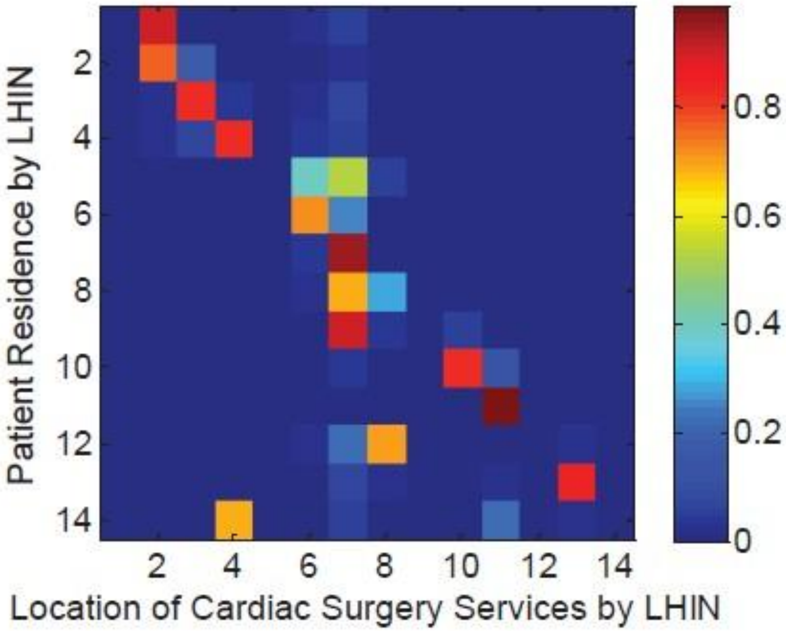
$$|v_{t+1}| = \left| \frac{x_{t+1} - x_{min}}{x_{max} - x_{min}} - \frac{x_t - x_{min}}{x_{max} - x_{min}} \right|$$

Data source: Cardiac Care Network of Ontario (accessed these data in February 2011)

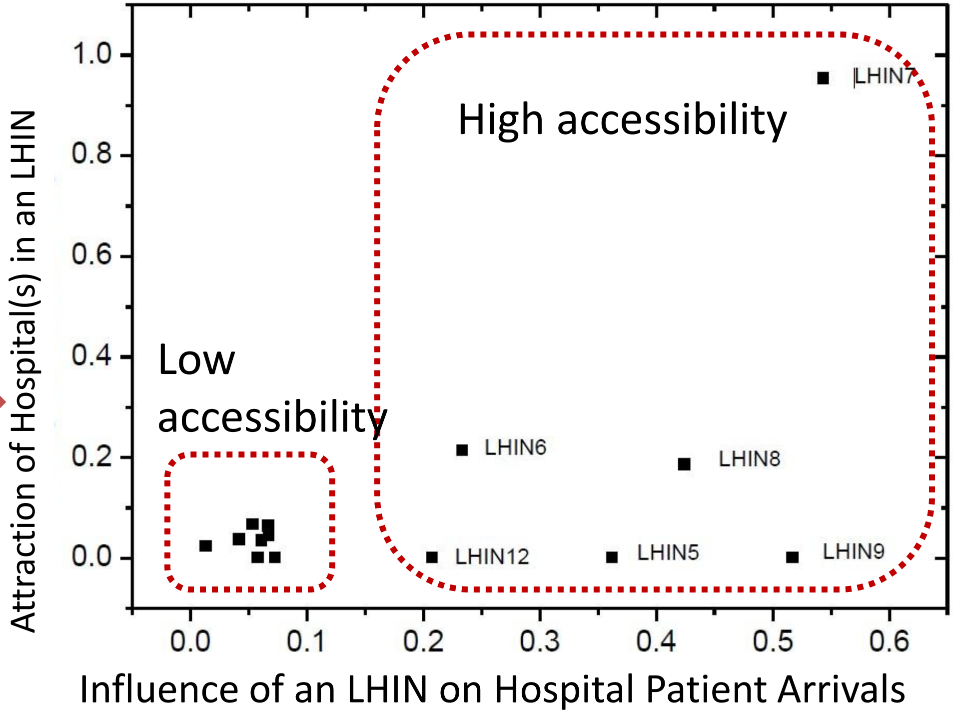
Self-Organized Regularities in the Cardiac Care System (2)

(Spatial patterns?)

- Patient flow distribution



- Function classification for LHINs



How to understand such emergent self-organized regularities?

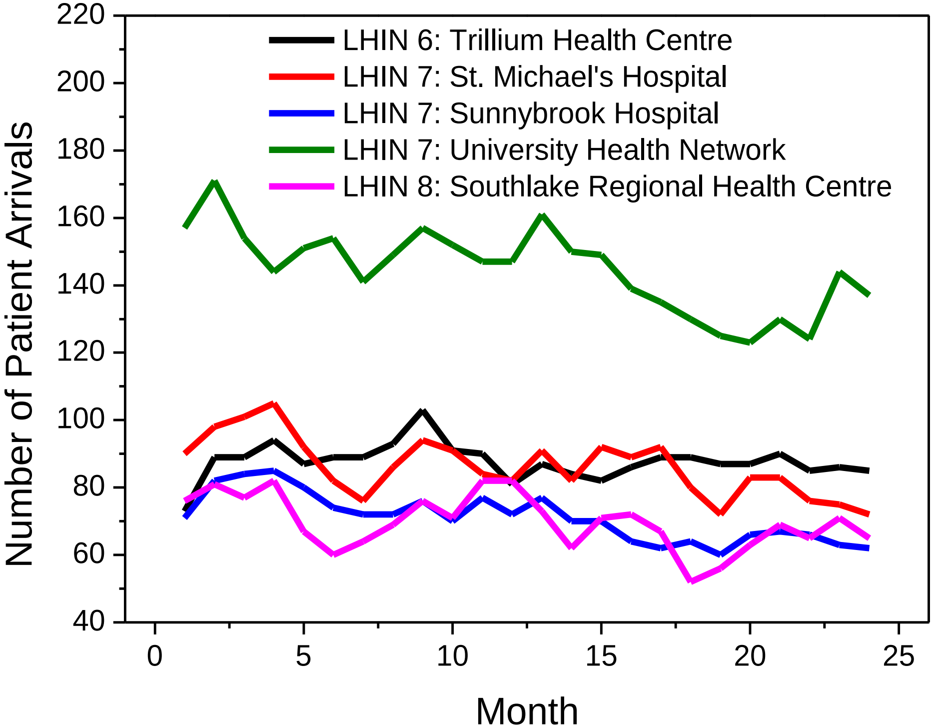
Data Source: CCN Annual Report 2007/2008: Cardiac Care Network----Moving Forward.
http://www.ccn.on.ca/ccn_public/UploadFiles/files/CCN%202007-2008%20Annual%20Report.pdf

Self-Organized Regularities in the Cardiac Care System (3)

(Tempo-spatial patterns?)

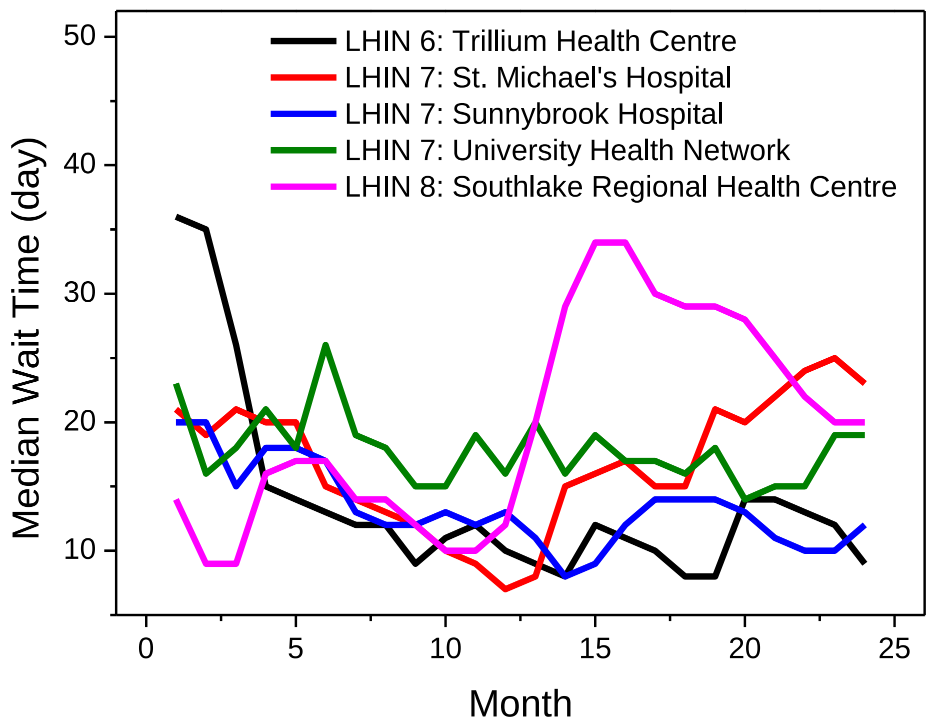
- Dynamically-changing **arrivals**

(Jan. 2005~Dec. 2006)



- Dynamically-changing **median wait time**

(Jan. 2005~Dec. 2006)



Data source: Cardiac Care Network of Ontario (accessed these data in February 2011)

Question:

How to understand the emergent self-organized regularities?

Scales

Biological Environmental Socioeconomic

Mu

Impa

- Weath
- Patient
- Geogra for healthcare
- Hospital resou
- Hospital perfor
- Patient/ selecti

Indicators

No. arrivals

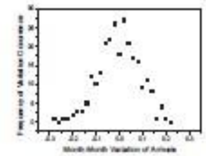
No. throughput

Average/Median wait time

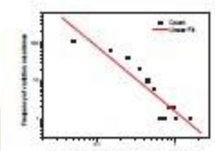
Average queue length

mpo-Spatial Patterns

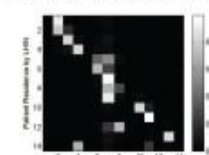
Self-organized patient arrivals regularity



Self-organized wait time regularity



ial patient flow pattern



Challenge

How to model, simulate, reproduce, and explain?

healthcare systems?

✓How do these self-organized regularities

Solution

Modeling and simulating dynamically-changing patient arrivals and wait time in **a complex cardiac surgery system based on AOC**

How to capture the heterogeneity of patients

Interactions

What are the interrelationships or local feedback loops among the impact factors and variables?

Modeling Method: Autonomy-Oriented Computing

- Steps in AOC modeling:

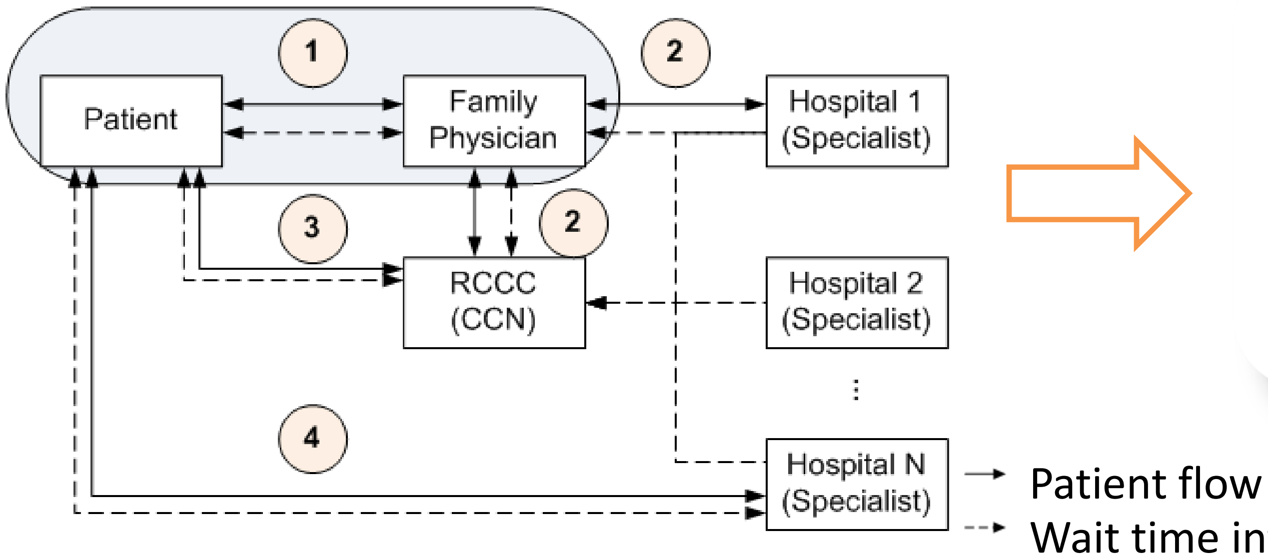
1. **Real-world observations:** Self-organized regularities/patterns in a real system
2. **Identify and design entities**: Synthetic behaviors, impact factors, local feedback loops, and an environment where entities reside
3. **Modeled system observations:** Self-organized regularities/patterns emerging from the modeled system
4. **Validation:** Behaviors of the system vs. the real-world counterpart
5. **Explanation:** Explaining the regularities/patterns with the "white-box" model

•Jiming Liu, Xiaolong Jin, and KC Tsui, *Autonomy Oriented Computing (AOC): From Problem Solving to Complex Systems Modeling*, Kluwer/Springer, 2005.
•Jiming Liu, "Autonomy-oriented computing (AOC): The nature and implications of a paradigm for self-organized computing." *Natural Computation, 2008. ICNC'08. 4th International Conference on*. Vol. 1. IEEE, 2008 (Keynote).

AOC-Based Model (1)

➢ Entity identification

✓ Hospital selection by a cardiac surgery patient



Entities

✓ Patient

✓ GP

✓ Hospital

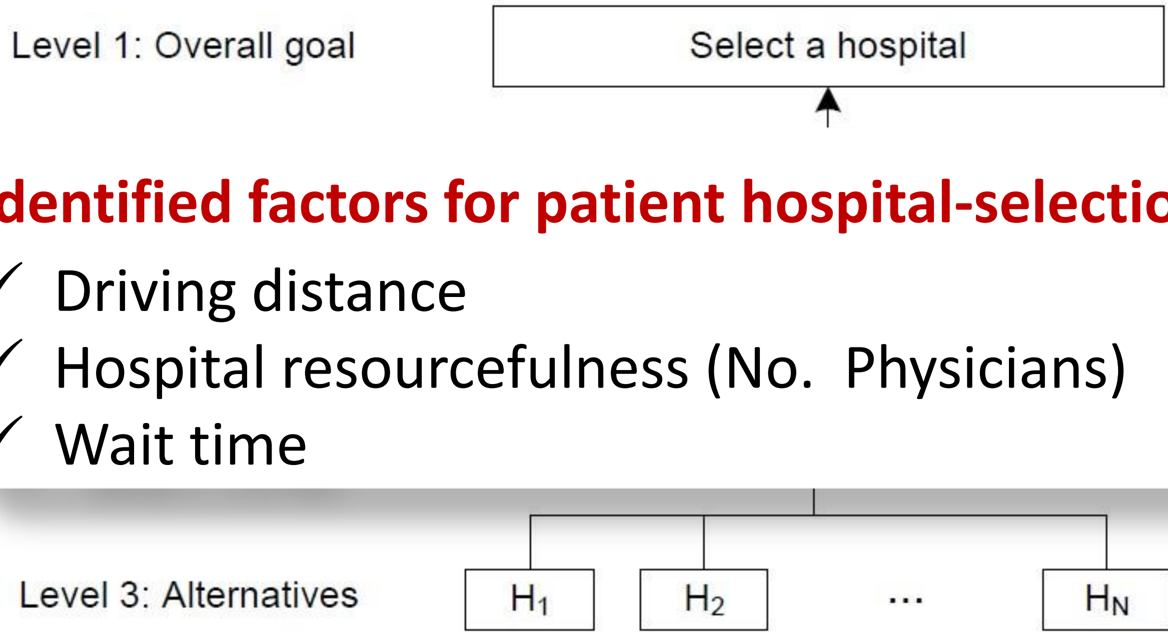
- 93% population in Ontario have GP (http://www.health.gov.on.ca/en/news/release/2012/may/nr_20120507_1.aspx)
- GP is the "gatekeeper" for referrals to cardiac surgery [Chan99]

[Chan99] Ben Chan. Access to Physician Services and Patterns of Practice. In: Naylor D, Slaughter P eds. Cardiovascular Health and Services in Ontario. 1999.
http://www.ices.on.ca/webpage.cfm?site_id=1&org_id=67&morg_id=0&gsec_id=0&item_id=1390&type=atlas

AOC-Based Model (2)

- **Major impact factor identification**

✓ Multi-attribute analysis



Identified factors for patient hospital-selection behaviors

- ✓ Driving distance
- ✓ Hospital resourcefulness (No. Physicians)
- ✓ Wait time

[CCN05] Cardiac Care Network of Ontario. Cardiac Care Network of Ontario Patient, Physician and Ontario Household Survey Reports: Executive Summaries. 2005.

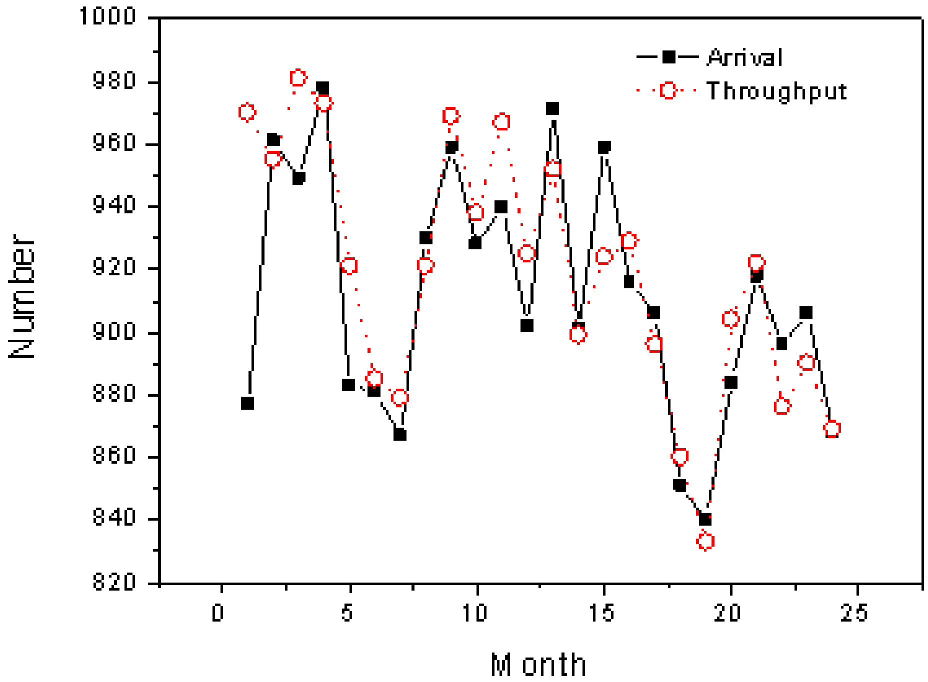
[Harindra10]Harindra C Wijeysundera, Therese A Stukel, Alice Chong, Madhu K Natarajan, David A Alter. Impact of clinical urgency, physician supply and procedural capacity on regional variations in wait times for coronary angiography. *BMC Health Services Research* 2010, 10:5.

[Grace08] Sherry L Grace, Shannon Gravely-Witte, Janette Brual, Neville Suskin, Lyall Higginson, David Alter, and Donna E Stewart. Contribution of patient and physician factors to cardiac rehabilitation referral: a prospective multilevel study. Nat Clin Pract Cardiovasc Med. 5(10): 653–662, 2008. doi:10.1038/ncpcardio1272.

AOC-Based Model (3)

➢ Major impact factor identification

- For hospital service adjustment: **Accumulated arrivals**



Relationship between patient arrivals and throughput of cardiac surgery services in Ontario

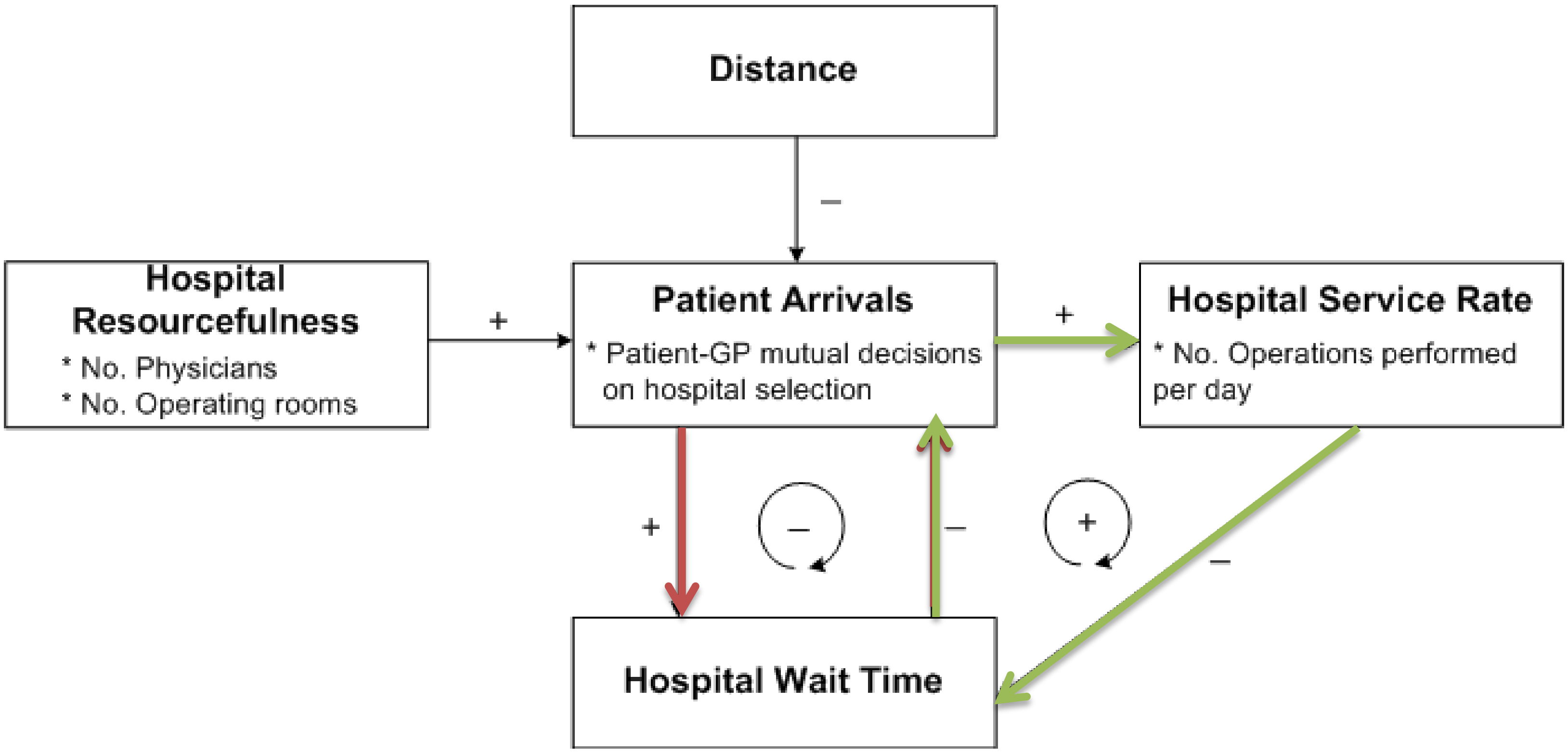
(Jan. 2005~Dec. 2006)

- Supporting observations:
  - ✓ Linear positive relationship between accumulated arrivals and throughput
  - ✓ Correlation between patient arrivals and throughput: 0.896** ($p<0.001$)

Data source: Cardiac Care Network of Ontario (accessed these data in February 2011)

AOC-Based Model (4)

➢ **Two local feedback loops**



AOC-Based Model (5)

➢ Environment ***E***: maintains information (e.g., distance, hospital resourcefulness, wait time) for patients and GPs

Definition 1: City-Hospital Network $CH = (C, H, D)$, where $C(N) = \{c_i\}$ $(i \in [1, N])$ and $H(M) = \{h_j\}$ $(j \in [1, M])$ are two node sets, $H \cap C = \emptyset$; $D = \{d_{ij}\}$ $(i \in [1, N], j \in [1, M])$ is a set of weighted edges.

➢ Entity ***General Physician*** (*GP*): makes hospital selection decisions on behalf of patients based on hospital-selection behavior rules

➢ Entity ***Patient***: records the information (e.g., profile, join in and exit time for services) for an individual patient

➢ Entity ***Hospital***: provides cardiac surgery services based on an M/M/1 queueing model and service adjustment behavior rules

AOC-Based Model (6)

- Stylized facts:
  - ✓ (1) Distance ↓ → arrival probability ↑
  - ✓ (2) No. physicians ↑ → arrival probability ↑
  - ✓ (3) Wait time ↓ → arrival probability ↑
  - ✓ (4) A large pro… pat… ow information for…

Driving time from city *i* to hospital *j*

No. physicians in hospital *j*

Reference wait time for hospital j at time step τ

- Behavior rules for patient… P hospi… selection

• DHW-rule: $a_{ij,\tau} = p * f(d_{ij}) * f(s_j) * f(w_{j,\tau})$

Arrival probability of patients in city *i* to hospital *j* at time step τ

$$f(d_{ij}) = \frac{d'_{ij}}{\sum_{h_k \in H} d'_{ik}} \qquad f(s_j) = \frac{s_j^{\alpha_s}}{\sum_{h_k \in H} s_k^{\alpha_s}}$$

$$d'_{ij} = \frac{\sum_{h_k \in H} \ldots^{\alpha_d}}{d_{i\ldots}^{\alpha\ldots}} \qquad f(w_{j,\tau}) = \frac{\sum_{h_k \in H} w_{k,\tau}^{\alpha_w}}{w_{j,\tau}^{\alpha_w}}$$

Adjustment parameters

• DH-rule … $f($

Accumulative patient arrivals, i.e., queue length, of hospital *j* at the end of week

Mean patient arrivals in a week

- Behavior rules for hosp… service-…e adjustment

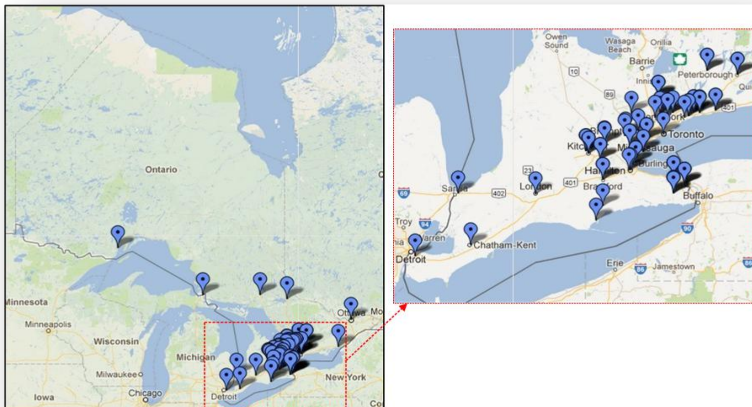
Service rate of hospital *j* at week $\tilde{T}$

$$\mu_{j,\tilde{T}} = \left(\frac{a_j A_{j,\tilde{T}-1}}{\bar{A}_j} + b_j\right) * \bar{\mu}_j$$

Mean service rate in a week

AOC-CSS Model-Based Simulation

- Simulated cities: 47 cities/towns with population >40,000 in 2006
- Simulated hospitals: 11 hospitals in Ontario providing cardiac surgery services
- Driving time estimation: Google map



- Simulation time period: Jan. 2005~Dec. 2006
- Simulation settings:
  - *p*: cities in LHINs 5-9 and LHIN 12: 0.2 — High service accessibility

    cities in LHINs 1-4, 10-11, 13-14: 0.1 — Low service accessibility
  - Estimated parameter values from empirical data :
    - Distance power: 3.5
    - Physician power: 1
    - Wait time power: 1
- Simulation runs: 1000

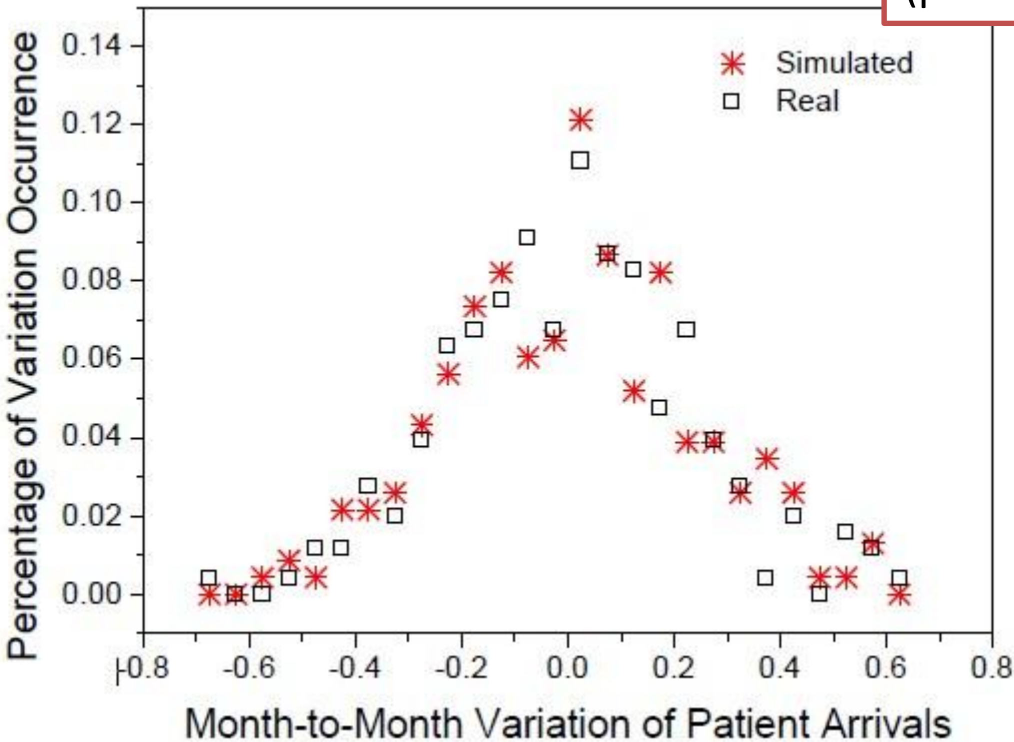
Results (1)

- **Statistical regularities** as observed from simulation

➢ month-to-month **arrival variations**

Normal distribution

(passed the Kolmogorov-Smirnov test)



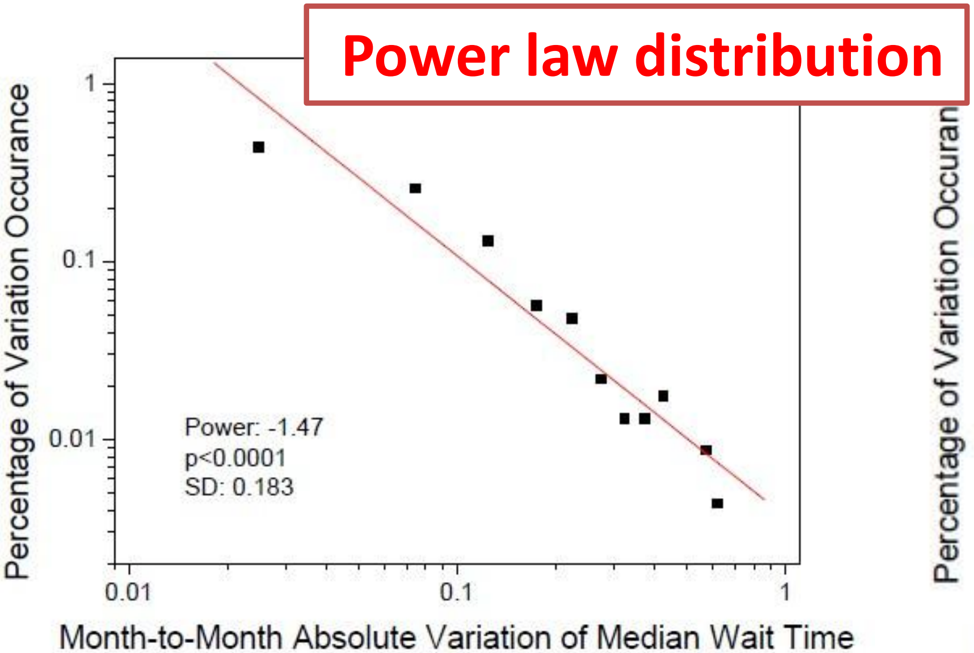
Distributions of simulated and real-world arrival variations

- Real
  - ✓ Mean: 0.0004
  - ✓ SD: 0.226
- Simulation
  - ✓ Mean: -0.0013
  - ✓ SD: 0.232

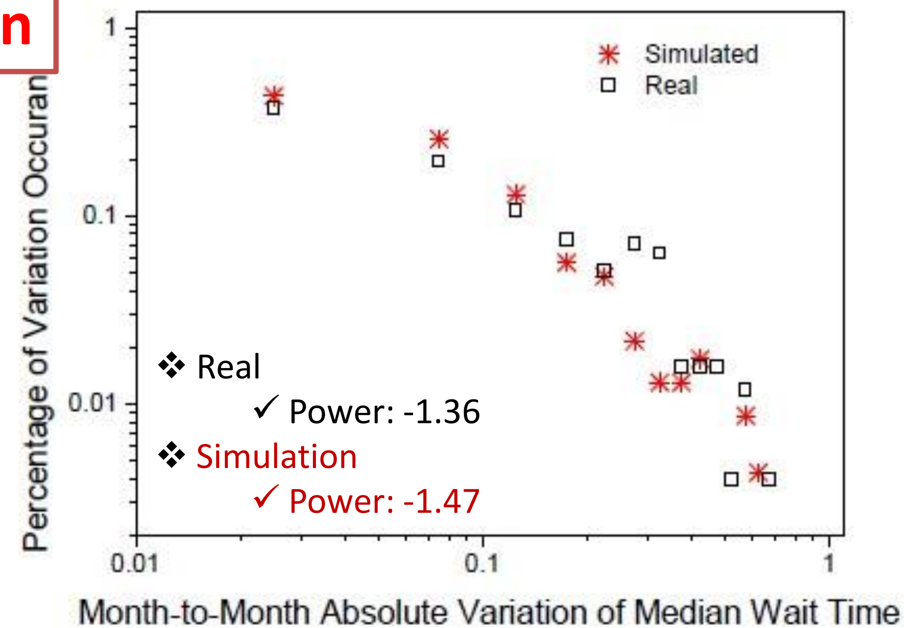
Results (2)

- **Statistical regularities** as observed from simulation

➢ month-to-month **absolute variations of median wait time**



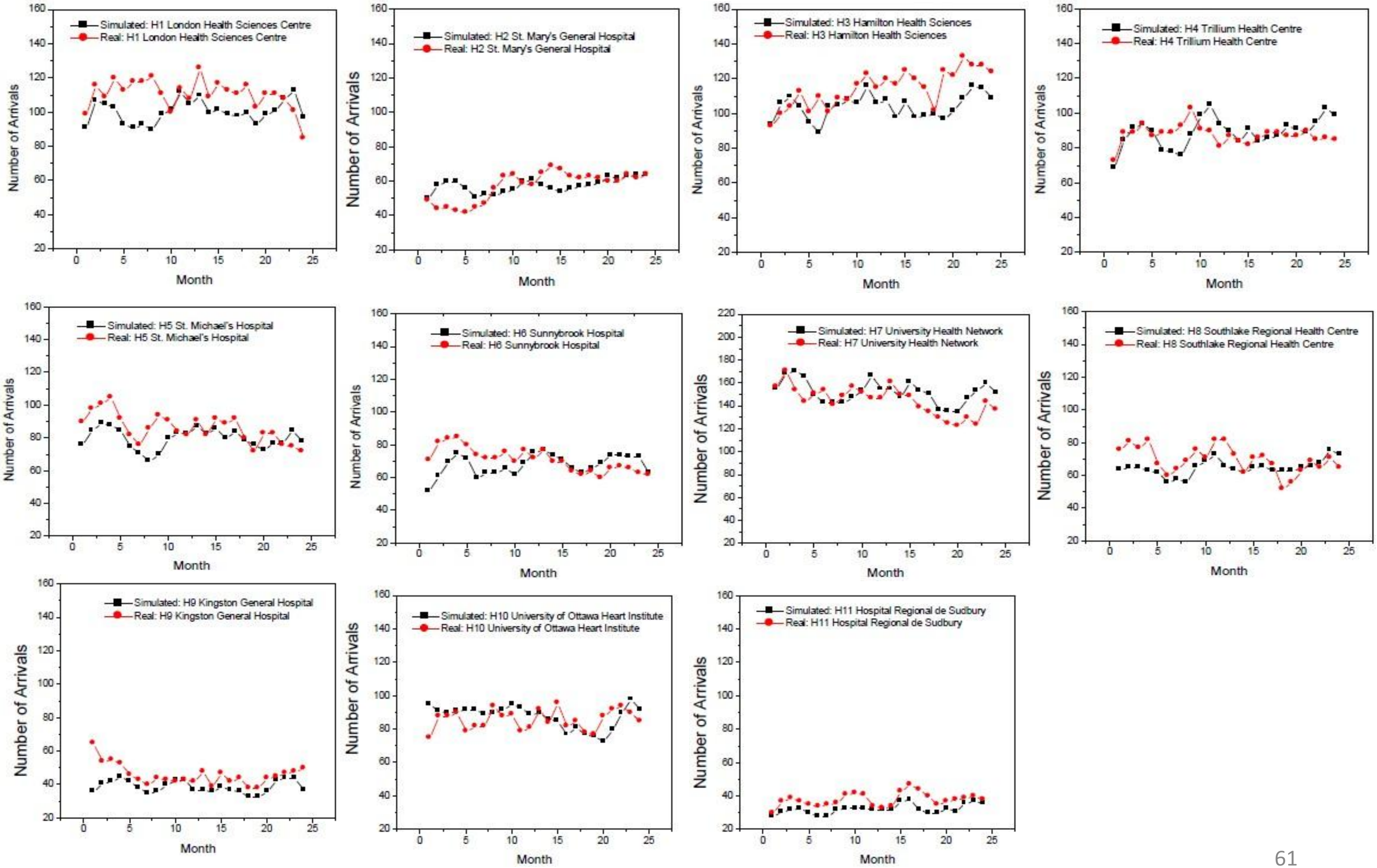
Distribution of simulated absolute variations of median wait time



Distributions of simulated and real-world absolute variations of median wait time

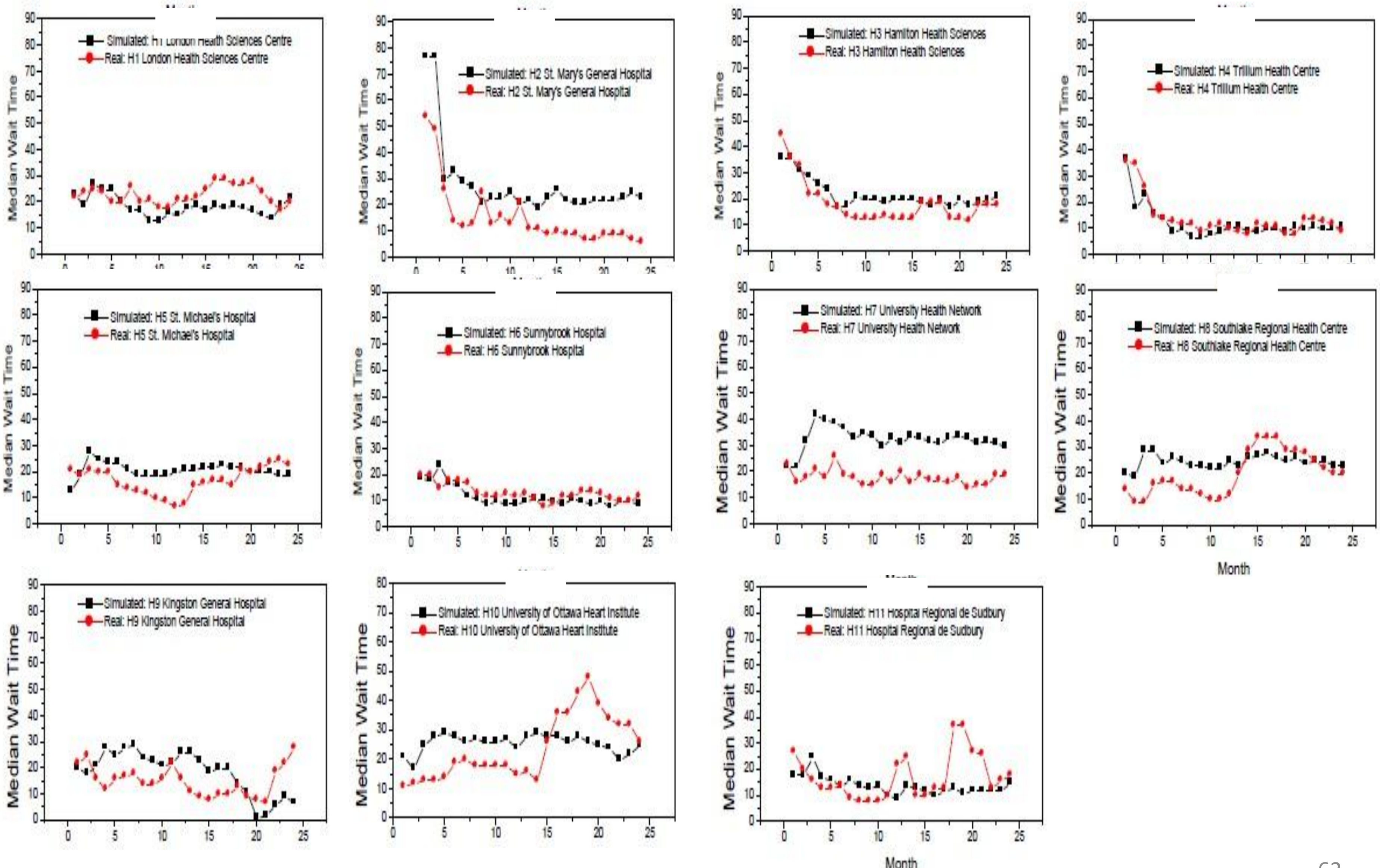
Results (3)

- Temporal patterns of **patient arrivals** in 11 hospitals



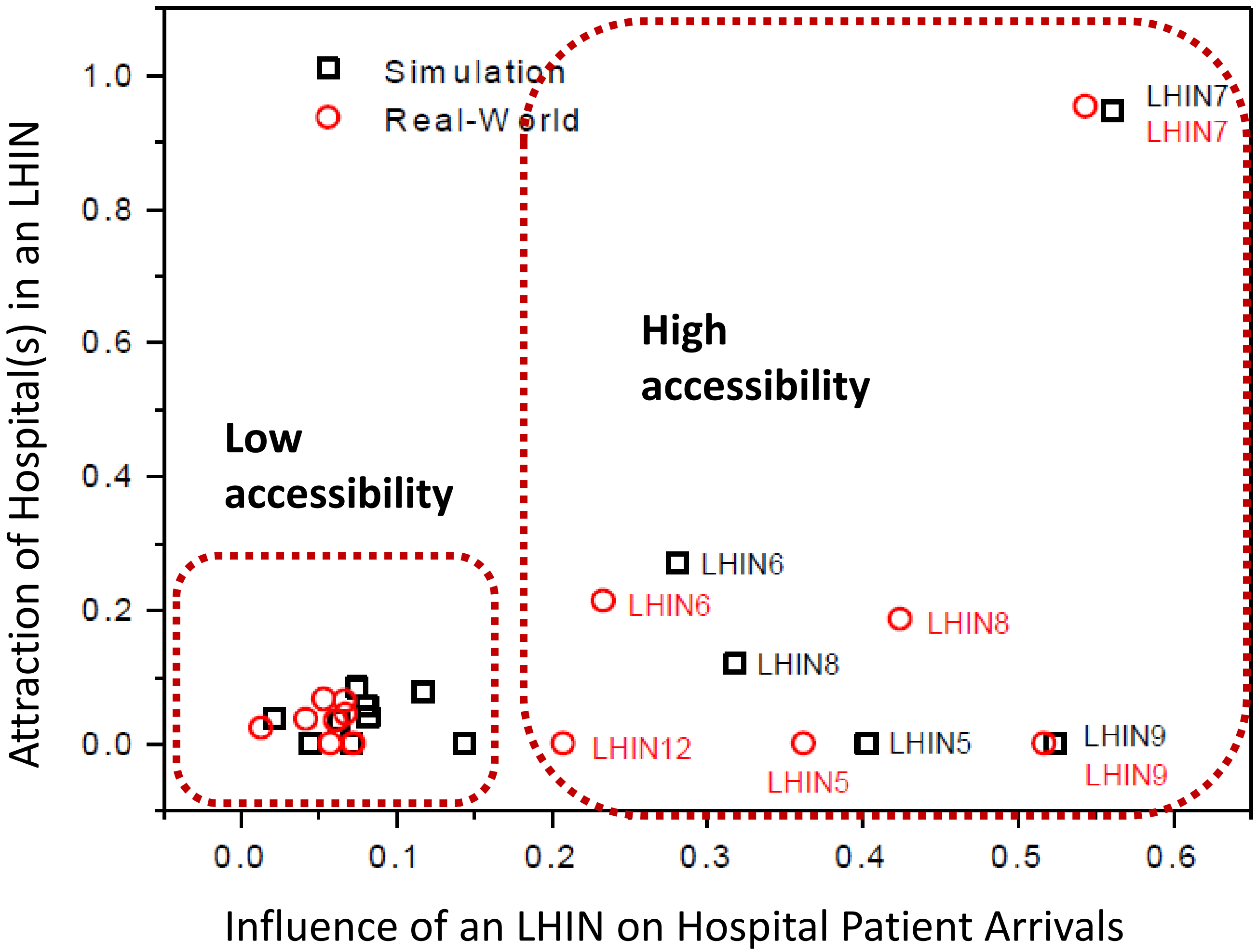
Results (4)

- Temporal patterns of **median wait time** in 11 hospitals

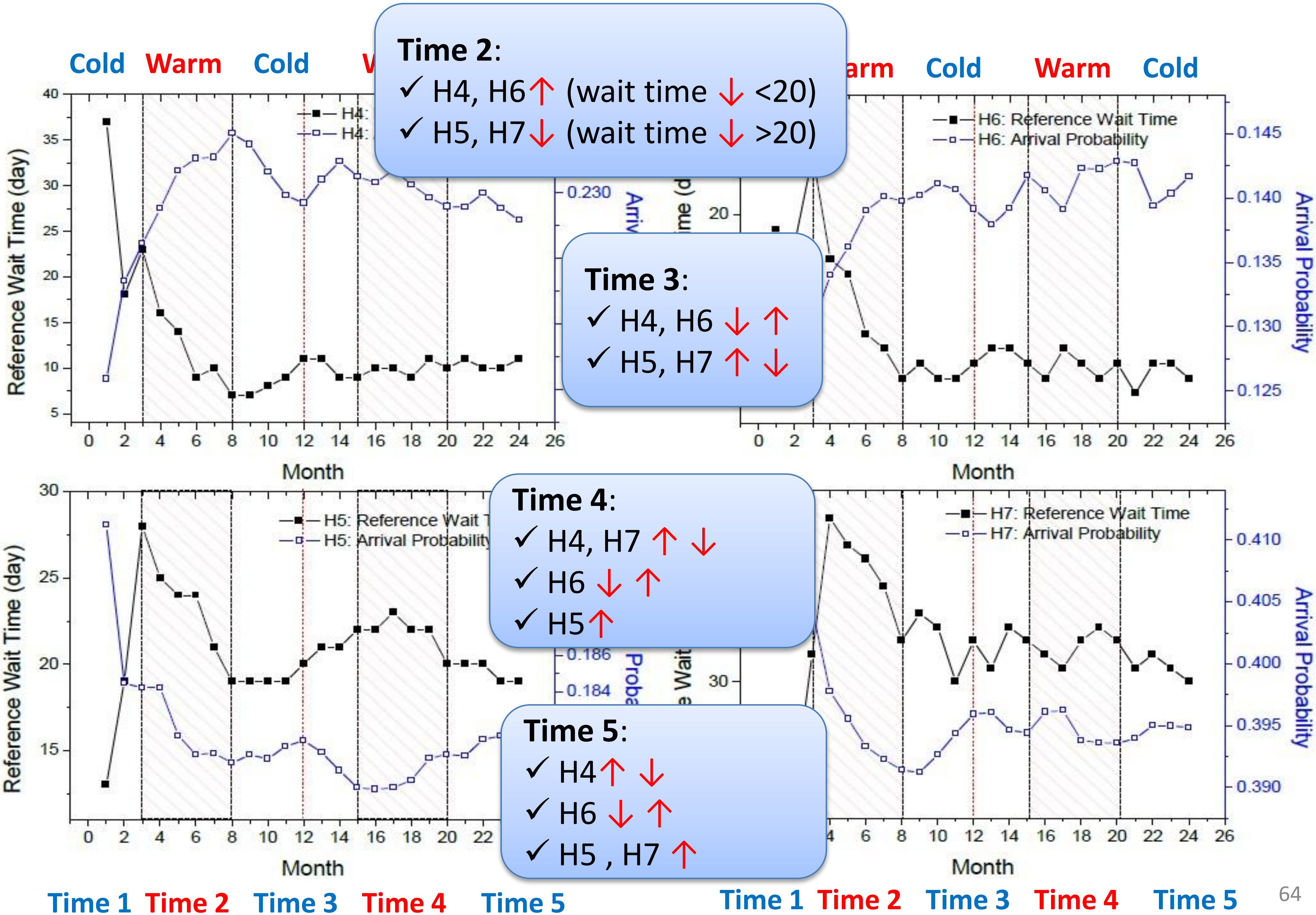


Results (5)

- Accessibilities of LHINs: **real-world** vs. **simulation**



Results (6): Explaining Tempo-Spatial Patterns



FoCAS 'Best Paper Award' @ CoSMoS 2013

FoCAS supported a Best Paper Award at the 6th Complex Systems Modelling and Simulation Workshop (CoSMOS 2013), University of Milano-Bicocca, Italy **1st – 5th July**.

The winner of the FoCAS award for best CAS paper at CoSMoS 2013 was:

Li Tao, **Jiming Liu**: Understanding Self-Organized Regularities: AOC-Based Modeling of Complex Healthcare Systems

Abstract: A healthcare system, as a well-recognized complex system, exhibits certain types of self-organized regularities, such as the statistical distribution of wait-time variations. What remains to be a challenge in understanding a complex healthcare system is how to model and characterize emergent self-organized regularities by taking into account the underlying individual-level behavior (e.g., patient hospital selection

Conclusion

- Real-world healthcare problems involve *interactions* among *impact factors* at *multiple levels and scales*
- Two challenges in Global Healthcare:
  1. **How diseases spread** (at a metapopulation level)
  2. **Why services vary** (with self-organizing behaviors)
- **Complex systems modeling** will play an important role in **evidence-based healthcare** (e.g., decision support)

Thank You!

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Credits:

- Past students: **Benyun Shi, Xia Shang, Li Tao & Xiaofei Yang**
- National Institute of Parasitic Diseases (NIPD), China CDC
- Centre for Health Protection (CHP), Hong Kong SAR

References (Health Informatics):

- Shi, B., Liu, J., Zhou, X.N., and Yang, G.J., Inferring P. vivax transmission networks from tempo-spatial surveillance data. ***PLoS Neglected Tropical Diseases***.
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- Xia, S., and Liu, J., A computational approach to characterizing the impact of social influence on individuals' vaccination decision making. ***PLoS ONE.***
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