

A prototype Malaria Early Warning System

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Quantifying Weather & Climate Impacts



Why can we develop a Malaria Early Warning System (MEWS) now?

Malaria is a very old disease. Fossils of mosquitoes 30 millions years old show that the vector for malaria was present well before the earliest history of man.

- Several African nations have implemented improved health monitoring systems over the last decade, which in combination with malaria detection kits, has greatly improved health data for evaluation
- latest generation seasonal forecast systems are now starting to exhibit skill in temperature and precipitation with lead times of one or two months and beyond.
- Improved understanding of malaria transmission had lead to better dynamical malaria modelling systems capable of modelling the disease transmission on a regional scale.

Contents

Relation between malaria and climate

Malaria modeling

Malaria forecasting system

ECMWF input

Preliminary malaria forecast

Contents

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Malaria Transmission

The parasite

Malaria parasites are from the genus *Plasmodium*. 4 species are known to infect humans. Two are wide-spread and particularly dangerous, *falciparum* and *vivax*. *Vivax* can lie dormant in the liver for weeks to years and cause frequent relapses, while *falciparum* has wide-spread drug resistance and causes the most fatal cases due to the potential cerebral complications.

The vector

The parasite is spread by the anopheles genus of mosquito :



Figure: Anopheles gambiae vector

Malaria is constrained by weather/climate conditions

- **Rainfall** : provides breeding sites for larvae.
- **Temperature**: larvae growth, vector survival, egg development in vector, parasite development in vector (plasmodium falciparum/ plasmodium vivax).
- **Relative Humidity** : dessication of vector.
- **Wind** : Advection of vector, strong winds reduce CO₂ tracking.

Please note that two bites are required to pass on the disease. Each mosquito (Anopheles Gambiae) is born malaria free

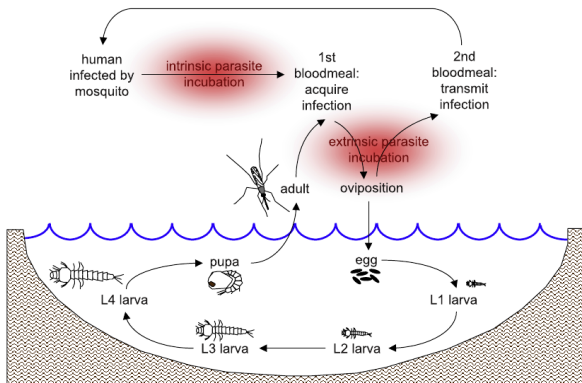


Figure: schematic of transmission cycle from Bomblies WATER RESOURCES RESEARCH 2008

Other factors that influence the geographical extension of malaria

Factors that can reduce the disease range:

- land use changes (drainage)
- interventions (bed nets, spraying, treatment)
- socio-economic factors (access to health facilities, behaviour, poverty)
- predators, competition and dispersion limits

Factors that can increase the disease range:

- land use changes (clearance of papyrus brings host closer to vector; papyrus produces chemical that limits larvae development)

NEWS

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WHO highlights disease from unhealthy environments

Sophie Hedden
19 June 2008 | EN | 中文

Unhealthy environments cause nearly one-third of all death and disease in developing countries, according to a report released on Friday (16 June) by the World Health Organization.

The report, a review of literature and surveys from over 100 experts, shows that Africans are most vulnerable to death, illness and disability caused by unsafe drinking water, poor hygiene, and other environmental factors.

In West Africa and parts of North Africa 350-500 deaths per 100,000 people are caused by



Spraying bodies of water to kill the larvae of mosquitoes that pass malaria to humans through their bites
WHO/DR/Bahar

Figure: Headline extracted from the World Health Organization Report 'Preventing disease through healthy environments'



Malaria distribution since preintervention

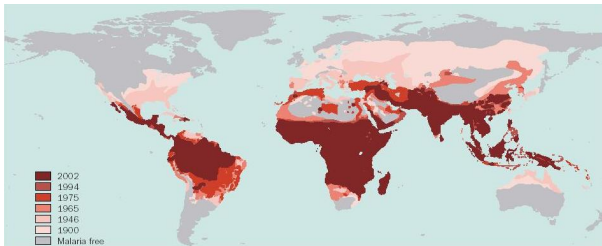


Figure: The global distribution of malaria since preintervention from about 1900 to 2002 (Fig. 1 in Hay et al. 2004).

Graphical collection of maps from various sources. Areas of high and low risk were merged throughout to establish all-cause malaria transmission limits. Each map was then overlaid to create a single global distribution map of malaria risk which illustrates range changes through time.

Hay, S. I., C. A. Guerra, A. J. Tatem, A. M. Noor, and R. W. Snow, 2004: The global distribution and population at risk of malaria: past, present, and future. *The Lancet Infectious Diseases*, 4, 327-336.

Malaria distribution after intervention

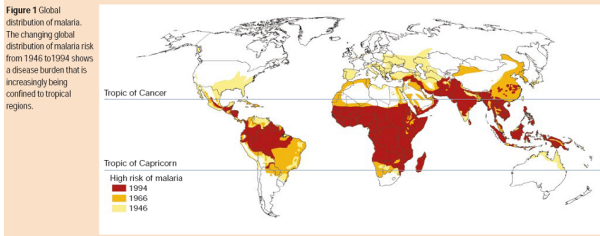


Figure: Global distribution of malaria. The changing global distribution of malaria risk from 1946 to 1994 shows a disease burden that is increasingly being confined to tropical regions (Fig. 1 in Sachs and Malaney 2002).

" The global distribution of per-capita gross domestic product shows a striking correlation between malaria and poverty, and malaria-endemic countries also have lower rates of economic growth"

Sachs, J., and P. Malaney, 2002: The economic and social burden of malaria. *Nature*, 415, 680-685.

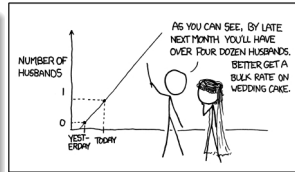
Approaches to Modelling Malaria

Statistical model

Relate predictor to climate and non-climate disease drivers

- Can include poorly understood drivers (e.g. poverty/interventions) easily
- Can be simple and fast to implement
- Needs (long/wide) training dataset in target area (transferable?)
- Care required to avoid overfitting data
- Trial/error required to determine best model
- Not easy (but possible) to include sub-seasonal information

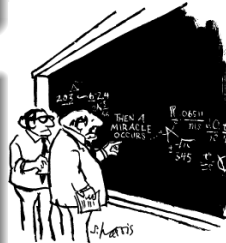
MY HOBBY: EXTRAPOLATING



Dynamical model

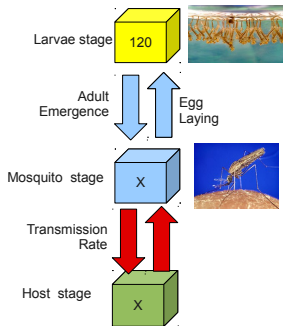
Solve equations describing the vector/parasite cycle where equations are mostly derived from controlled lab (or field) studies

- Can account for sub-seasonal variability of climate drivers
- More transferable from one location to another
- More difficult to account for confounding factors?
- Good data/understanding required for accurate model, tuning still required for poorly specified parameters.



Bulk dynamical models

The simplest dynamical models use 'bulk' variables for larvae, vector, and human population, often dividing these into two or more relevant sub-categories (e.g. susceptible, infected and recovering humans).



Disadvantage

Cannot simulate the delay between the starting of the rainy season and the beginning of the malaria transmission.

Figure: Example of bulk dynamical model.

The VECTRI model

The most recent models divides the categories into many sub-categories, or *bins*, or order to try and model delays in e.g. adult emergence, and have been applied to **spatial modelling**

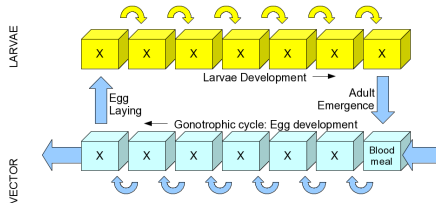


Figure: Schematic of the the dynamic malaria model VECTRI (Tompkins and Ermert Journal of Malaria 2012)
Freely available at <http://users.ictp.it/~tompkins/vectri/>

Malaria diagnostic

EIR - entomological inoculation rate Force of infection is the number of infected bites per person per unit time. An EIR of around 10 infected bites per year marks the division between epidemic and endemic areas (red box divided by the population)

PR - Parasite Rate
Proportion of population which has a detectable parasite (green boxes)

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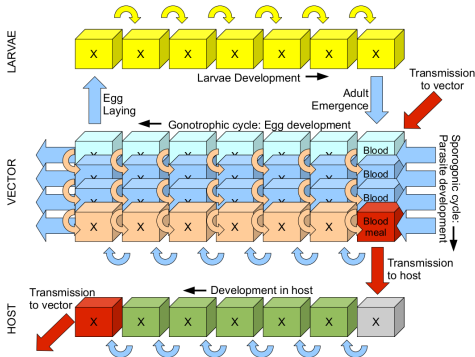


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What do we want to know from a Malaria forecasting system?

The spatial extension and length of season for malaria transmission is set by climate, and is reduced by other factors, such as control and interventions.

- Endemic Areas [high immunity, mortality mainly in <5 years] **potential prediction of seasonal onset**
- Epidemic Areas [low immunity, mortality across all age groups] **prediction of outbreaks**
- **decadal timescales:** potential shift of epidemic areas to higher altitudes (e.g. *Pascual et al Proc. Natl. Acad. Sci. USA*), and changing epidemic and endemic patterns.

(c) Epidemic Malaria

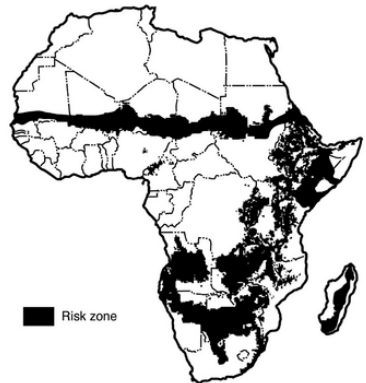
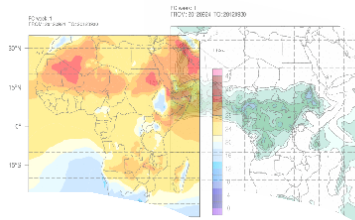


Figure: The epidemic belt on the edge of the Sahara is associated with lack of rainfall, while cold temperatures reduce or eliminate malaria incidence at high altitudes over eastern Africa from *Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 2007*

The Malaria Early Warning System: concept and implementation

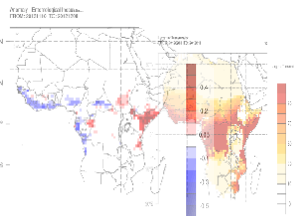
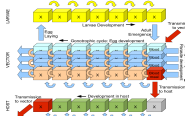
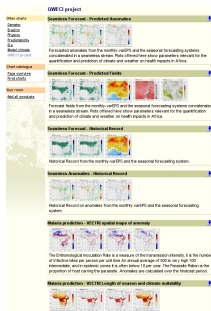


Biases corrected
Seamless joint forecast
120 days [25 days from
monthly and 95 from
system-4]



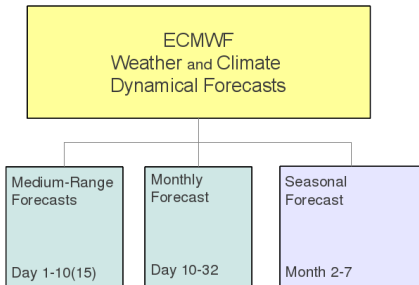
Fed into multi-model
dynamical and
statistical malaria
model

To provide ensemble
diseases risk map



<http://nwmstest.ecmwf.int/products/forecasts/d/inspect/catalog/research/qweci/>

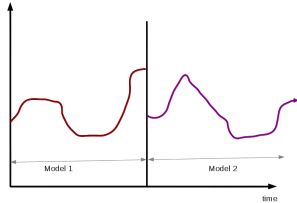
ECMWF forecasting systems



- 1 **Deterministic high-resolution global atmospheric model**
TL1279 91 levels; range=10 days
- 2 **Medium-range ensemble prediction system** TL639 / TL319
62 levels; range=15 days control + 50 perturbed members merged with the **Monthly forecast system** TL319 62 level (atm.), 1.4 deg x 0.3-1. deg, 29 vertical levels (ocean) 51member ensemble; range=32 days
- 3 **Seasonal forecast system** TL255
91 level (atm.), 1.4 deg x 0.3-1.4deg, 29 vertical levels (ocean) 51-member ensemble; range=7 months

Seamless forecast

In accessing products from different sources we ideally want seamlessly in

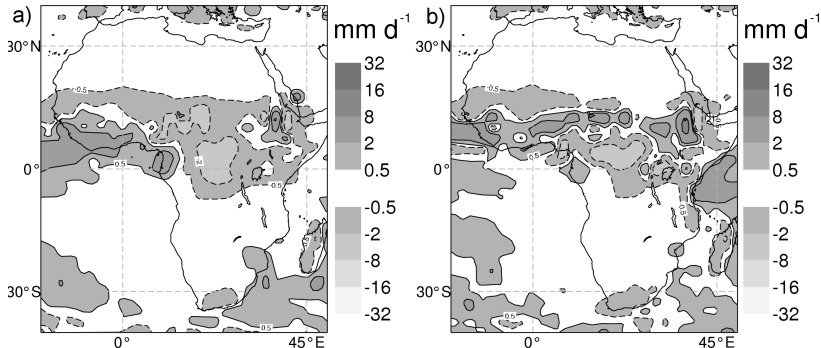


time



space

The atmospheric forcing: precipitation over Africa



Seasonal

mean JJA bias for the period 1993-2010

The two systems adopt different model cycles; model cycle 37R2 for the EPS-monthly and model cycle 36R4 for System-4. Both models are compared to GPCPv2.1 dataset, units are in mm day⁻¹.

Monthly

Different biases across model cycles. The idea is to take advantage of the decreasing biases in the newest realise of the model

Calibration of precipitation: a new method based on EOF

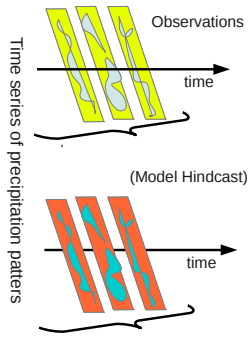


Figure: For the specific nature of the bias in Africa the correction needs to reshape the precipitation patterns by a known 'observed' climatology

Calibration of precipitation: a new method based on EOF

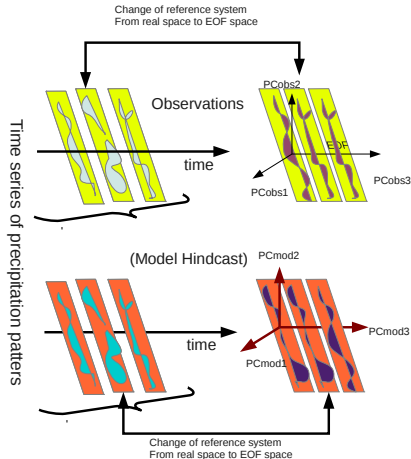


Figure: This can be achieved through the mapping of dominant modes of variability in the model parameter to the equivalent (correlated) mode observed in the observational field, We use the empirical orthogonal functions (EOF) to identify the modes of variability

Calibration of precipitation: a new method based on EOF

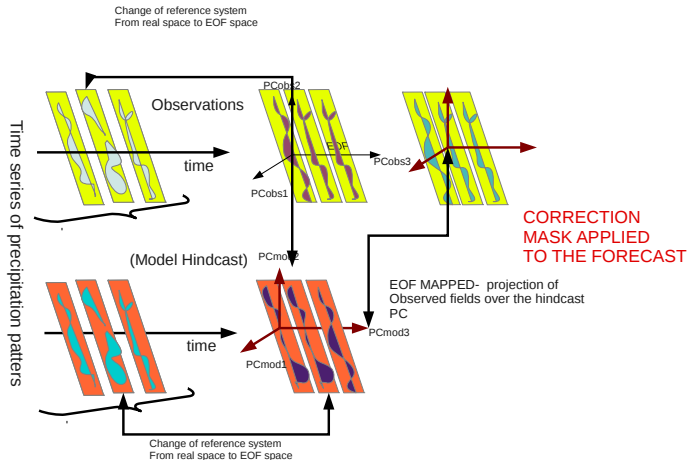
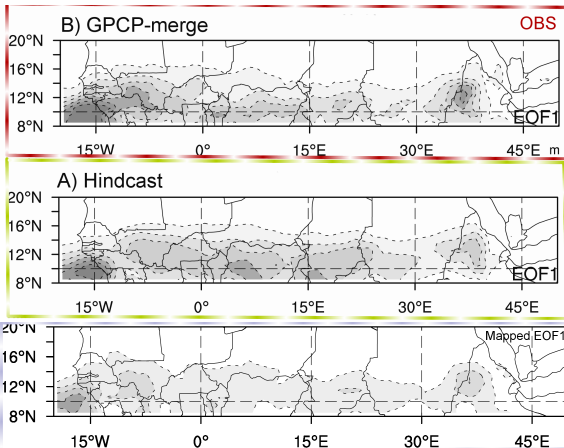


Figure: The mapped EOFs can also be thought as a spatial "correction" mask. They uncover model skills and represent the spatial variability the observation should have to match the model time variability

EOF decomposition example

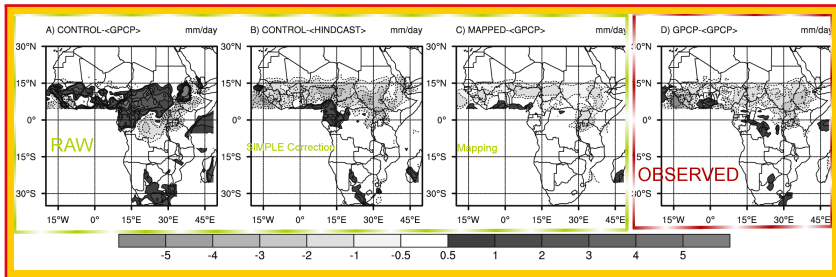


1st EOF shows south-north dipole due to the latitudinal of the tropical rain-band roughly 30 % of total variance

The mapped EOFs can also be thought as a spatial "correction" mask. They uncover model skills and represent the spatial variability the observation should have to match the model time variability.

$$\text{MEOF}_i(x, y) = \langle \text{OBS}_{\text{anomaly}}(x, y, t) \text{PC}_{\text{model}}^i(t) \rangle_i$$

calibration assessment: Precipitation anomaly for JJA 2009



(A) Control member of the VarEPS-monthly forecasting system against the GPCP 1991-2008 climate

(B) Control member of the VarEPS-monthly forecasting system against the model climate. This is equivalent to a point-wise bias correction

(C) Control member of the VarEPS-monthly forecasting system after the generalised calibration presented in this work has been applied against the GPCP 1991-2008 climate

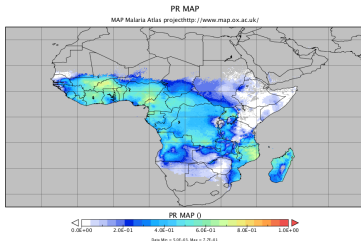
(D) observed precipitation anomalies

Malaria Early Warning system evaluation

The first step consists in checking the system capability to reproduce the observed distribution of malaria transmission

MAP-Malaria Atlas Project

MAP data provides a "climatology" nominally for 2010 but the surveys are from many different years. This is not a DATASET it is a statistical model that uses Parasite Rate field data as one input (they are isolated samples) and a Bayesian regression model with rain and temperature inputs.



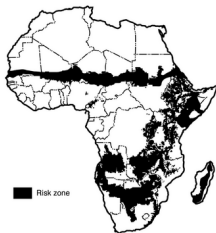
The model is JUST CLIMATE does not take into account things such as interventions, bed nets, spraying or people taking medicine to cure themselves. These all reduce PR. Not only does taking medicine clear you it also reduces PR generally

Malaria Early Warning system evaluation

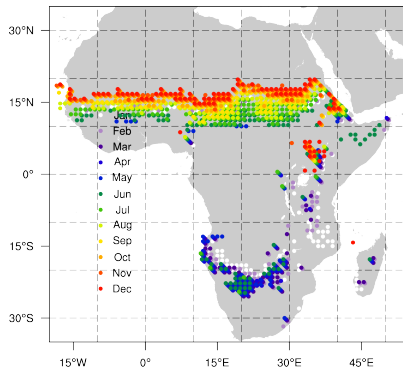
Epidemic areas definition

Epidemic areas are defined by looking at the time variance of the parasite ratio over 30 years of re-analysis runs. Small variances (≤ 0.02) defines endemic areas. High variance (≥ 0.02) defines epidemic areas.

(c) Epidemic Malaria

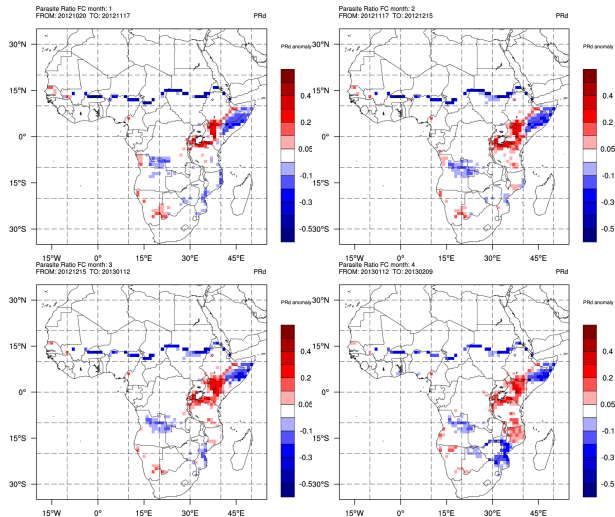


Epidemic Areas [variance of PR > 0.2]
ERA-Interim + VECTRI [1981-2011]



Ref: F. Di Giuseppe and A.M. Tompkins 2012: Climatic predictability of malaria epidemic outbreaks and endemic onset in Africa. *Proceedings of the National Academy of Sciences. In preparation*

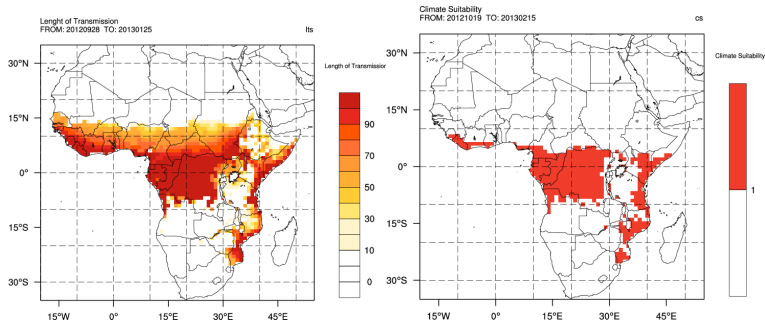
Malaria Early Warning system: Real Time product



Forecast issued on the 18 October 2012

Anomaly on the intensity of transmission. Anomaly is compared to the 'climate' calculated using the hindcast for the period 1994-2011

Malaria Early Warning system: Real Time product



Forecast issued the 18 October 2012

Length of transmission (number of consecutive days with $EIR \geq 0.05$)

Climate suitability (Length of transmission ≥ 90 days)

Conclusions

- Introduced the Prototype Malaria Early Warning system (MEWS)
 - Need a seamless forecasting system to take advantage of fast model developments.
 - Need for a “smart” calibration technique able to re-positioning precipitation patterns in the right place
 - Creation of the necessary infrastructures to make the products easily available.
- Validation phase
 - validation at pan-Africa level has started by looking at survey data
 - further validation with Malawi and Uganda case data provided by the national Ministry of Health
- System improvements
 - further developments of the VECTRI model to include immunity, migration and a better surface hydrology representation (questions on the VECTRI can be addressed to Adrian M Tompkins email: tompkins@ictp.it)
 - A further development of the system will need a dynamical downscaling of ECMWF outputs to provide high resolution maps (distric level) so to provide products specially tailored for stakeholders.

Contact: Francesca Di Giuseppe [email:F.DiGiuseppe@ecmwf.int]

Products:<http://nwmstest.ecmwf.int/products/forecasts/d/inspect/catalog/research/qweci/>

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