Prendre en compte notre environnement fluctuant pour la modélisation des maladies vectorielles.

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Cette intervention est faite en toute indépendance vis-à-vis de l’organisateur de la manifestation.

Je n’ai pas de conflit d’intérêts en lien avec le sujet traité.

Accounting for Non-Stationarity in Epidemmiology

Overview

- **Non-stationarity and transients in Epidemiology**
- Accounting for Non-Stationarity in Statistical Analysis
- Accounting for Non-Stationarity in Modeling

Non-stationarity and transients in Epidemiology

- Modification of pathogens, their transmissibility, their virulence
- Characteristics of the epidemics can evolve due to vaccination or others public health interventions
- Climate can influence the propagation of a pathogen
- Societal responses and/or changing human behavior during the course of an epidemic
    - Changing their social network
    - Social distancing
    - Voluntary avoidance behavior

Non-stationarity and transients in Epidemiology

- Example of measles and whooping cough in UK

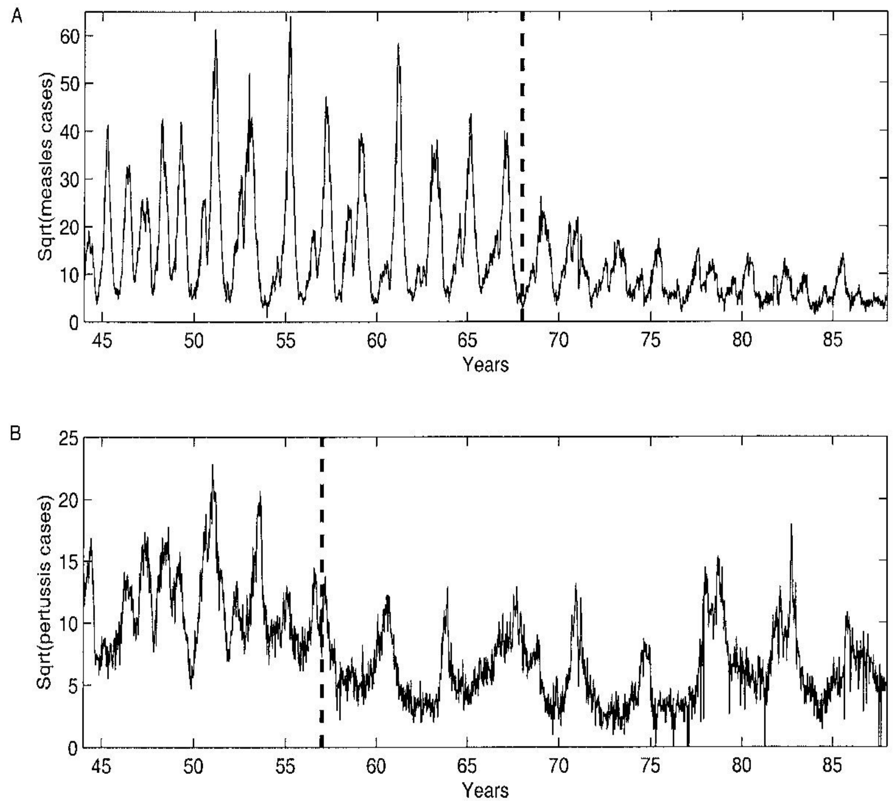
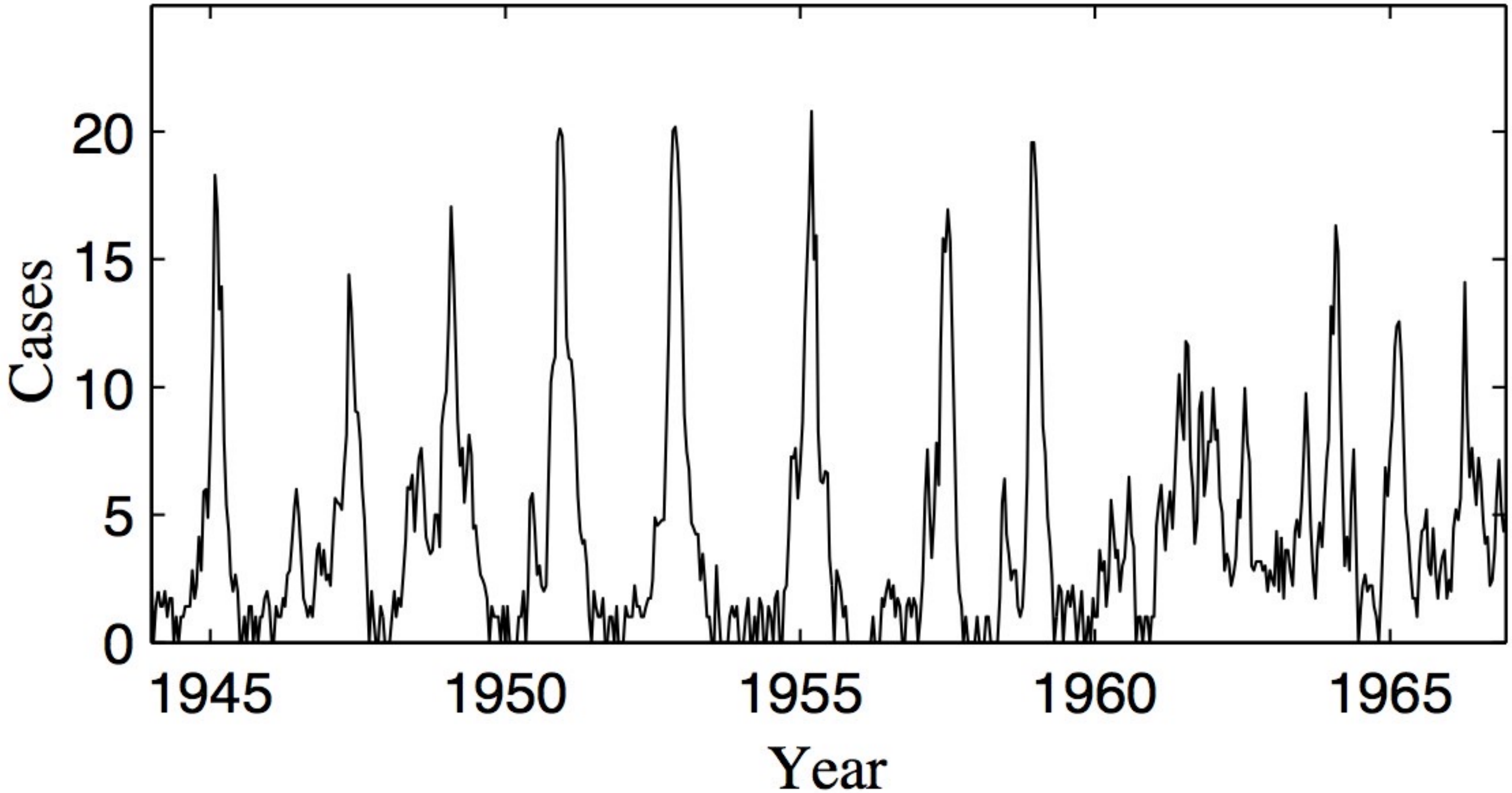


Figure 1: Aggregate measles and whooping cough notifications in England and Wales from 1944 to 1994; data obtained from the Registrar General's Weekly Returns. *A*, Time series for square root of measles cases in England and Wales, with vaccination starting in 1968 (*dotted line*). *B*, Square root of cases of whooping cough in England and Wales, with the onset of national vaccination indicated by the dotted line.

Non-stationarity and transients in Epidemiology

- An example of measles epidemics in York (UK)



Characteristics evolve with time => Non-Stationarity

Overview

- Non-stationarity and transients in Epidemiology
- **Accounting for Non-Stationarity in Statistical Analysis**
- Accounting for Non-Stationarity in Modeling

Accounting for Non-Stationarity in Statistical Analysis

- For statistical approaches I have developed numerous tools using wavelet decomposition
- Wavelet analysis decomposes a signal into **time-space** and **frequency-space simultaneously**
- Wavelet analysis estimates the spectral characteristics of a time series as a function of time

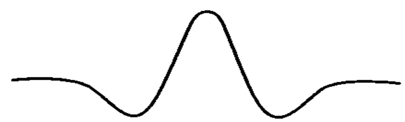
Wavelet Analysis

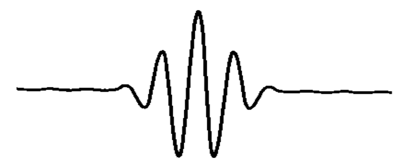
Different wavelet functions

Mexican hat

Morlet

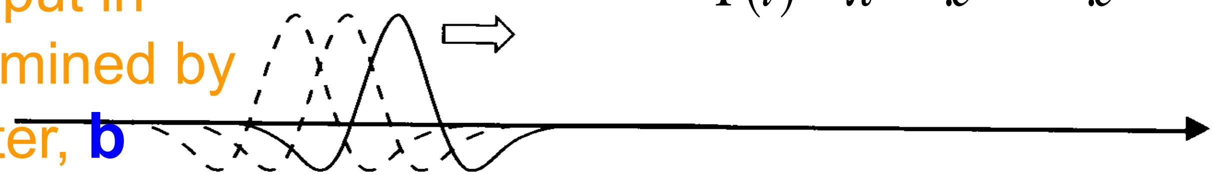
$$\Psi(t) = (1 - t^2).e^{-t^2/2}$$



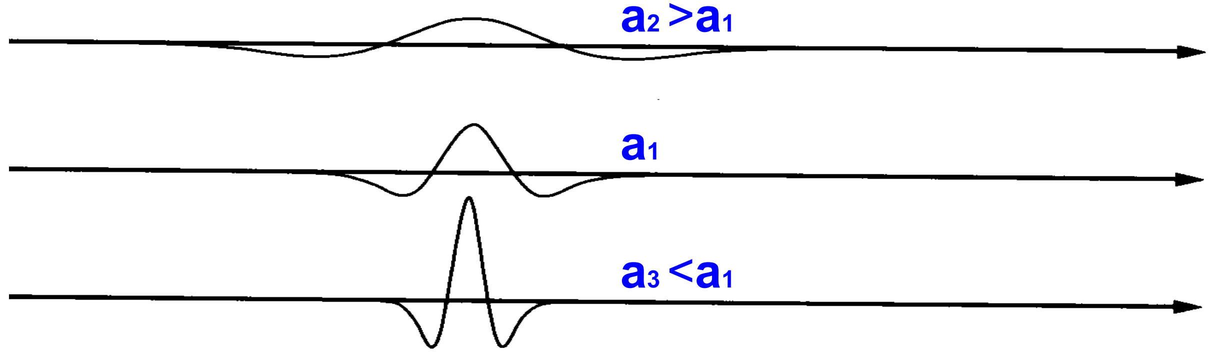


$$\Psi(t) = \pi^{-1/4}.e^{i.2\pi.f_o.t}.e^{-t^2/2}$$

The wavelet function is put in different positions determined by the translation parameter, **b**



and with different dilatation parameter, **a**

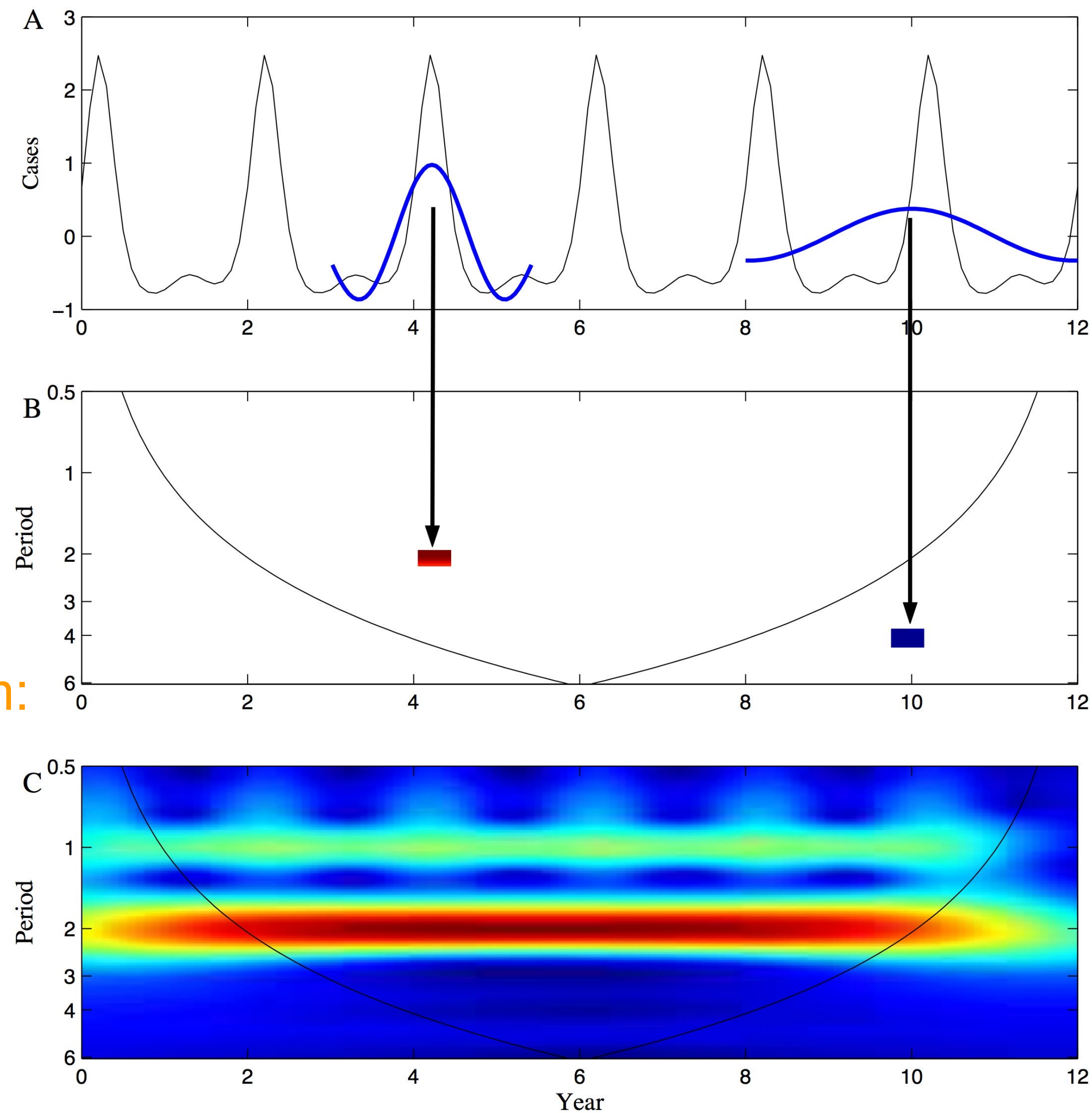


$$\Psi(a,b) = \Psi(\tfrac{t-b}{a})$$

Wavelet Analysis

Wavelet Transform:

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t).\Psi^*\left(\frac{t-b}{a}\right).dt$$



Wavelet Power Spectrum:

$$W_x(a,b) = \left|T(a,b)\right|^2.$$

Wavelet Analysis

Wavelet Transform:
(and Inverse Wavelet Transform)

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t).\Psi^{*}\left(\tfrac{t-b}{a}\right).dt$$

Wavelet Amplitude, Imaginary Part and
Wavelet Modulus:

$$\mathrm{Re}(T(a,b)) \qquad \mathrm{Im}(T(a,b))$$

$$\left|T(a,b)\right|$$

Wavelet Power:

$$W_x(a,b) = \left|T(a,b)\right|^2.$$

Averaged Wavelet Power:
(by analogy with the Fourier Power)

$$P_W(f) = \frac{1}{\tau f_c C_g} \int_0^{\tau} \left|T(a,b)\right|^2.db$$

CrossWavelet Power:

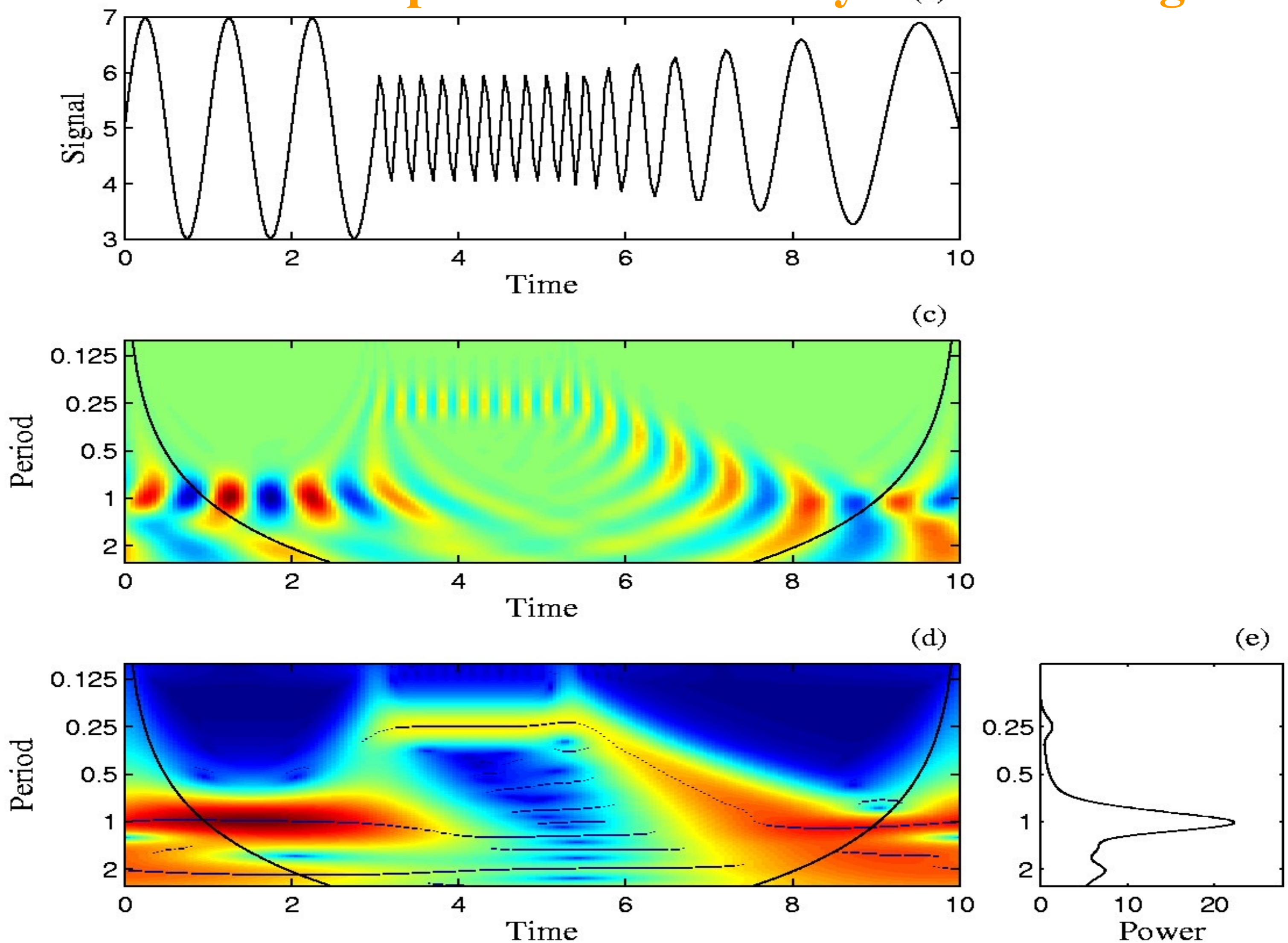
$$W_{xy}(a,b) = \frac{W_x(a,b).W_y(a,b)^{*}}{\sigma_x.\sigma_y}$$

Square Wavelet Coherency:

$$CW_{xy} = \frac{\left|< W_{xy}(a,b) >\right|^2.}{\left|< W_x(a,b) >\right|.\left|< W_y(a,b) >\right|}$$

Wavelet Analysis

A “simple” non-stationary sinusoidal signal



Dengue in Thailand

Travelling waves in the occurrence of dengue haemorrhagic fever in Thailand

Derek A.T. Cummings[1,2], Rafael A. Irizarry[3], Norden E. Huang[4], Timothy P. Endy[5], Ananda Nisalak[6], Kumnuan Ungchusak[7] & Donald S. Burke[2]

[1] *Department of Geography and Environmental Engineering, Johns Hopkins University, Baltimore, Maryland 21218, USA*
[2] *Department of International Health, and* [3] *Department of Biostatistics, Johns Hopkins Bloomberg School of Public Health, Baltimore, Maryland 21205, USA*
[4] *Laboratory for Hydrospheric Processes/Oceans and Ice Branch, NASA Goddard Space Flight Center, Greenbelt, Maryland 20771, USA*
[5] *Virology Division, United States Army Medical Research Institute in Infectious Disease, Fort Detrick, Maryland 21702, USA*
[6] *Department of Virology, Armed Forces Research Institute of Medical Sciences, Bangkok 10400, Thailand*
[7] *Bureau of Epidemiology, Ministry of Public Health, Nonthaburi 11000, Thailand*

Dengue fever is a mosquito-borne virus that infects 50–100 million people each year[1]. Of these infections, 200,000–500,000 occur as the severe, life-threatening form of the disease, dengue haemorrhagic fever (DHF)[2]. Large, unanticipated epidemics of DHF often overwhelm health systems[3]. An understanding of the spatial–temporal pattern of DHF incidence would aid the

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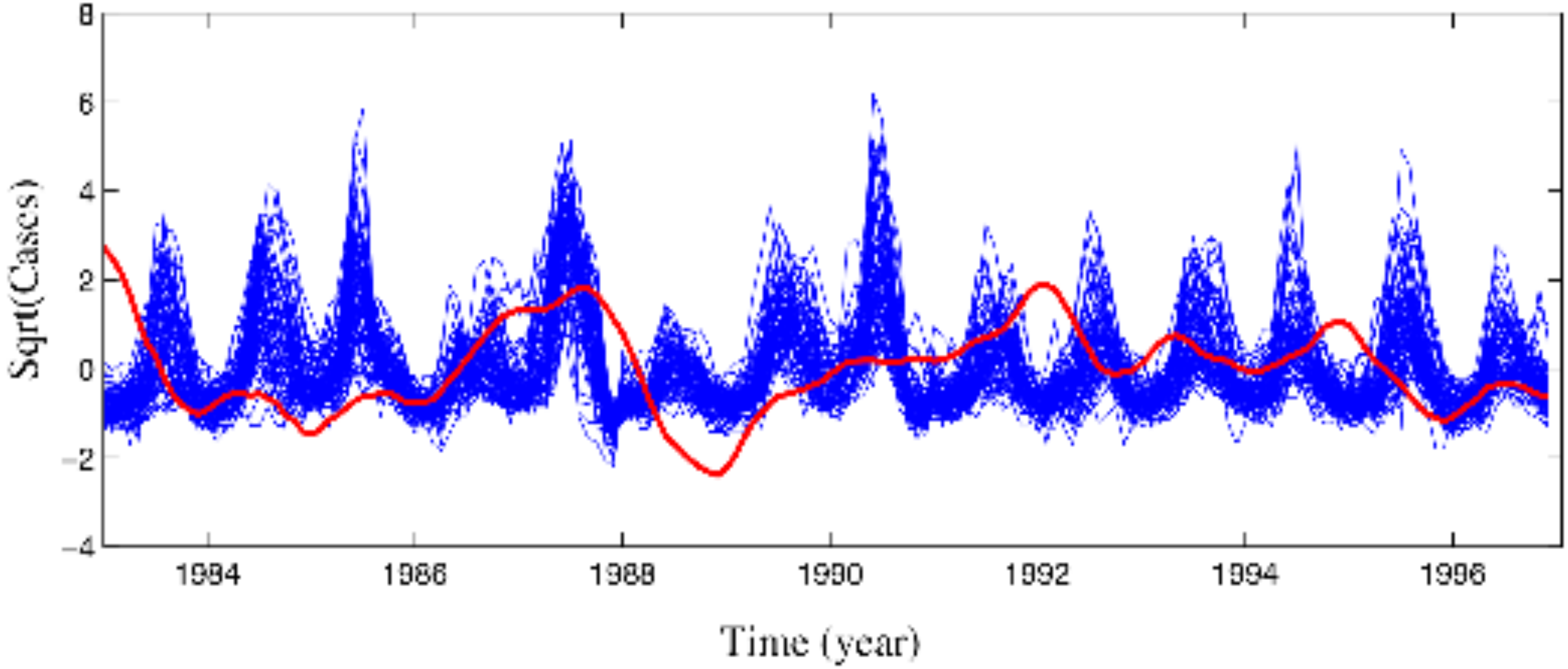
But any links with climate!

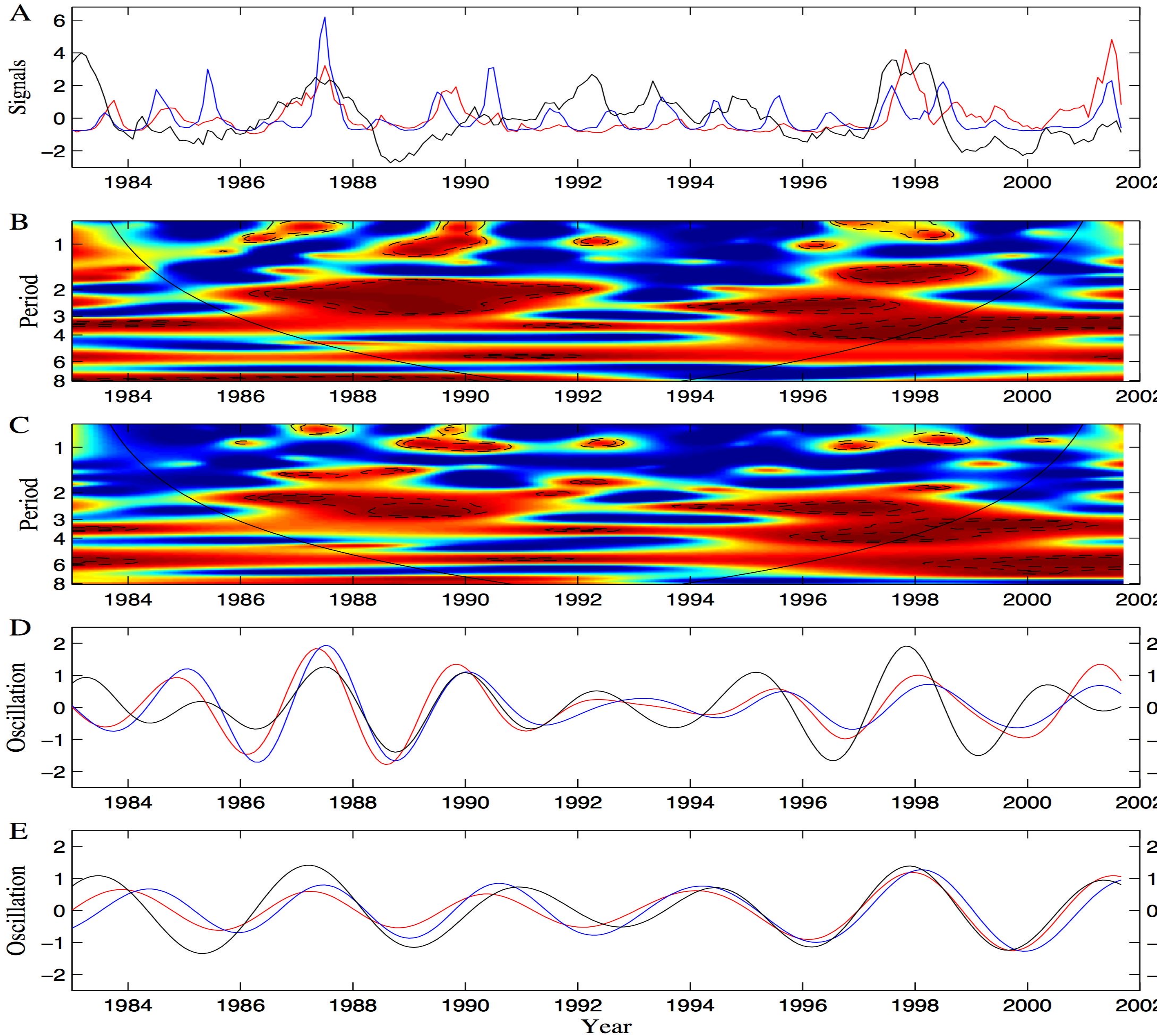
Dengue in Thailand



- Monthly DHF cases reported in the 76 provinces of Thailand
- Focus on the incidence in Bangkok and the averaged incidence for the rest of Thailand

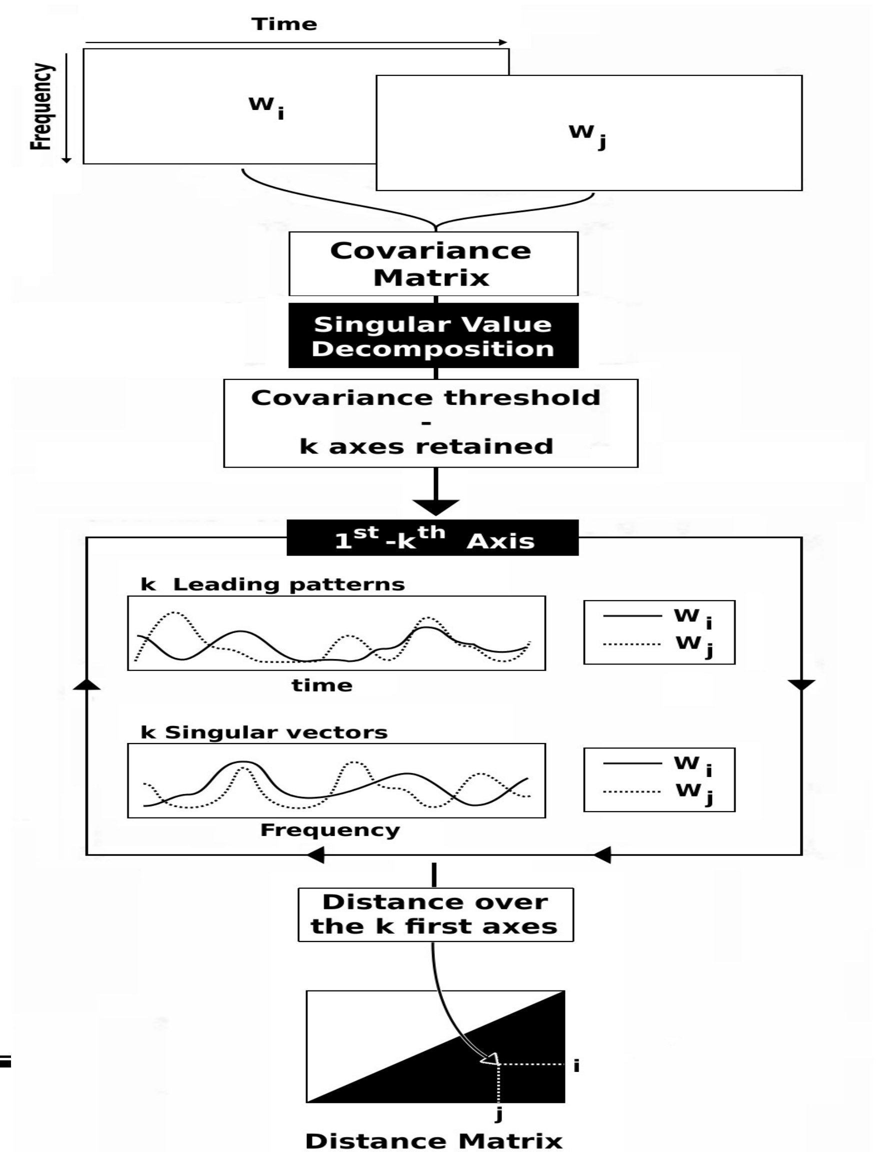
Wavelet Coherency

Dengue in Thailand and ENSO



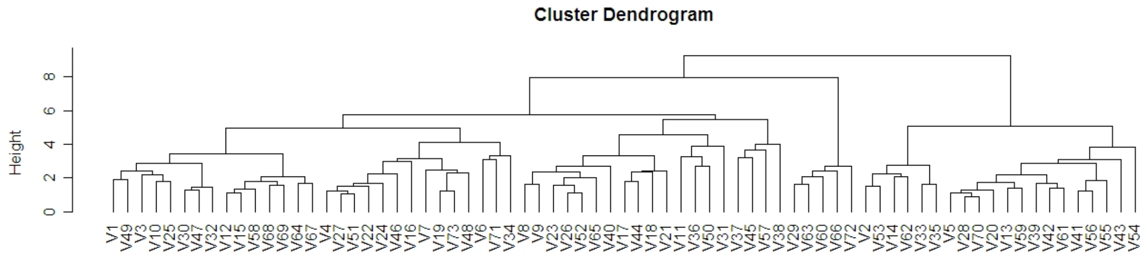
The Rouyer's Method

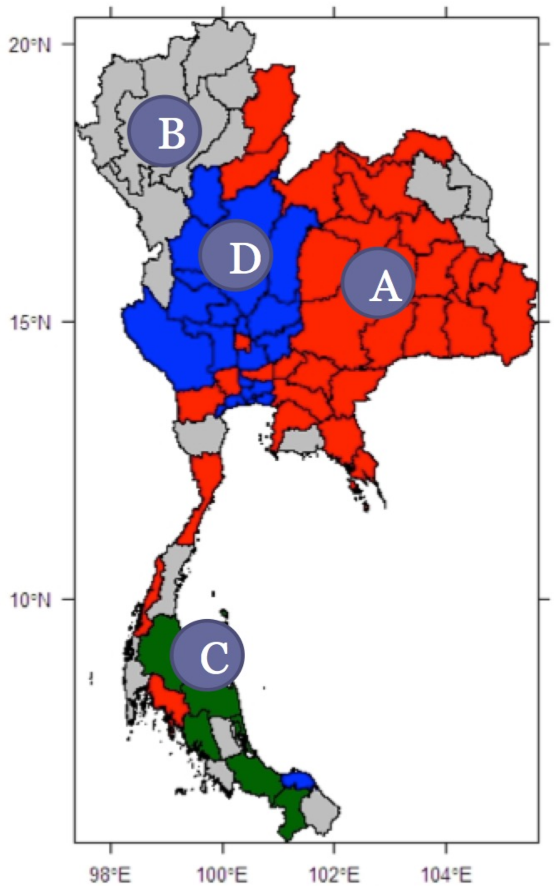
Rouyer, T., Fromentin, J.M., Stenseth, N.C. & Cazelles, B., 2008. Analysing multiple time series and extending significance testing in wavelet analysis. *Marine Ecology Progress Series*, 359, 11-23.

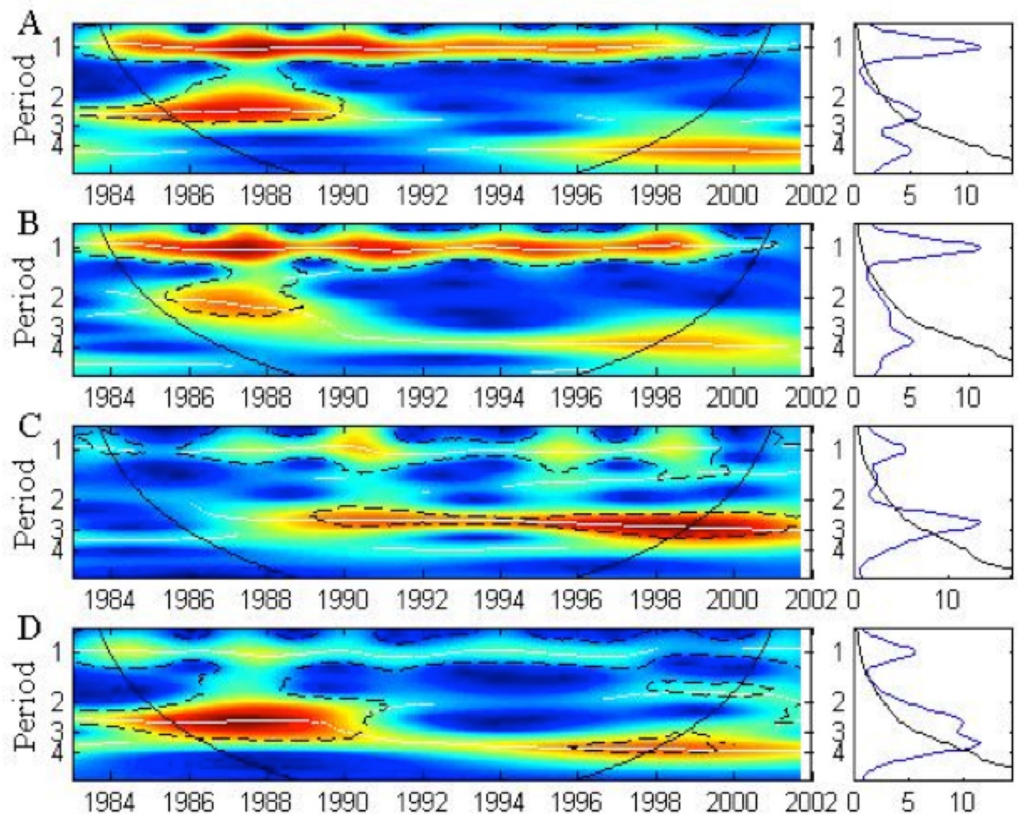


Classical clustering based on this Distance Matrix

Wavelet Clustering

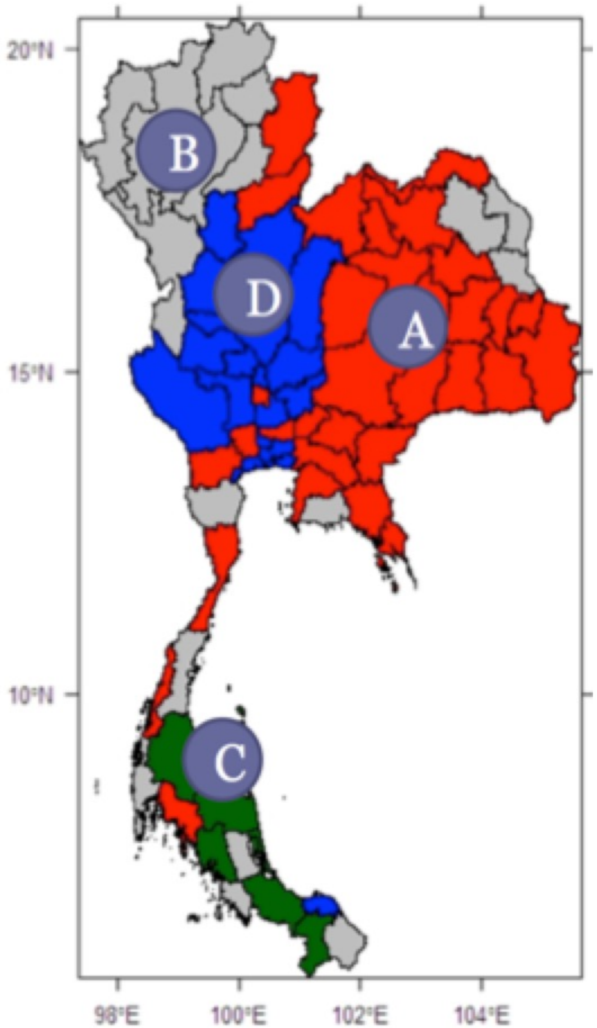




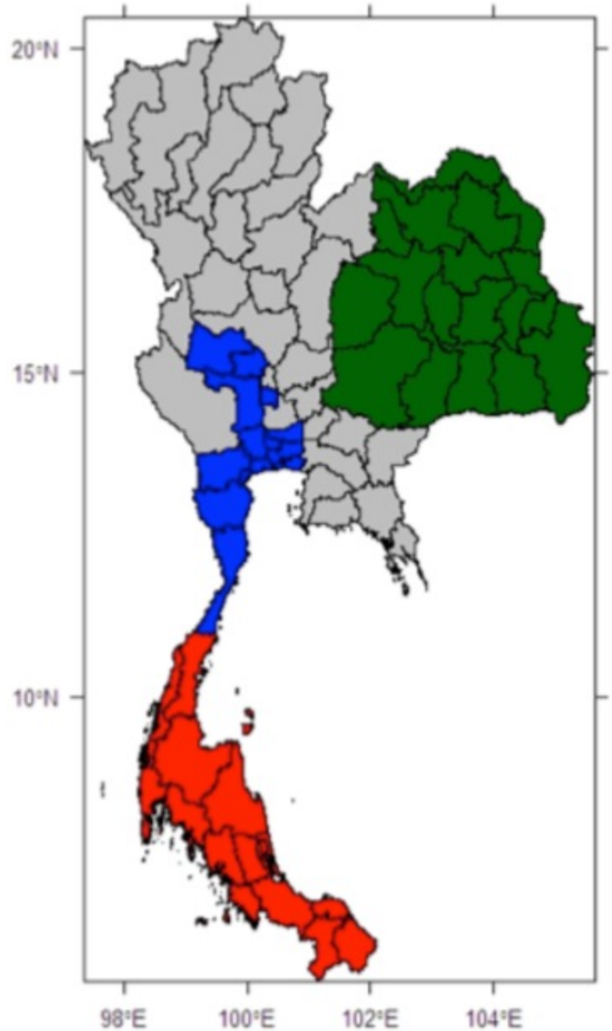


Wavelet Clustering

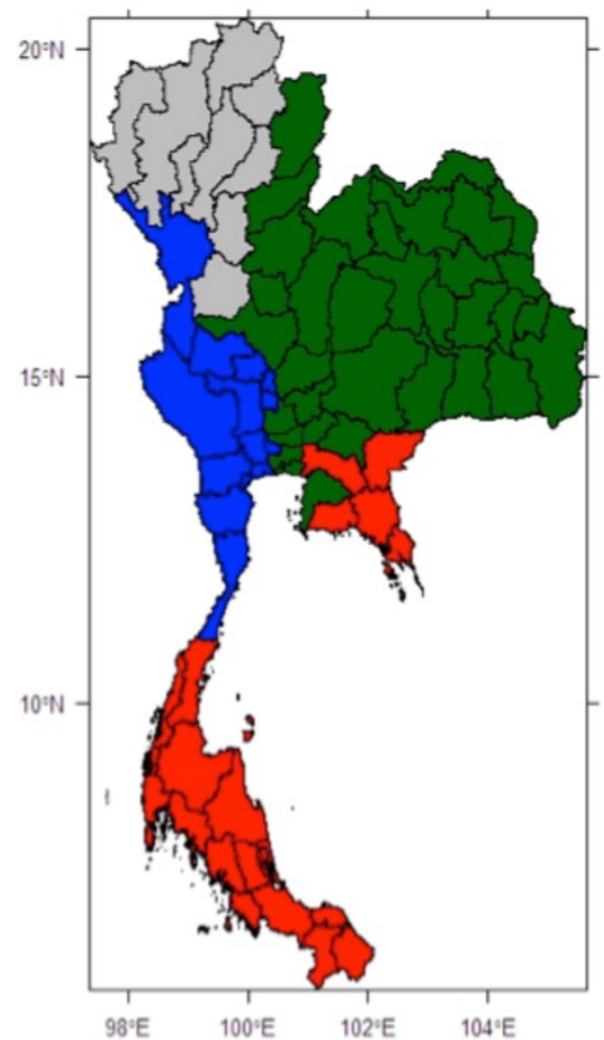
Dengue



Rainfall



Average temperature



Partial Wavelet Coherency

SCIENCE ADVANCES | RESEARCH ARTICLE

HEALTH AND MEDICINE

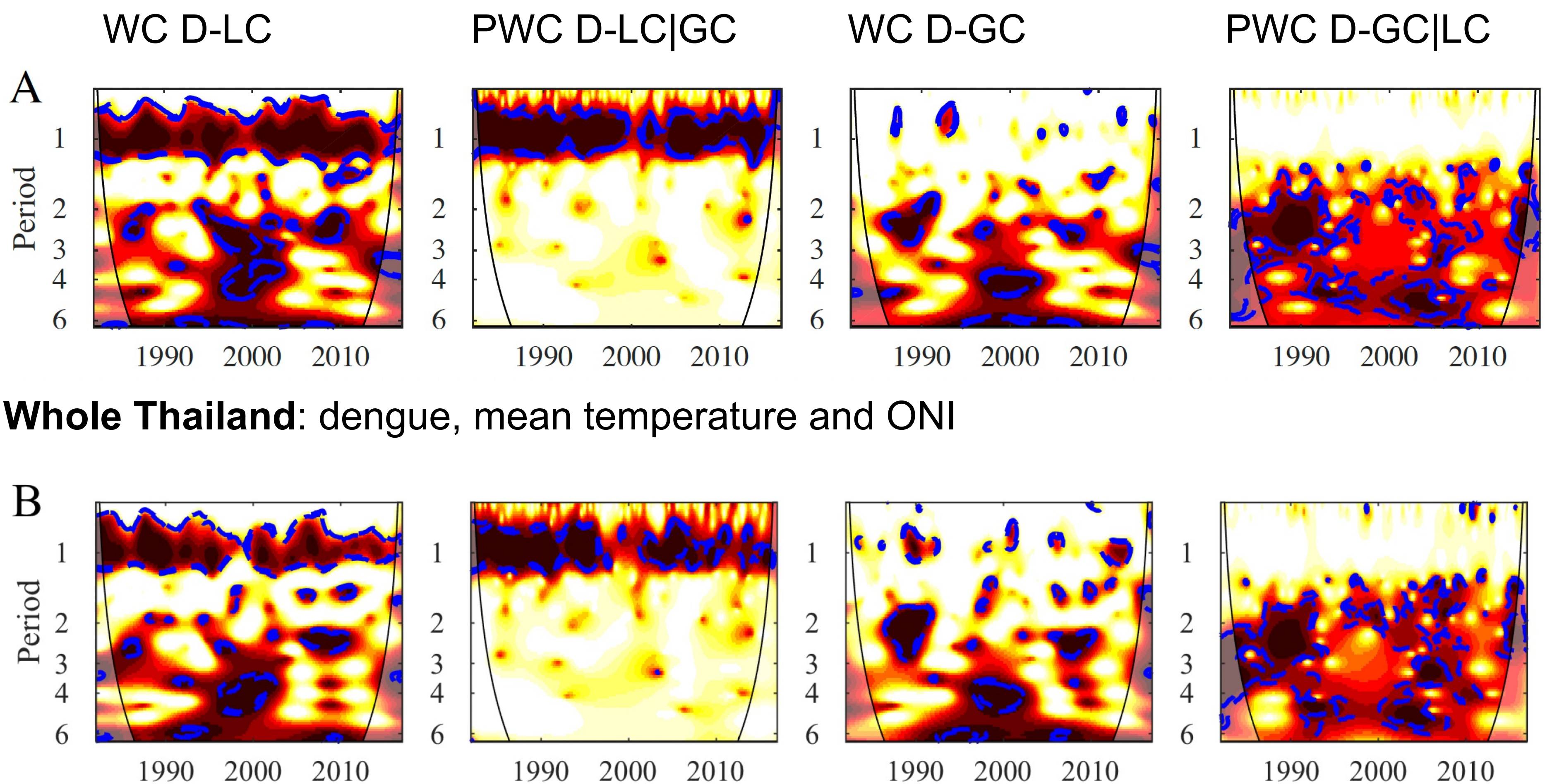
Disentangling local and global climate drivers in the population dynamics of mosquito-borne infections

Bernard Cazelles[1,2], Kévin Cazelles[3,4], Huaiyu Tian[5], Mario Chavez[6]*, Mercedes Pascual[7,8]*

Identifying climate drivers is essential to understand and predict epidemics of mosquito-borne infections whose population dynamics typically exhibit seasonality and multiannual cycles. Which climate covariates to consider varies across studies, from local factors such as temperature to remote drivers such as the El Niño–Southern Oscillation. With partial wavelet coherence, we present a systematic investigation of nonstationary associations between mosquito-borne disease incidence and a given climate factor while controlling for another. Analysis of almost 200 time series of dengue and malaria around the globe at different geographical scales shows a systematic effect of global climate drivers on interannual variability and of local ones on seasonality. This clear separation of time scales of action enhances detection of climate drivers and indicates those best suited for building early-warning systems.

Disentangling the local and global climatic influences on dengue

Application to Dengue in Thailand

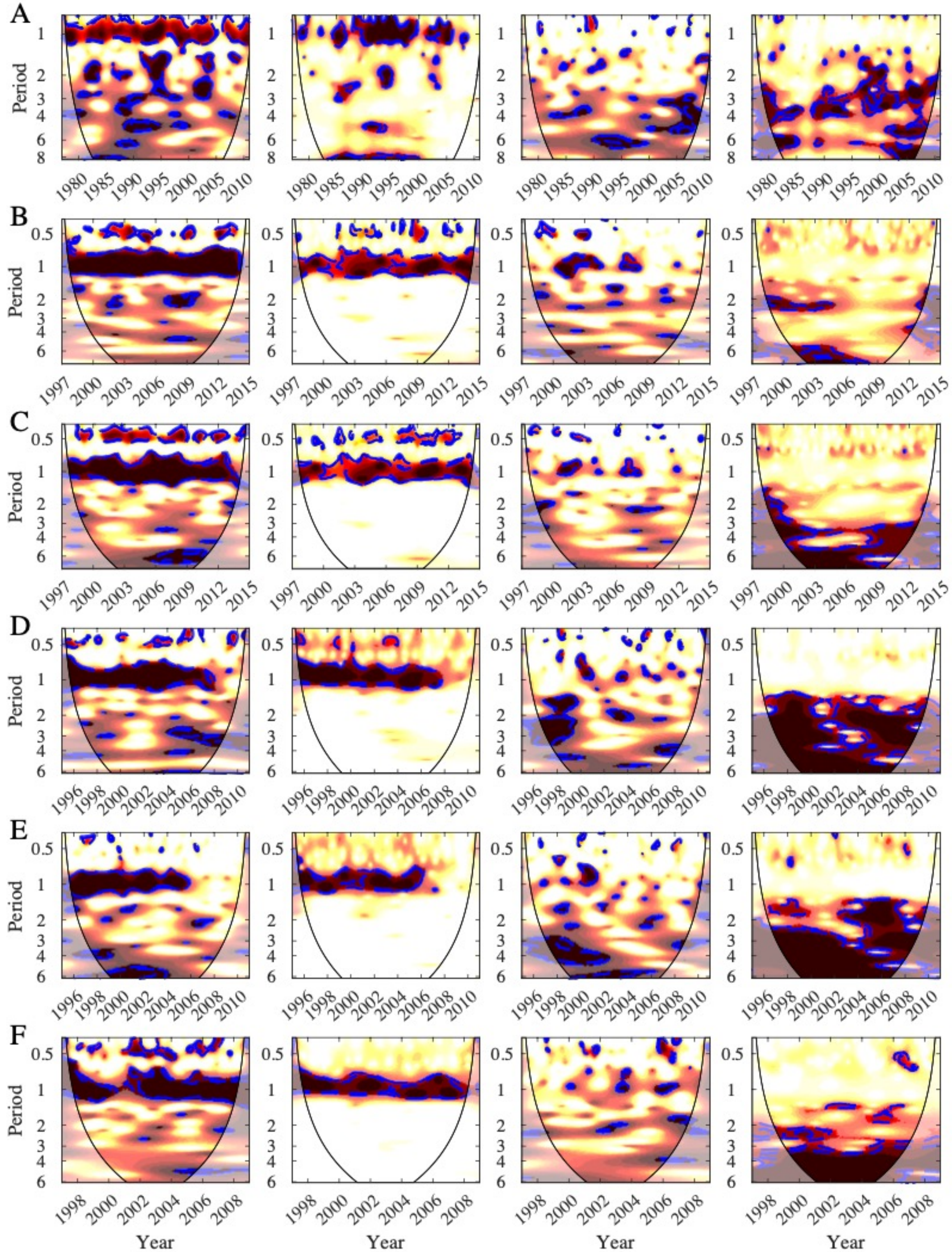


Whole Thailand: dengue, mean temperature and ONI

Zone 4: dengue, rainfall and MEI

…ionarity in Statistical Analysis

Application to Malaria



Kutch district (India): Malaria, Rainfall, DMI.

Surat (India): Malaria, Relative Humidity, SOI

Ahmedabad (India): Malaria, Temperature, MEI.

Hainan province: Malaria, Rainfall, ONI.

Hainan province: Malaria, Temperature, MEI.

Anhui : Malaria, Temperature, Nino34.

Non-Stationnarité et Modélisation des Epidémies

Overview

- Non-stationarity and transients in Epidemiology
- Accounting for Non-Stationarity in Statistical Analysis
- **Accounting for Non-Stationarity in Modeling**

Accounting for Non-Stationarity in Modeling

- Reconstruction the time evolution of some key parameters without any specific hypothesis:
- We have used:
  - State space models

$$\begin{cases} \dot{x}_t = g(t, x(t), \theta) + u_t \\ y_t | x_t = f\big(h\big(x(t)\big), y_t, \theta\big) + v_t \end{cases}$$

  - Parameters considered to be state variables that follow a diffusion process
  - Inference tools as Kalman Filter or Bayesian approaches (MCMC, K-MCMC and P-MCMC)

Accounting for Non-Stationarity In Modeling

- State space models

$$\begin{cases} \dot{x}_t = g(t, x(t), \theta) + u_t \\ y_t | x_t = f\left(h\left(x(t)\right), y_t, \theta\right) + v_t \end{cases}$$

  - System process: an epidemiological model
  - Observational process: a probabilistic law with an observation rate, ρ
    - *Poisson*
    - *Negative Binomial*
    - *Normal*

Accounting for Non-Stationarity in Modeling

- State space models

$$\begin{cases} \dot{x}_t = g(t, x(t), \theta) + \ u_t \\ y_t | x_t = f\big(h\big(x(t)\big), y_t, \theta\big) + v_t \end{cases}$$

- Parameters considered to be state variables that follow a diffusion process

$$d\theta_t = \sigma dB_t$$

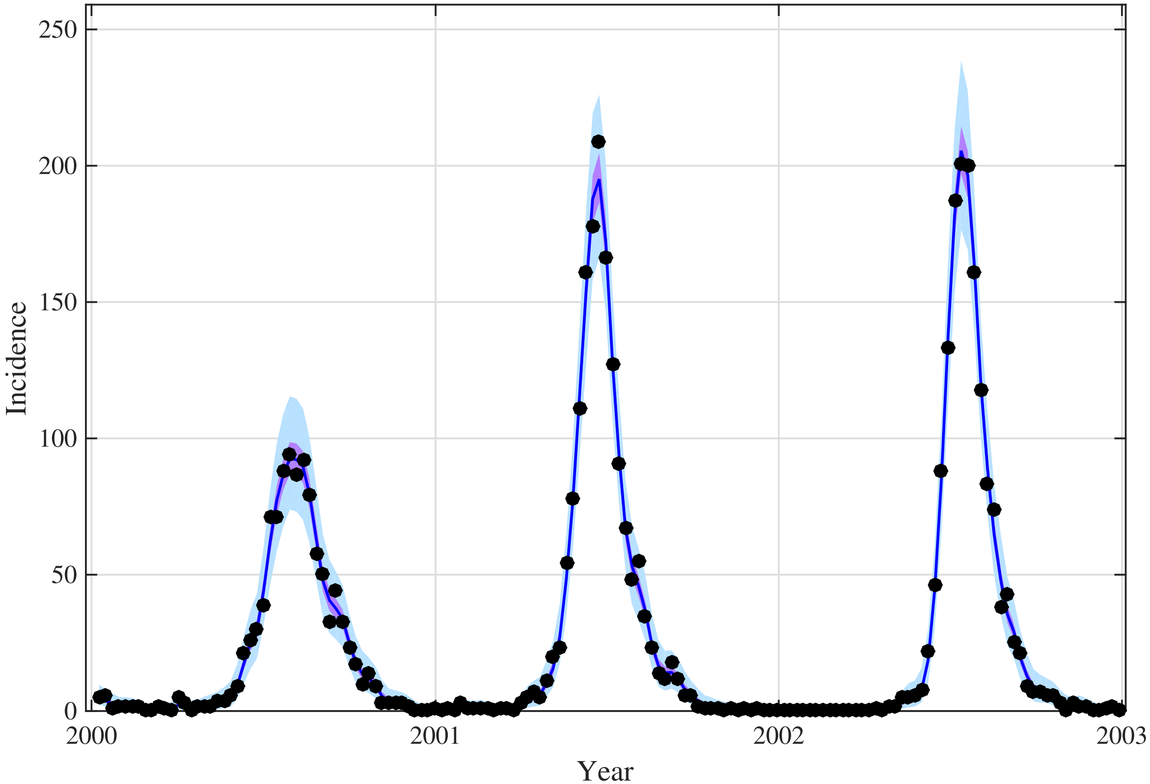
$$d\log(\theta_t) = \sigma dB_t$$

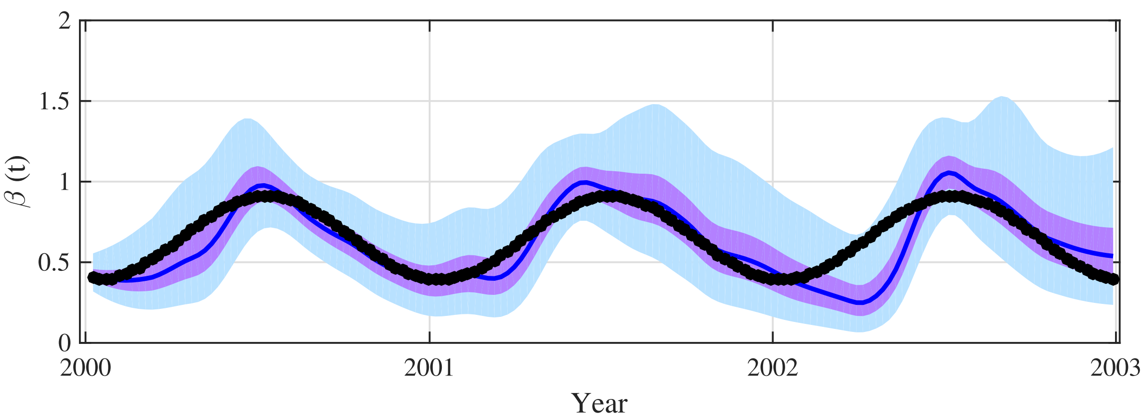
$$\theta_{t+1} = \theta_t + \sigma B_t$$

Accounting for Non-Stationarity in Modeling

- We used a stochastic framework with Markov jump process (or an approximation of it)
- In the stochastic framework, the likelihood is intractable thus EKF or SMC is used to compute it in the MCMC
- Thus we coupled time varying parameters approach with Bayesian methods coupling MCMC and EKF (K-MCMC) or SMC (P-MCMC) (Andrieu et al. 2010; Dureau et al. 2013)

A SIRS toy model





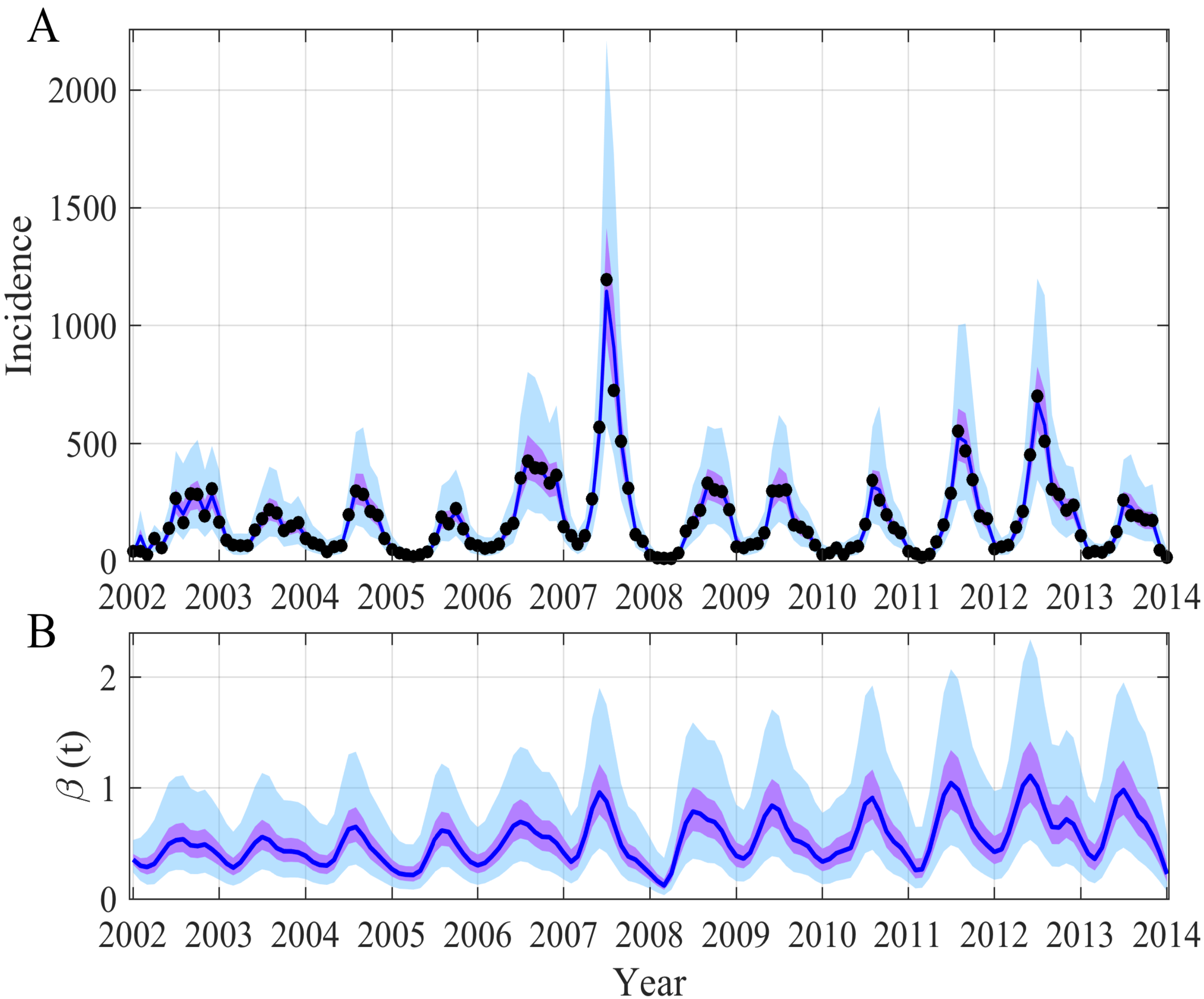
$$\frac{dS}{dt} = \mu.\left(N - S\right) - \beta(t)\frac{S.I}{N} + \alpha.R$$

$$\frac{dI}{dt} = \beta(t)\frac{S.I}{N} - \left(\gamma + \mu\right).I$$

$$\frac{dR}{dt} = \gamma.I - \left(\alpha + \mu\right).R$$

$$\beta(t) = \beta_0.\left(1 + \beta_1.\sin\left(\frac{2\pi t}{365} + 2\pi\phi\right)\right)$$

Application to Dengue in Phnom Penh



SEIR model

$$\frac{dS}{dt} = \mu.\left(N - S\right) - \beta(t).\left(\frac{S.I}{N} + i\right)$$

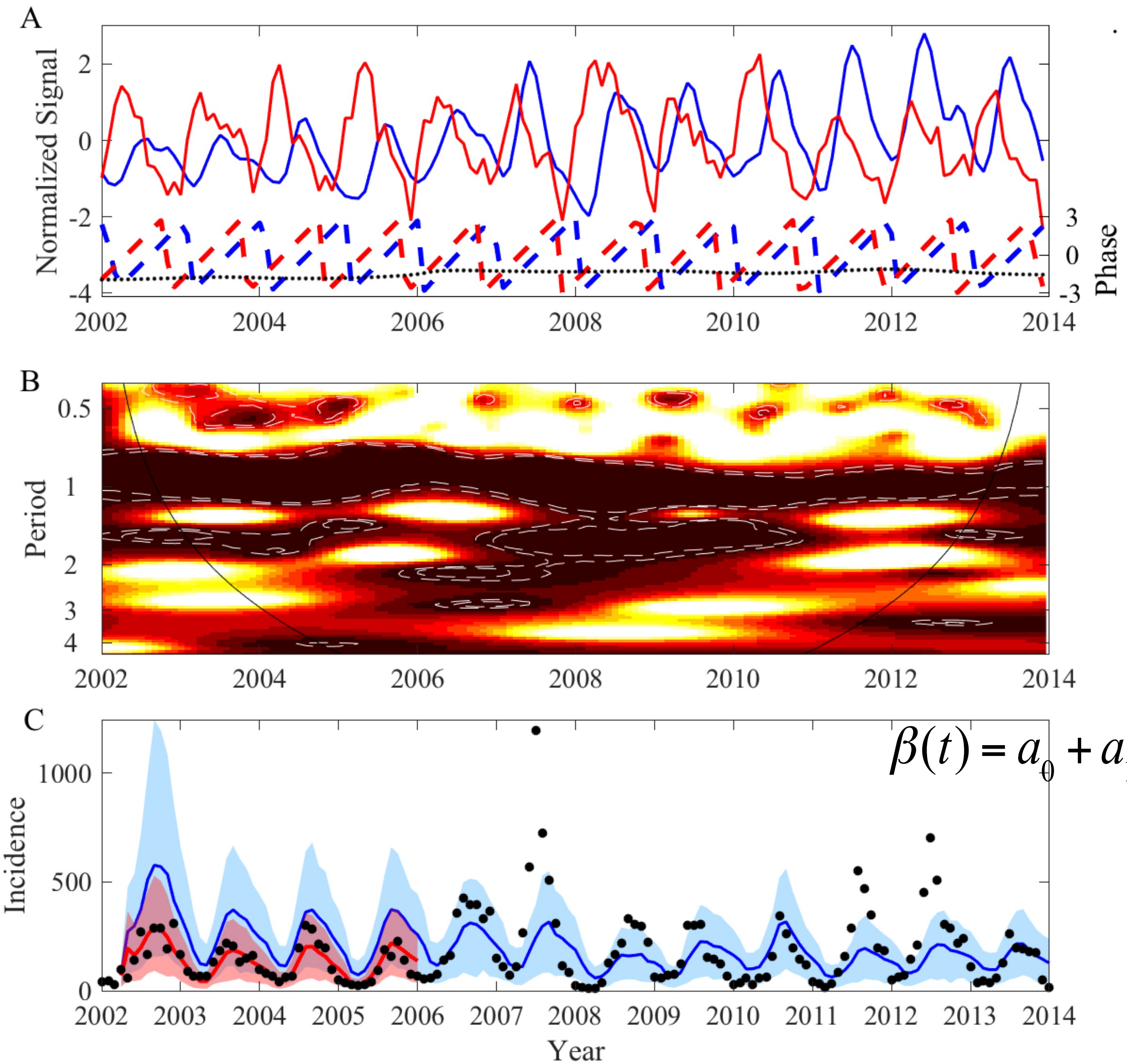
$$\frac{dE}{dt} = \beta(t).\left(\frac{S.I}{N} + i\right) - \left(\delta + \mu\right).E$$

$$\frac{dI}{dt} = \delta.E - \left(\gamma + \mu\right).I$$

$$\frac{dR}{dt} = \gamma.I - \mu.R$$

$$d\log(\beta(t)) = \sigma.dB(t)$$

Application to Dengue in Phnom Penh



$$\beta(t) = a_0 + a_1.\theta_{\max}(t-k) + a_2.\theta_{\min}(t-k)$$

Concluding remarks

- **It is important to take into account non-stationarity when analyzing epidemiological datasets.**
- Wavelet analysis is one of the adapted statistical approaches considering these features of epidemiological time series
- Time-varying parameters modeled with a diffusion process is an alternative to the use of more complex model.
- Models with time-varying parameters can be easily used to predict an epidemic in real time.

Thanks to all my collaborators and particularly to

- Mario Chavez from ICM, Paris and
  Mercedes Pascual from New-York University

- The members of the Eco-Evolutionary Mathematics team at IBENS

- Kévin Cazelles for all the R graphs and for the *future* Wavelet package in R

Maladies transmises par les moustiques, météo et climat : des liaisons dangereuses

Publié: 4 octobre 2023, 20:39 CEST

Aedes aegypti est une espèce d'insectes diptères, un moustique qui est le vecteur principal de la dengue, de l'infection à virus Zika, du chikungunya et de la fièvre jaune. U.S. NAVY

Lors de la crise sanitaire liée au SARS-CoV-2, nos sociétés ont pris conscience de l'importance et de l'utilité des outils mathématiques et statistiques pour caractériser la propagation d'une maladie dans la population générale, prévoir ses conséquences en termes de santé publique et anticiper les répercussions économiques à court terme. Au-delà du Covid-19, les maladies propagées par les moustiques, dont l'aire de répartition s'élargit régulièrement sous l'influence du changement climatique, représentent aujourd'hui une menace émergente.

auteur

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Déclaration d'intérêts

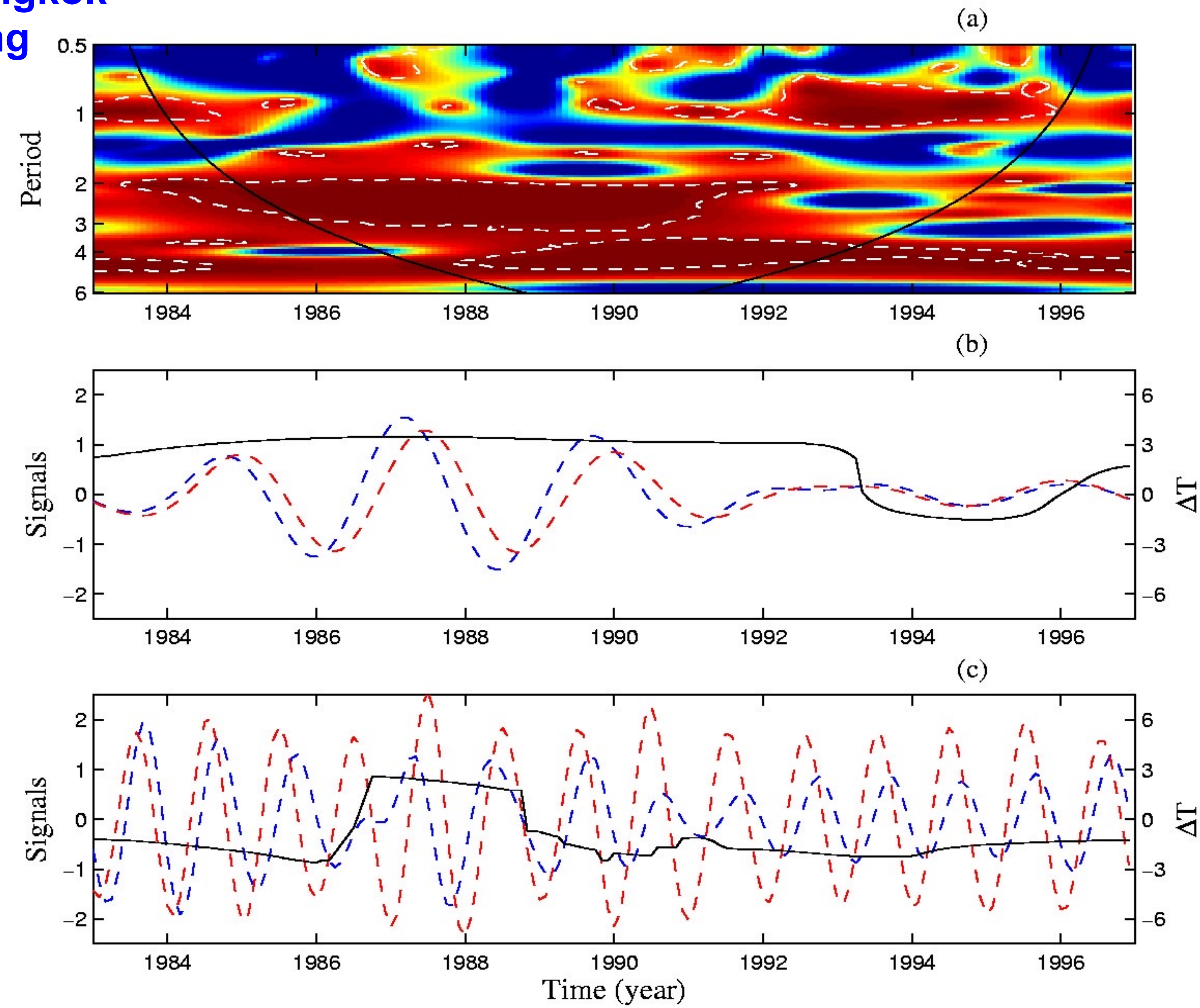
Bernard Cazelles a reçu des financements de l'Agence National de la Recherche (ANR).

Partenaires

SORBONNE UNIVERSITÉ

Wavelet Analysis

Relation beween Bangkok and the remaining Thailand



Importance of non-stationarity

Disentangling th

Whole Thailand: Dengue, Rainfall, SOI.

Application to Dengue In Thailand

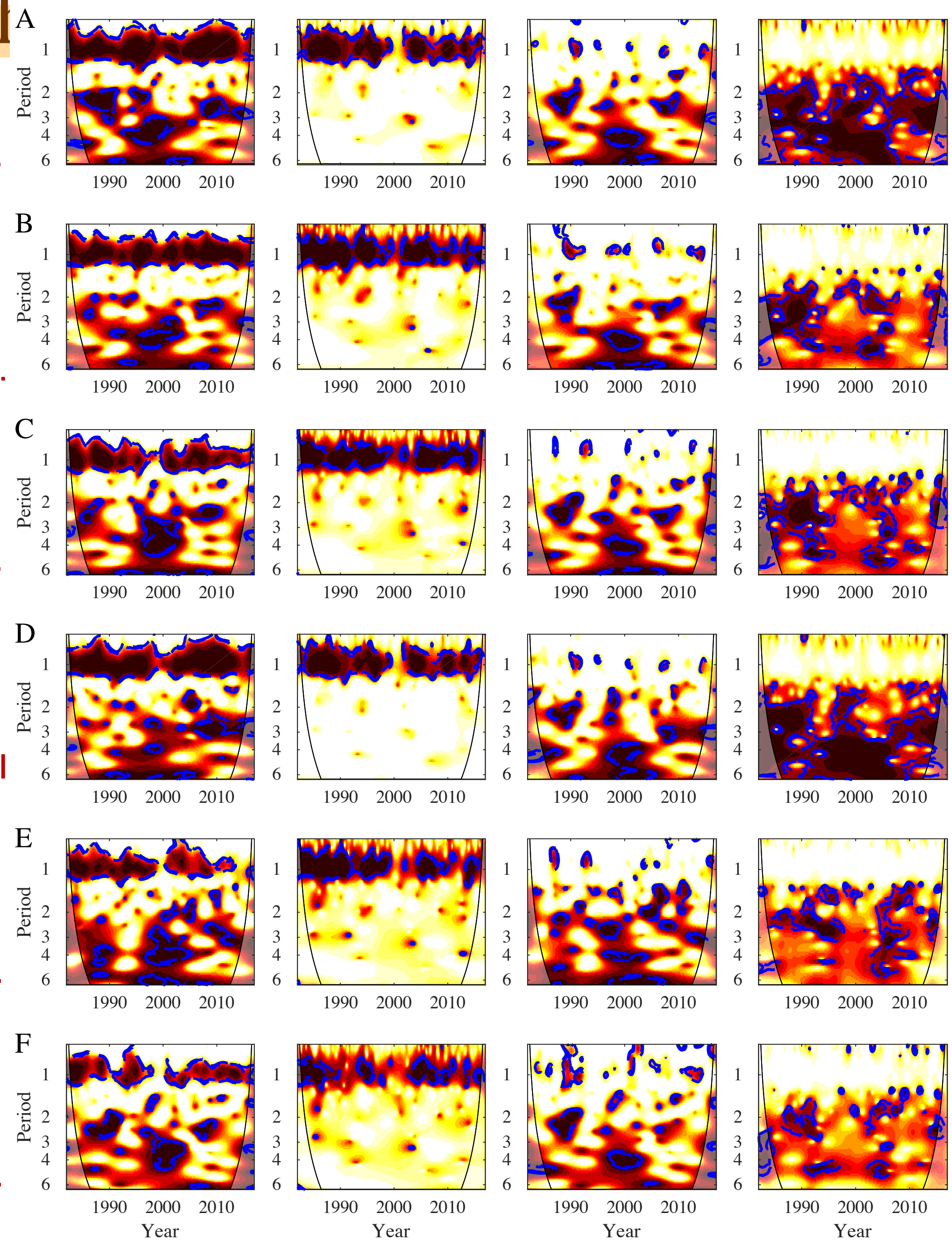
Northern Thailand: Dengue, Temperature MEI.

Central Thailand: Dengue, Temperature, ONI.

North-Eastern Thailand: Dengue, Temperature, ONI

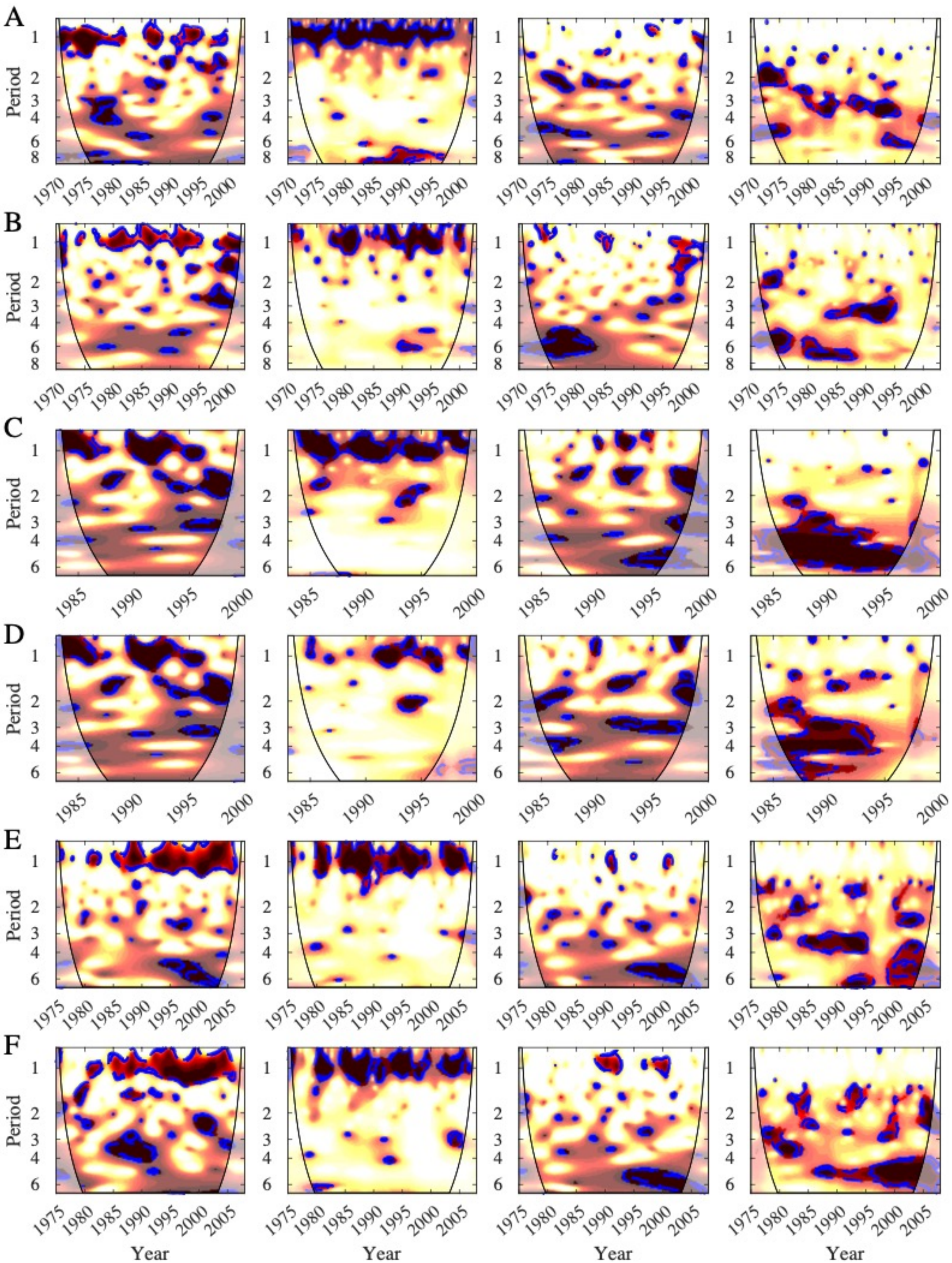
Southern Thailand: Dengue, Rainfall, SOI.

Bangkok: Dengue, Temperature (min), MEI.



onarity in Statistical Analysis

Application to Malaria In Kenya and Ethiopia



Tea Plantation (AHP): Rainfall (Kaisugu), ONI.

Tea Plantation (BBF): Rainfall (Kaisugu); DMI.

Kapsabet district: Rainfall, Nino3.

Kisii district: Rainfall, DMI.

Ethiopia: Temperature (min), SOI.

Ethiopia: Temperature (max), MEI.

Application to Dengue in Phnom Penh