

Improving Malaria Risk Monitoring with Flood Inundation Data from a SensorWeb

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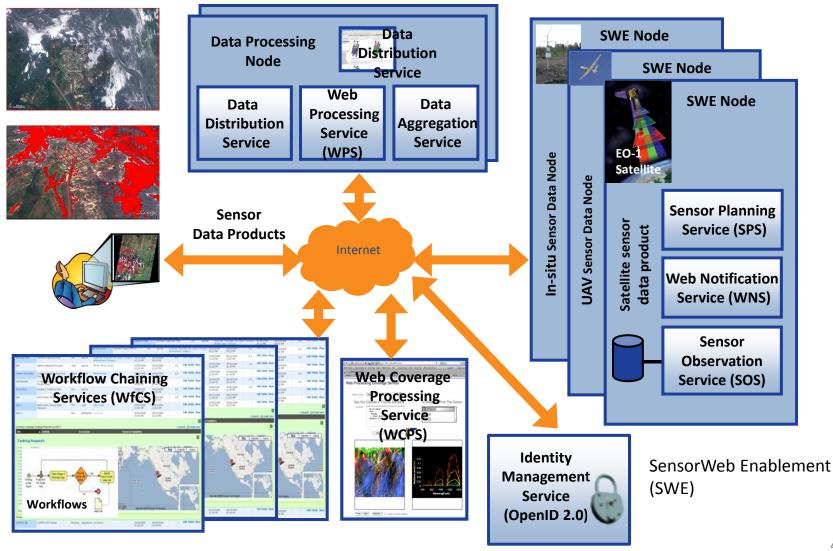
Agenda

- Overview
- Malaria Vector
- Data
 - Malaria
 - Satellite Data and Physical Principal
 - > Flood Impact on Malaria and Vegetation health
- Methodology
- Results
- Conclusions

Overview

- •Experiments conducted in Namibia on Flood and Disease Early Warning SensorWeb
- •Created Flood Dashboard to provide relevant flood data and assist in early flood warning in Namibia with satellite data and ground sensors
- Preliminary results show as much as a 10 day early warning for floods downstream based on experiments
- •These type of flood predictions can improve risk modeling for Malaria
- •Bangladesh used as proxy for Namibia since we have not received all of the Namibia Malaria epidemiological data

SensorWeb Reference Architecture



Namibia Flood Early Warning SensorWeb

In 2009, 2010 and 2011, record floods hit Namibia with as much as ¼ of the population of 2 million affected by the floods, along with hundreds of deaths and millions in property damage. SensorWeb technology is being integrated to help Department of Hydrology implement a Flood Early Warning system to save lives and property.

Detect: TRMM rainfall estimate monitored upstream, AMSR-E based Riverwatch used to monitor river widths, daily MODIS flood extent maps

Respond: Trigger EO-1 and Radarsat imagery based on

detection of triggers

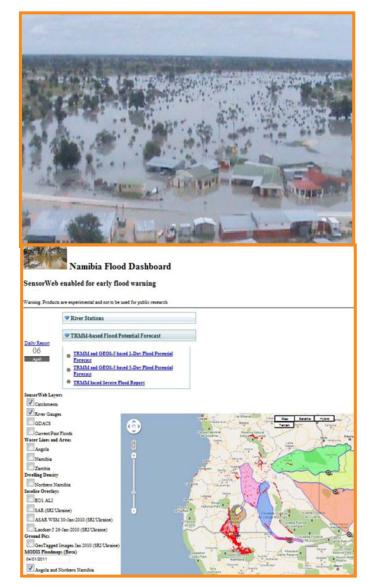
Product Generation: MODIS daily flood extent overlays, EO-1

flood extent overlays, river gauge plots

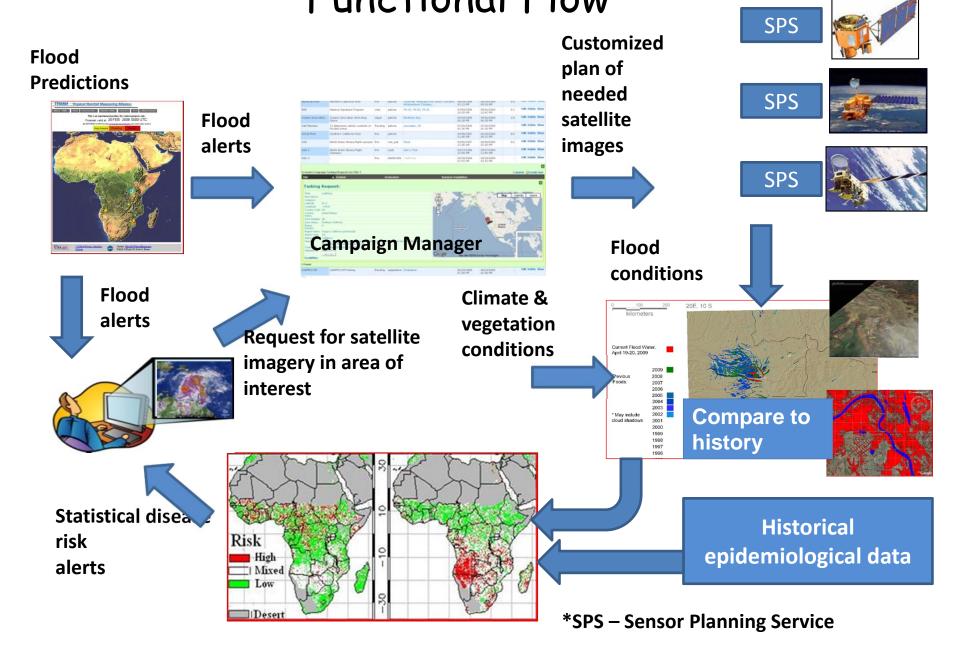
Delivery: Aggregated data layers on Flood Dashboard

"This is to reiterate and stress support and enthusiasm for ongoing efforts during the past two years to integrate SensorWeb components for use by us and other flood disaster response workers and institutions."

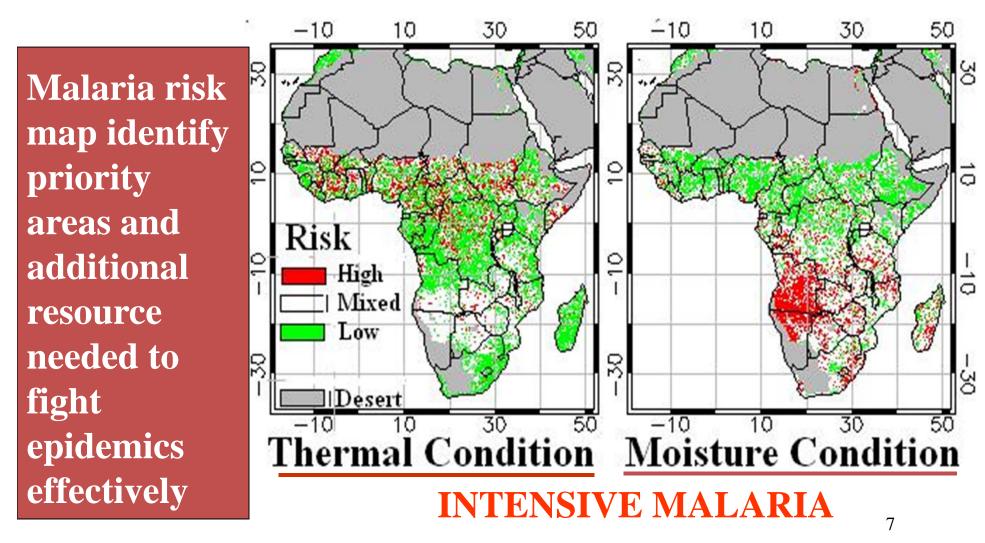
Guido Van Langenhove, Head of Namibia
 Department of Hydrology



Top Level Water Borne Disease SensorWeb Functional Flow

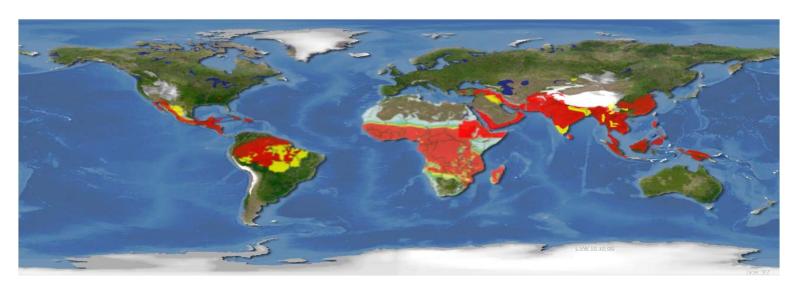


Strategy: WEATHER PROXY AUGUST 26, 2008



Overview: Global situation

- 300 to 500 million clinical cases of malaria each year
- Malaria kills more than 2,000,000 people per year
- 40% of the world's population are at risk in about 90 countries and territories
- 80% to 90% of malaria deaths occur in Sub-Saharan Africa.
- Malaria and HIV have a wide geographic overlap
 - Malaria has substantial population-level implications



Overview: Goal of detection and monitoring of malaria

- Use satellite data for prediction of epidemics (generating malaria risk maps)
- Advise the government on appropriate siting of relocation camps to reduce the malaria risk
- Boosts economy

- (a) explore sensitivity of regional ecosystems condition to malaria events for the period of available satellite records;
- (b) identify some features in the impact of ecosystems in malaria transmission; and
- (c) estimate the similarities and difference in the impacts weather on different malaria epidemic areas in the world.
- (d) devise robust statistical model for forecasting malaria

Impact of Malaria

Factors affecting Malaria

- Growth penalty 1.3%
- Reduce investment
- Poverty
- Loss of work

- Climate
- Flood
- Availability of Health Care
- Population Density
- Use of DDT
- Urbanization
- Irrigation
- Life Style

Largest factors that affect rate and risk of Malaria is change of climate and flood condition.

Other non-climatic factors have a lesser influence on risk and rate of Malaria.

Malaria Vector

Malaria

- Malaria is a vector-borne disease
- Malaria caused by genus Plasmodium .
- It needs an organism for transmission.
- Transmitted from person to person by the female mosquitoes of certain species.

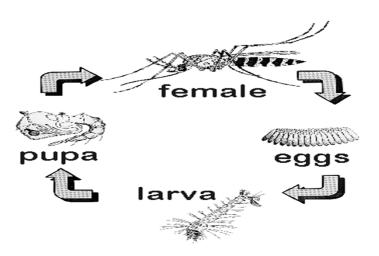


Malaria Vector and Life Cycle

2,500 known species of mosquitoes

- Aedes
- Anopheles
- Culex
- Psorophora

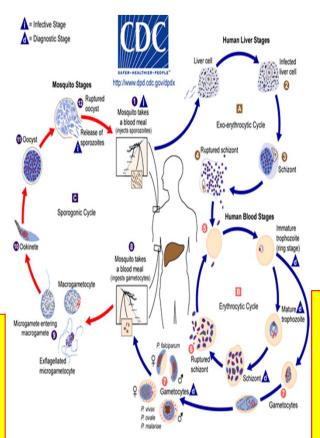




Malaria Parasite

- Plasmodium falciparum
- Plasmodium vivax
- Plasmodium malariae
- Plasmodium ovale

The gametocytes, male (microgametocytes) and female (macrogametocytes), are ingested by an *Anopheles* mosquito during a blood meal . is sporogonic cycle .



Malaria parasite life cycle

Sporozoites infect liver cells and mature into schizonts, which rupture and release merozoites

Merozoites infect red blood cells. The ring stage trophozoites mature into schizonts, which rupture releasing merozoites. Some parasites differentiate into sexual erythrocytic stages (gametocytes)

Relationship of Temp. & Relative Humidity with Malaria Parasite and Mosquito Development



Effect of Rise in Temperature on mosquitoes Vectors

- Rate of development (from egg to adults) will be faster
- Rate of digestion of blood meal will be faster.
- Frequency of feeding will be faster
- Survival affected by RH.
- Death of mosquitoes at 40° C

Data

- ➤ Malaria Statistics
- ➤ Satellite Data and Physical Principal
- > Flood level

Malaria Data

Malaria Statistics (Ministry of health)

Performance Indicator

Annual parasite Incidence (API) = $\frac{\text{Number of blood smears positive for malaria Parasite in a year}}{\text{Total population}} \times 1000$

Slide Positive rate (SPR) = $\frac{\text{Number of blood smears positive for malaria Parasite in a year}}{\text{Number of Blood smears examined}} \times 100$

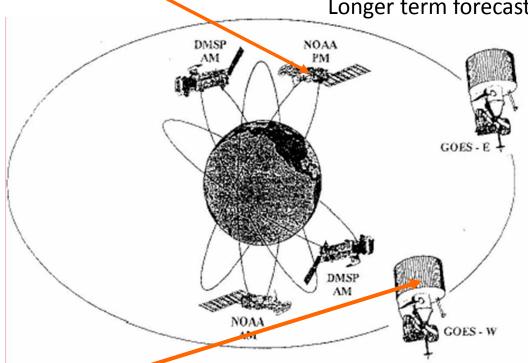
Number of positive cases of malaria from all patient with fever visited hospital

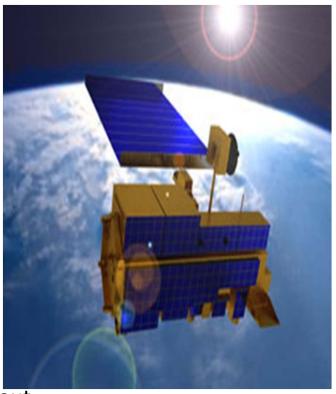
NOAA Operational Environmental Satellites

polar orbiting satellites

860 km altitude north—south orbit sun synchronous 1:40 p.m pass equator

Longer term forecasting





Geostationary satellites

orbit around the Earth at an altitude of about 35800 km above the equator temporal resolution 30 minutes limited spatial resolution

DATA from NOAA operational polar orbiting satellites

Sensor: Advanced Very High Resolution

Radiometer (AVHRR)

Satellites: NOAA-7, 9, 11, 14, 16, 18

(afternoon.), 17

Data Resolution:

Spatial - 4 km GVI, sampled to 16 km;

Temporal - Daily sample 7-day composite

Period: 1981-2009

Coverage: World (75 N to 55 S)

Channels: VIS (ch1), NIR (ch2),

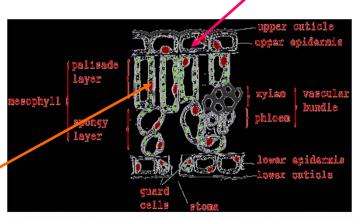
Thermal (ch4, ch5)

Radiation detection imager used to detect earth surface temperature



AVHRR Reflectance

Chlorophyll controls much of spectra response in visible part of spectrum



Inner

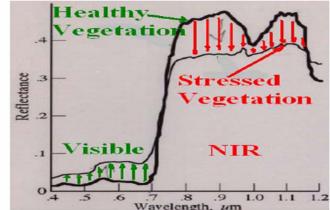
NIR

Structure -

Controls

spectral

Response



NDVI = (NIR-VIS)/(NIR + VIS)

DATA PROCESSING:

Pre-launch calibration of VIS and NIR

Post-launch calibration of VIS and NIR

Non-linear correction of IR4

Calculation of NDVI

Calculation of brightness temperature (BT)

High frequency noise removal from NDVI & BT time series

Derivation of 24-year climatology

Derivation of indices

Vegetation Condition (VCI)

Temperature Condition (TCI)

Vegetation Health (VHI)

AVHRR Reflectance

Chlorophyll controls much of spectra response in visible part of spectrum

palisade layer | wylan | wascular bundle | phloen | bundle | bundle | phloen | bundle | bundl

Inner

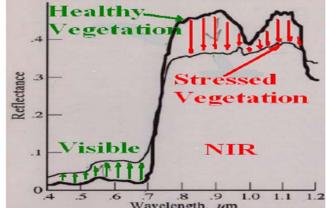
NIR

Structure -

Controls

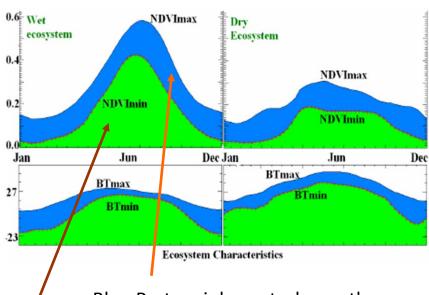
spectral

Response



NDVI = (NIR-VIS)/(NIR + VIS)

Weather and Ecosystem components in NDVI & BT



- •Blue Part mainly controls weather components (like temperature, humidity and rainfall
- Ecosystem component (green part) controls by slow changing environmental factor

Vegetation Health Indices and Algorithm

Normalized Difference Vegetation Index

NDVI = (CH2 - CH1)/(CH2 + CH1)

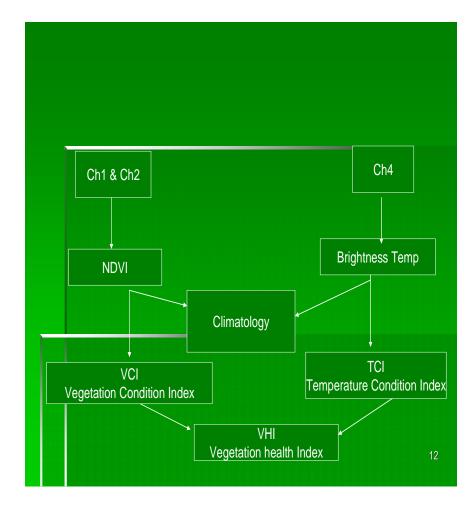
Vegetation Condition Index (VCI)
 VCI=100*(NDVI – NDVI min)/ (NDVImax – NDVImin)

Temperature Condition Index (TCI)

TCI=100*(BTmax – BT)/ (BTmax – BTmin)

Use Vegetation Health Indices to Assess

- Moisture Condition (VCI)
- Thermal Condition (TCI)
- Vegetation Health (VHI)



Methodology

Tools and Methods

- Trend Analysis
- Correlation Analysis
- Regression Analysis
- Principal Component Analysis
- Mat Lab, SAS

Trend Analysis

Extract weather related variations from malaria time series

$$T_{t} = a_{0} + a_{1*} t_{year}$$

$$\sum_{i=1}^{i=n} (\boldsymbol{Y}_i - \boldsymbol{T}_i)^2$$

slowly changing function representing the deterministic component (trend) (ecosystem and non climatic factors)

a₀ (intercept) and a₁ (slope) by minimizing the sum of squares

DY= (Y
$$_{actual}$$
 / T $_{t}$)*100

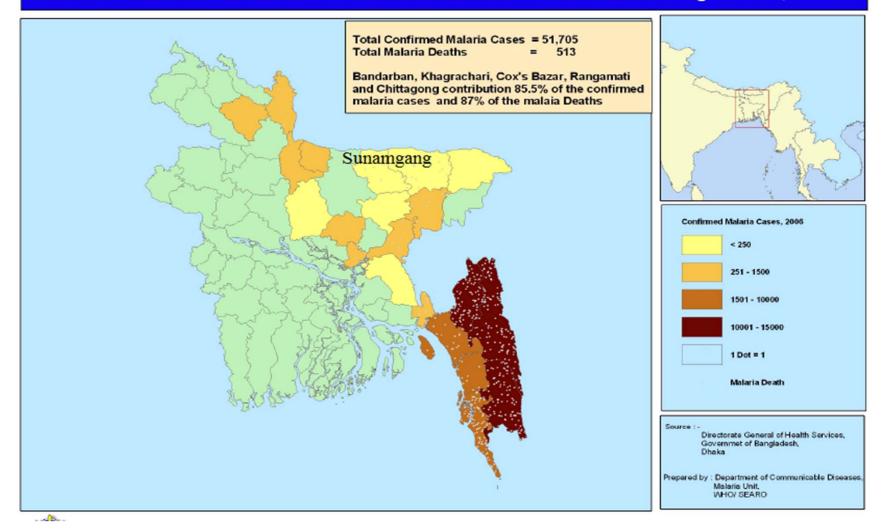
random component regulated by weather fluctuations (Deviation around trend line)

Correlation Dynamics

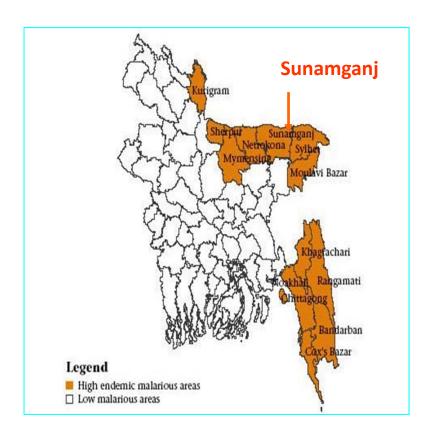
Correlation of 13 years (depends on Malarial data) of Deviation from Trend Line (DY) with 13 years of thermal and moisture condition indices (TCI and VCI) for all 52 weeks are calculated, Level of inundation has been correlated with Malaria for 365 days all 13 years

To explain the trend analysis, Correlation dynamics and Regression analysis, the malaria of Bangladesh dataset (1992-2004) has been presented here

Distribution of Positive Malaria Cases and Malaria Deaths in Bangladesh , 2006



Malaria endemic districts of Bangladesh



- Malaria Parasite
 - Plasmodium falciparum (95%)
 - Plasmodium vivax (5%)
- Female Anopheles Vectors
 - > An Dirus
 - > An minimus

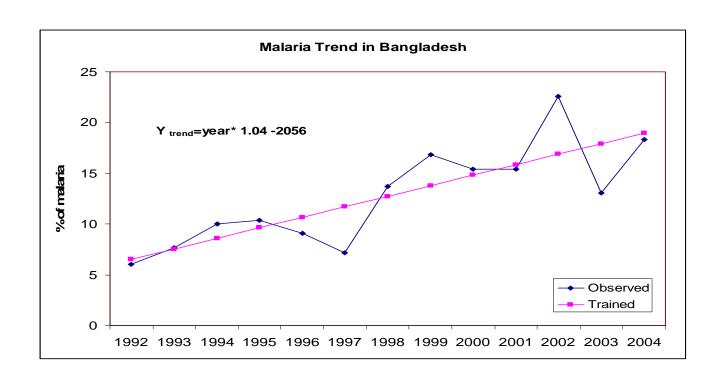
Climate of Bangladesh

- Wet hot (flooding season) -April to October
- Cool dry –November to February
- Hot dry –February to April

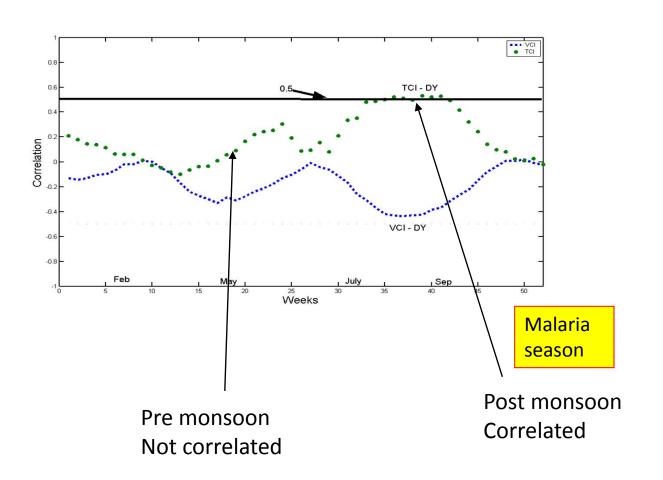
Bangladesh_Situation

- Out of 64 districts, 13 bordering districts in the east and north-east region belongs to the high-risk malaria zone.
- Plasmodium falciparum is the predominant parasite (61%-71%).
- 14.7 million people are at high-risk of malaria in the country.
- 1.0 million clinical cases are treated every year.
- In 2002 a total of 598 deaths were reported in Bangladesh.

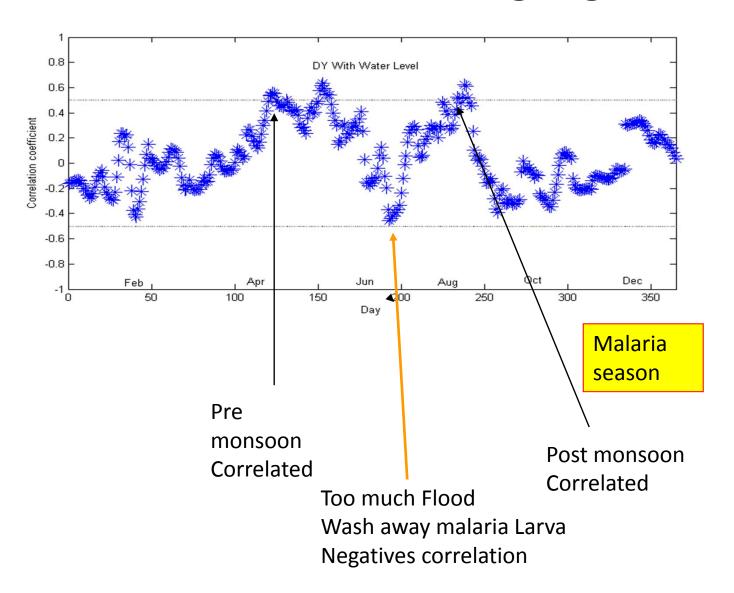
Annual malaria cases, and Trend line 1992-2004 in Bangladesh



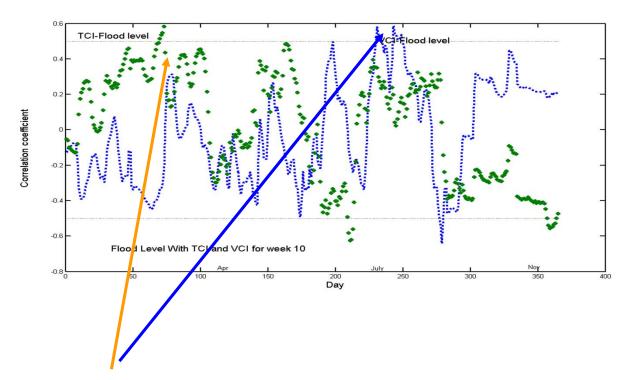
Correlation dynamics of DY versus TCI and VCI in Bangladesh



Correlation dynamics of DY versus Water Level at Sunamgong



Correlation dynamics of Water Level at Sunamgong versus TCI and VCI in Bangladesh



Because of inter-Correlation multicolinearity exists in OLS Regression method

Regression Analysis

Variation inflation and tolerance

DY=b ₀ +		Parameter	Variance		•		
	Variable	Estimate	Error	t value	Pr≻ltl	Tolerance	Inflation
Small Tolerance	Intercept	53.61238	35.35812	1.52	0.1638		0
High variance inflation	TCI34	0.6971	0.4354	1.6	0.1438	0.95011	1.05251
P>10%	day120	5.64404	4.33054	1.3	0.2248	0.67609	1.47909
	VCI34	-0.05714	0.38583	-0.15	0.8855	0.65676	1.52262

Correlation matrix

Predictor variable are highly correlated Predictor variables are not independent This is collinearity Violation of assumption of OLS method

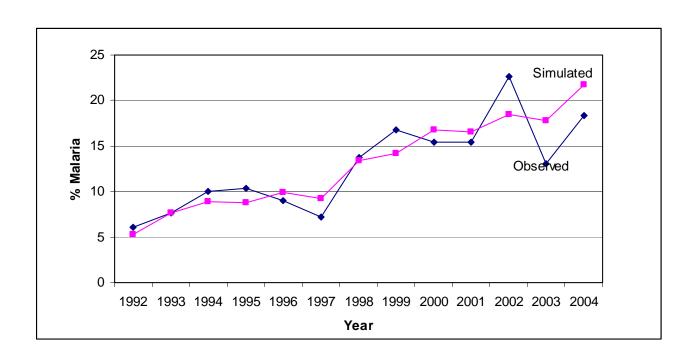
	TCl34	day120	VCI34
TCI34	1	0.146	-0.2221
day120	0.146	1	-0.5688
VCI34	-0.2221	-0.5688	1

Principal Component Regression

Transforms another set of variables
They are orthogonal to each other
These are Principal components

	Parameter	Standard			
Variable	Estimate	Error	t Value	Pr> t	
Intercept	99.87334	4.62302	21.6	<.0001	
Prin1	8.64547	3.72325	2.32	0.0404	

Simulated and observed malaria



$$R^2 = 0.74$$

Conclusion

- TCI and VCI identify climatic features that have impact on malaria transmission
- TCI and VCI can be used for malaria prediction
- Model for Malaria prediction that relies on (Vegetation health indices /VCI&TCI) will allow for reliable prediction of epidemics 1-2 months in advance. It's shown here that addition of flood level parameter as the third input vector (in addition to VCI&TCI) for the Malaria Model improves the capability to as much as 4-6 months of advanced warning
- This increased lead time will allow for improved government response to deploy assets to fight epidemics
- Presented Malaria model allows for comparison of malaria epidemics in different ecosystems
- PCR allows for model improvement

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