Towards Real-Time Spatiotemporal Monitoring and Forecasting of Meningitis Incidence in sub-Saharan Africa

M. Stanton, L. Agier, B. Rowlingson, P. Diggle
m.stanton@lancs.ac.uk l.agier@lancs.ac.uk

CHICAS combining health information, computation and statistics
LANCASTER UNIVERSITY
School of Health & Medicine

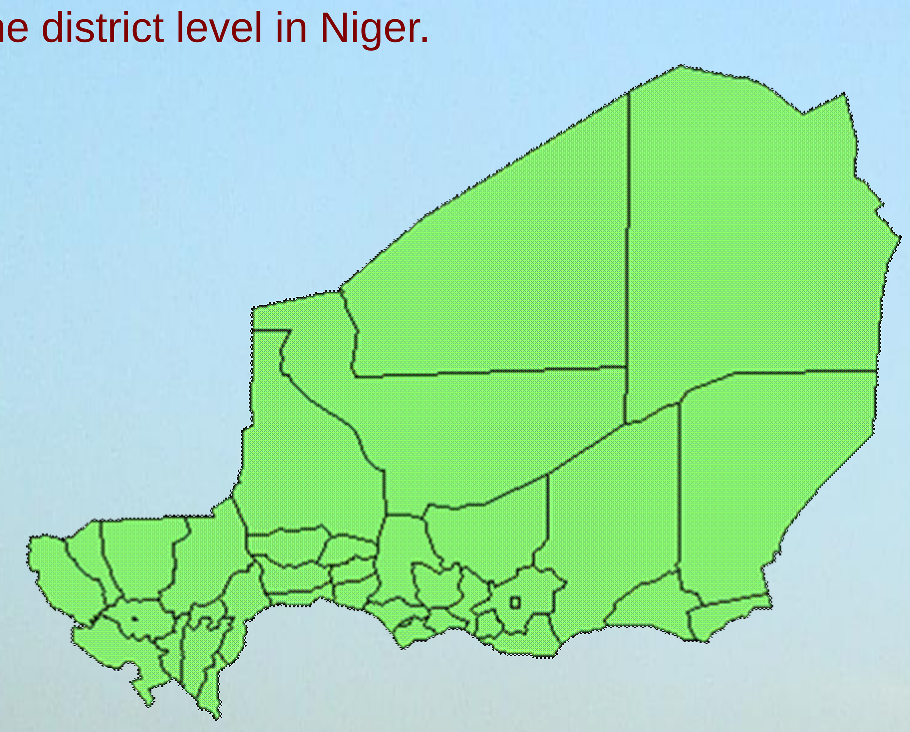
RATIONALE

Current control strategy of meningitis epidemics

- reactive vaccination strategy at a district level
- Prevents at most 60% of cases
- Numerous factors can delay its implementation (i.e. quality of surveillance, logistic constraints, limited vaccine supply, etc)

Our goal

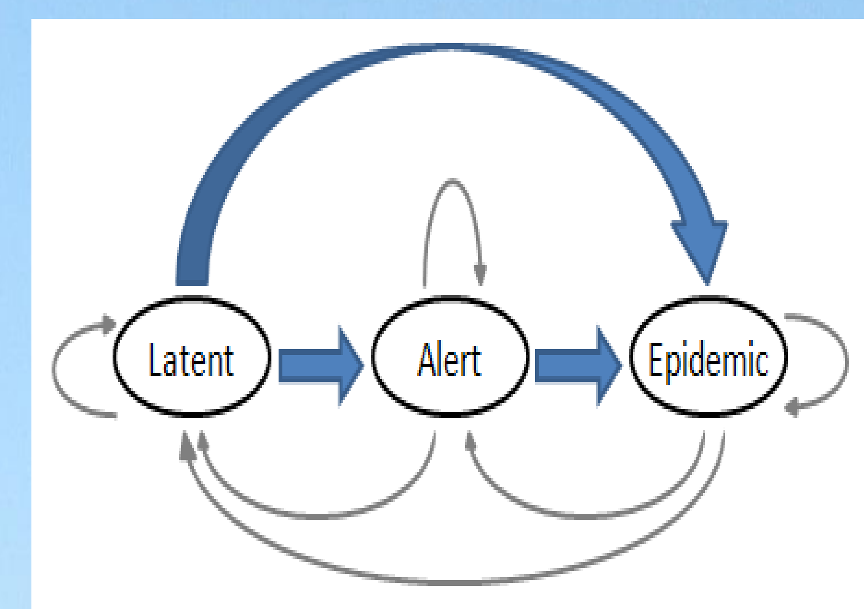
- develop **short-term forecasting** to enable pre-emptive vaccination
- focus on **predicting the risk of exceeding the weekly epidemic threshold** (10/100,000 pop) at the district level in Niger.



METHODS

Two different approaches have been considered:

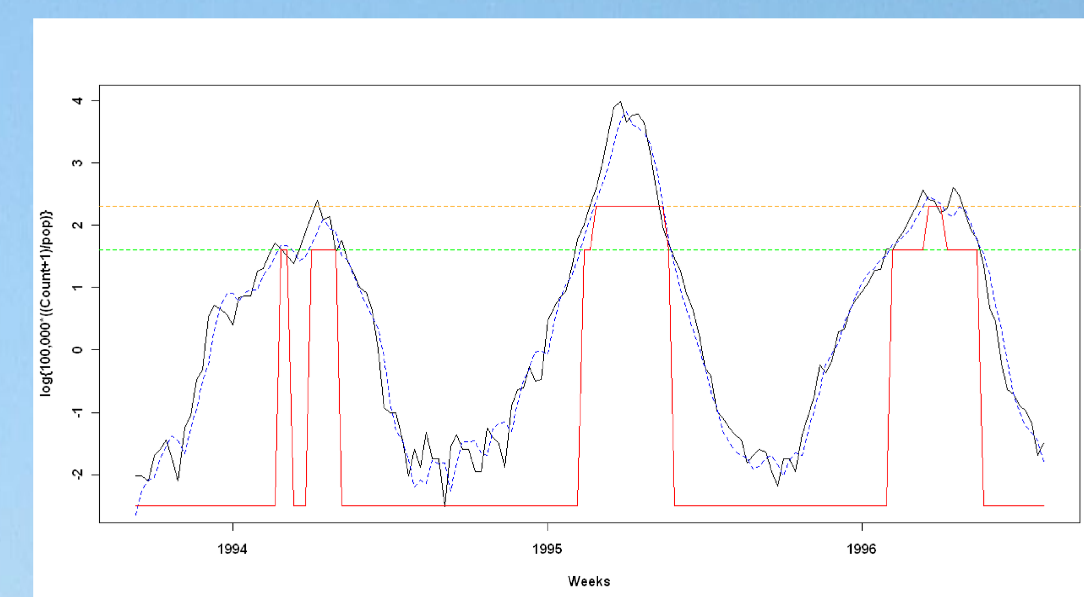
1) Discretizing the weekly incidence rates into states and modelling them (MARKOV CHAIN MODEL)



States are defined from weekly incidence rates :
- **Latent** if <5/100,000 pop
- **Alert** if >=5 and <10/100,000 pop
- **Epidemic** if >=10/100,000 pop

Model the transition probabilities between 2 consecutive weeks

2) Modelling and predicting the log-transformed weekly incidence rates (DYNAMIC LINEAR MODEL)



Log-transformed national incidence rate (solid black line) , and its discretized version (i.e. states) used in the Markov model (solid red line). The one-step ahead predictions (blue dashed line) are obtained by fitting the dynamic linear model. The epidemic threshold and the alert threshold are plotted as dotted orange and green lines respectively.

Harmonic regression terms were included in both models to account for **seasonality** of the disease.

We allow the incidence/state of **neighbouring districts** to **influence** future incidence/states.

The output of both models are the district-level predictive probabilities of exceeding the epidemic threshold

Sensitivity analysis

Compared predictions with observed values using:
- sensitivity
- specificity,
- positive predictive value (PPV)
- negative predictive value (NPV)

OBSERVATIONS

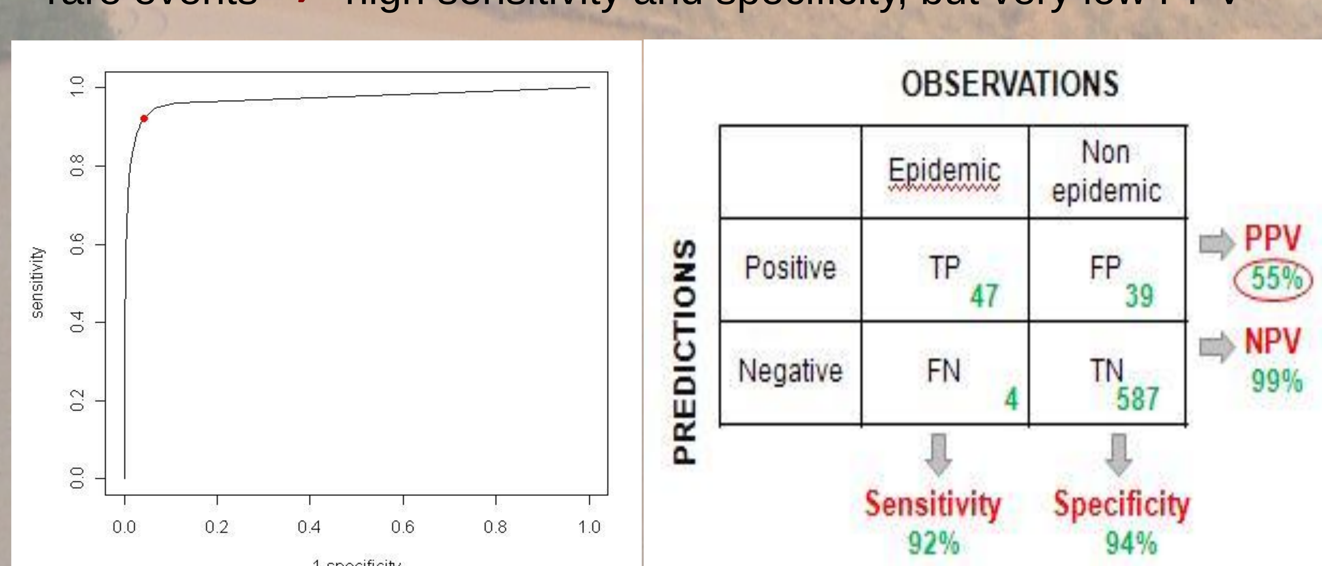
PREDICTIONS	Epidemic	Non epidemic	
Positive	TP =True Positive	FP =False Positive	Positive Predictive Value =TP/(TP+FP)
Negative	FN =False Negative	TN =True Negative	Negative Predictive Value =TN/(TN+FN)
	Sensitivity =TP/(TP+FN)	Specificity =TN/(TN+FP)	

∴ **Define a cut-off point, such that:**

Predicted probability > cut-off point ⇒ predicted epidemic.

This cut-off is usually defined by the ROC curve **BUT**

rare events ⇒ high sensitivity and specificity, but very low PPV



The use of the ROC selected cut-off value (red point) results in poor PPV

Select cut-off that maximises sensitivity, specificity, PPV and NPV

Predictions considered

-1, 2 and 3-weeks ahead predictions (*∴ measure statistical performance)*

-Predicting whether a district will exceed the threshold within a meningitis-year *(∴ measure performance from decision maker's perspective)*

RESULTS

1) MARKOV CHAIN MODEL

Spatial Dependence

- We considered the **number/percentage** of neighbouring districts having exceeded the **alert/epidemic** threshold over the last 1-4 weeks, and since the beginning of the calendar year.
- The most significant impact was the **proportion of neighbours having exceeded the alert threshold over the last 2 weeks.**
- Population density shows significance, but does not improve the predictions

2) DYNAMIC LINEAR MODEL

Spatial Dependence

- Preliminary results are based on fitting a dynamic linear model to the data **under the assumption that the districts were independent**.
- These results are considered to be our **baseline**, and we anticipate our predictions to improve once spatial dependence is incorporated into the model.

1,2, and 3 steps ahead predictions

	1-step	2-step	3-step
sensitivity	76%	66%	63%
specificity	99%	92%	92%
PPV	74%	72%	64%
NPV	99%	99%	99%
cut-off	*33%*	*37%*	*33%*

	1-step	2-step	3-step
sensitivity	64%	61%	63%
specificity	99%	98%	97%
PPV	67%	59%	47%
NPV	99%	99%	99%
cut-off	*39%*	*37%*	*31%*

Predicting an epidemic year

		Observed Epidemic	
		Yes	No
Predicted	Yes	32/104	7/48
	No	195/123	564/523
		227	571

		Observed Epidemic	
		Yes	No
Predicted	Yes	23	12
	No	201	562
		224	574

If, during a meningitis-year at least 1 epidemic week was predicted before the epidemic threshold was exceeded (using 1-step ahead/up to 3-weeks ahead forecasts) ⇒ positive prediction Predictions are compared to whether the district exceeded the epidemic threshold at least once during the year.

CONCLUSION

- **Markov chain model gives better results than the current dynamic linear model** (likely to be due to inclusion of spatial dependence).
- For one-step to three steps ahead predictions the specificity and NPV are very high in both models (>90%). Therefore there is a **trade-off to be made between the sensitivity and the PPV**
- We can better predict epidemic years when considering longer lead time forecasts (Figure 6), but we also mistakenly predict more non-epidemic years to be epidemic.
- **Preliminary results are satisfactory from a statistical modeller's point of view**, but it is currently unclear **how useful they might be to the policy maker** for the purpose of improving the current meningitis control
- Further **collaboration** is therefore needed with the **policy makers** to fully assess the predictive abilities of our models.

NEXT STEP

- **Test our results** on most recent data, and possibly test it over next epidemic season (potentially at CERMES).
- investigate whether **other specifications of the spatial dependence** would improve the predictions.
- incorporate **district-level meteorological variables** (in collaboration with IRI) and assess whether this improves their predictive performances.
- Extend the dynamic linear model to a dynamic generalized linear model, treating case reports as Poisson counts.
- Possibly **increase the predictions lead-time** according to decision maker's requirements.

Bibliography, Acknowledgements

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