A Rift Valley fever risk surveillance system for Africa using remotely sensed data: potential for use on other continents

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Summary

The authors developed a monitoring and risk mapping system using normalized difference vegetation index (NDVI) times series data derived from the advanced very high resolution radiometer (AVHRR) instrument on polar orbiting national oceanographic and atmospheric administration (NOAA) satellites to map areas with a potential for a Rift Valley fever (RVF) outbreaks in sub-Saharan Africa. This system is potentially an important tool for local, national and international organisations involved in the prevention and control of animal and human disease, permitting focused and timely implementation of disease control strategies several months before an outbreak. We are currently developing a geographic information system (GIS)-based remotely sensed early warning system for potential RVF vectors in the United States. Forecasts of the potential emergence of mosquito vectors will be disseminated throughout the United States, providing several months' warning in advance of potentially elevated mosquito populations. This would allow timely, targeted implementation of mosquito control, animal quarantine and vaccine strategies to reduce or prevent animal and human disease.

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Un sistema di sorveglianza sul rischio di insorgenza della febbre della Valle del Rift per l'Africa costruito mediante dati di telerilevamento: uso potenziale in altri continenti

Riassunto
Gli autori sviluppano un sistema di monitoraggio e mappatura del rischio utilizzando serie di dati temporali derivanti dalle differenze dell'indice normalizzato di vegetazione (NDVI) forniti dai radiometri e dagli strumenti ad altissima risoluzione presenti sui satelliti orbitanti sull'orbita polare appartenenti all'ufficio nazionale per l'oceanografia e lo studio dell'atmosfera (NOAA) con l'obiettivo di costruire mappe che identificano potenziali aree di insorgenza di focolai di febbre della valle del Rift nell'Africa sub-sahariana. Questo sistema è potenzialmente un importante strumento per le organizzazioni locali, nazionali ed internazionali coinvolte nella prevenzione e nel controllo delle malattie umane ed animali poiché permette di implementare le strategie di controllo in maniera tempestiva e focalizzata già alcuni mesi prima dell'insorgenza di un focolaio. Attualmente si sta sviluppando un sistema di allerta rapido basto su un sistema informativo geografico per i potenziali vettori della febbre della valle del Rift negli Stati Uniti. Questo sistema è in grado di fornire previsioni sulla potenziale emergenza di specie di zanzare vettori su tutto il territorio degli Stati Uniti, allertando con molti mesi di anticipo le autorità competenti sui potenziali incrementi di popolazione delle zanzare. Ciò dovrebbe consentire l'implementazione tempestiva e mirata dei sistemi di controllo delle zanzare, di quarantena per gli animali e delle strategie vaccinali al fine di prevenire l'insorgenza di patologie sia nell'uomo sia negli animali nonché di limitarne la diffusione.

Introduction

Rift Valley fever (RVF) is a mosquito-borne viral disease with pronounced health and economic impacts in domestic animal and human populations in much of sub-Saharan Africa (15). The disease causes high mortality and abortion in domestic animals and morbidity (ranging from fever to ocular, meningoencephalitis, and haemorrhagic disease) and mortality (case mortality rate of 0.2-5%) in humans. RVF epizootics and epidemics are closely linked to the occurrence of the warm phase of the *El Niño*/Southern Oscillation (ENSO) phenomenon (13). We have developed a monitoring and risk mapping system – using normalized difference vegetation index (NDVI) times series data derived from the advanced very high resolution radiometer (AVHRR) instrument on polar orbiting National Oceanographic and Atmospheric Administration (NOAA) satellites – to map areas with a potential for a RVF outbreak (1). This forecasting system operates in near-real time with a three-month lead to predict monthly RVF risk (3, 13). It offers an opportunity to identify eco-climatic conditions associated with disease outbreaks over a large area (24)**.** This system is potentially an important tool for local, national and international organisations involved in the prevention and control of animal and human disease. It permits focused and timely implementation of disease control strategies several months in anticipation of an outbreak.

The RVF outbreak on the west coast of the Arabian Peninsula in 2000 demonstrated that regions other than those in sub-Saharan Africa might be at risk of RVF (6). The forecasting system developed for Africa has been modified to include the Arabian Peninsula, and can potentially be adapted to assess the risk of RVF and other arthropod-borne disease outbreaks in new ecological settings (2).

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In order to enhance disease surveillance and forecasting, we are currently developing a geographic information system (GIS)-based early warning system for RVF vectors in the United States, based on the African model. Mosquito surveillance data collected by mosquito control and public health agencies, and climate data derived from satellite measurements and terrestrial weather stations, are being compiled in a GIS system for this task. Potential disease transmission patterns will be predicted, based on the quantitative relationship between the activity of potential RVF mosquito vectors and local and global climate indicators. Spatial and temporal statistics are used to evaluate associations between climate and predicted mosquito densities. Risk maps will be generated to inform vector control agencies. These will be disseminated throughout the United States, providing several months warning before conditions are suitable for elevated populations of potential RVF mosquito vectors. This will permit timely, targeted implementation of mosquito control, animal quarantine and vaccine strategies to reduce or prevent animal and human disease, should RVF virus enter the United States. The infrastructure and systems we develop in preparation for RVF can be laterally transferred to inform strategies against any other introduced mosquito-borne disease threats.

Methods

Identification of geographic areas at risk of RVF outbreaks is based on ecological interactions involving host animals, vector arthropods, the virus and the biological and physical environment. In developing our RVF risk model for Africa we considered the dynamics of mosquito species succession in flooded habitats (12). Next, we identified areas – where historic RVF outbreaks have occurred – with substantial interannual vegetation (as shown by NDVI) variability. Then we determined where in these areas there were persistent positive NDVI anomalies during the rainy season associated with above normal rainfall. We selected high-risk time periods

based on sea surface temperature (SST) anomalies in region 3.4 of the equatorial eastern Pacific (NINO 3.4) and in the equatorial western Indian Ocean (WIO), representing *El Niño* and *La Niña* periods (Fig. 1). Finally, we evaluated how periods with significant above or below departures in SSTs correlate with above or below normal NDVI in East Africa.
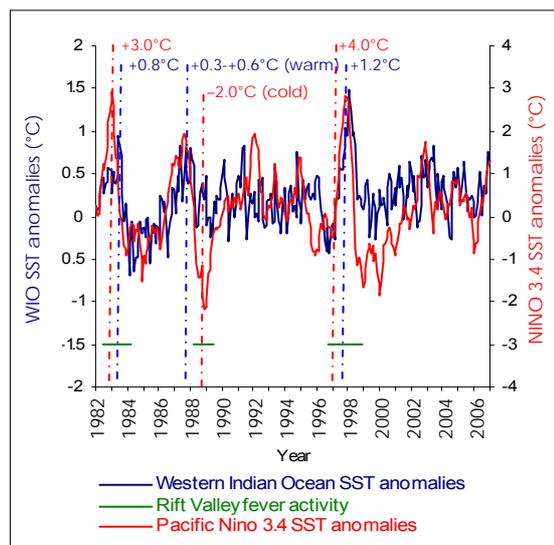

Figure 1
NINO 3.4 SST anomalies (red line) and WIO SST anomalies (blue line) SSTs elevated for 1982-1983 corresponding to Rift Valley fever virus transmission in East Africa, elevated WIO SSTs (blue line) elevated for 1988-1989 corresponding to localised RVF virus transmission in central Kenya and concurrent elevated NINO 3.4 (red line) and WIO (blue line) SSTs for 1997-1998 corresponding to extensive RVF virus transmission in East Africa

We used the following procedures to identify regions at elevated risk of a RVF outbreak (1):
- Create a long-term NDVI based climatology describing vegetation patterns for the entire African continent, at an 8 km spatial resolution, by calculating the mean NDVI for July 1981 to July 2000 (22).
- Develop a map of savannah complexes in Africa with a mean NDVI value between 0.15 and 0.40, corresponding to a mean yearly rainfall of 200-800 mm. These are primarily the regions where RVF outbreaks have been described (17). This product (a savannah mask) omits tropical forest, desert and some wet savannah areas, such as northern

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Zambia, and has been adjusted to include areas in the Nile River Valley and the Arabian Peninsula where RVF expanded its range in 1977 (17) and 2000 (6), respectively. This savannah mask includes areas that are likely to have RVF epizootics/epidemics.

- Calculate NDVI monthly anomalies, expressed and mapped as percent deviation of monthly values from the long-term mean value for each pixel in the savannah mask of continental Africa.

- Define areas at risk of RVF. Risk is defined as a persistent positive anomaly >0.025 NDVI units for any three consecutive months for any pixel within the savannah mask. Then identify all pixels with a mean monthly positive anomaly exceeding 0.1 NDVI units, a value observed in East Africa during the 1997-1998 RVF epizootic (13).

- Calculate frequency statistics on the number of RVF risk pixels. The savannah mask is divided into three regions (East Africa, South Africa and the Sahel) for analysis and data are expressed as a continuous three-month rolling average for all months (1). The results for the different periods show the highest risk by area coverage. A total of 164 850 pixels, representing 10 550 400 km², are included in the savannah mask.

Results and discussion

Current Rift Valley fever risk assessment system in Africa

Risk maps are generated and are interpreted in relation to interannual variability patterns in SST anomalies in the WIO and NINO 3.4 regions. RVF risk results are presented as binary images. Areas flagged as red within the savannah mask represent elevated risk for RVF for that period of time (Fig. 2). Areas shown in green are within the RVF endemic mask and show reduced risk. Other areas (shown in yellow), desert and dense tropical forest are not included in the analysis.

In East Africa, the RVF risk model retrospectively detected the last three RVF outbreaks in 1982-1983, 1989 and 1997-1998, and each of these events was correlated to positive SST anomalies. The 1982-1983

outbreak corresponded to a warm ENSO event with peak positive anomalies in the NINO 3.4 and WIO regions of 3.0 and 0.8°C, respectively (Fig. 1). Positive NDVI anomalies persisted for several months and covered most of the semi-arid lands of East Africa (Fig. 2).
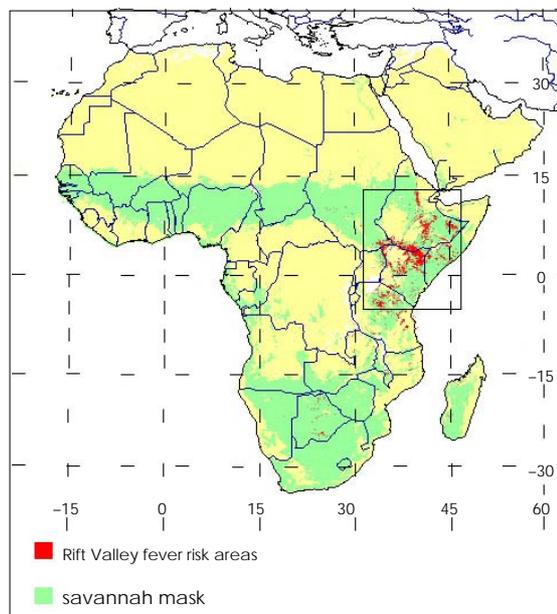

Figure 2
Rift Valley fever risk map, November 1982 to January 1983
Elevated RVF risk depicted in red for much of East Africa was convergent with a RVF epizootic in Kenya during this period

In 1988-1989, warm SST conditions prevailed in the WIO region but the NINO 3.4 changed to cold conditions (Fig. 1). Positive NDVI anomalies persisted in southern African and East Africa. We identified areas of potential RVF risk in north-west Kenya extending to the central Rift Valley region around Lakes Nakuru and Naivasha in Kenya, and other areas of South Africa (Fig. 3). Localised RVF activity in mosquitoes, domestic animals and humans was detected in the area around Lake Naivasha, Kenya (14).

Warming SST conditions commenced during May 1997 in both the WIO and NINO 3.4, reaching a peak of 1.2°C in the WIO and 4.0°C in the NINO 3.4 (Fig. 1). Large areas of East Africa received widespread and heavy rainfall during the short rainy season (September to November 1997) and this rainfall extended into the dry season (December 1997 to February

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1998). Significantly elevated NDVI values occurred in much of East Africa. This led to an increased risk of RVF transmission over an area of 1 280 000 km², including Kenya, Somalia, Tanzania, Sudan, Uganda and parts of Ethiopia (Fig. 4). The largest RVF outbreak in the last 20 years occurred during this period over the same area identified to be at risk (5).
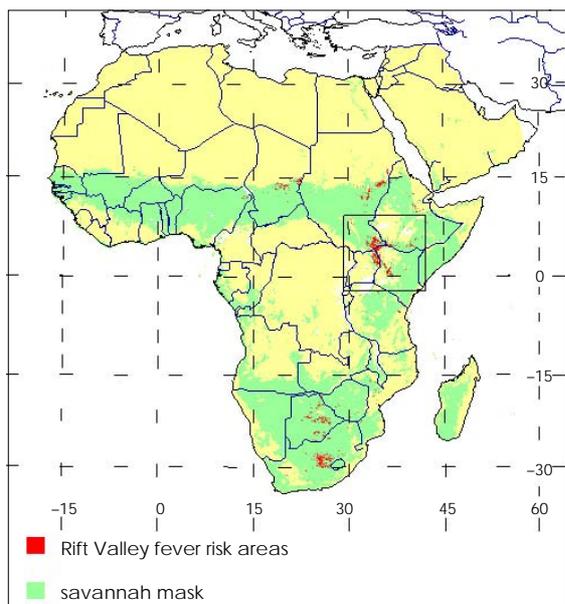

Figure 3
Rift Valley fever risk map for September to November 1988 showing elevated risk in Kenya where a limited RVF epizootic/epidemic occurred near Lake Naivasha

In the Sahel, the largest RVF outbreak in Senegal and Mauritania was detected in 1987; however, limited RVF activity in Senegal in 1993, Burkina Faso in 1983 and the Central African Republic in 1985 was not detected. In southern Africa, elevated RVF activity was detected in Zambia in 1985-1986 but RVF activity between 1982 and 1985 was variable. The initial stages of the RVF outbreak in Madagascar in 1992 were detected.

Currently (November 2006), positive NDVI anomalies 40-60% above normal in East Africa indicate heavy rainfall (Fig. 5). Elevated risk of RVF activity is noted in Somalia in East Africa and in Namibia and Botswana in southern Africa (Fig. 6). It has been 10 years since the 1997-1998 RVF outbreak in East Africa and current elevated rainfall, NDVI and RVF risk suggest that if current conditions persist there

is a high likelihood of another RVF outbreak. We provided the forecast for this outbreak in October and November 2006 (3).
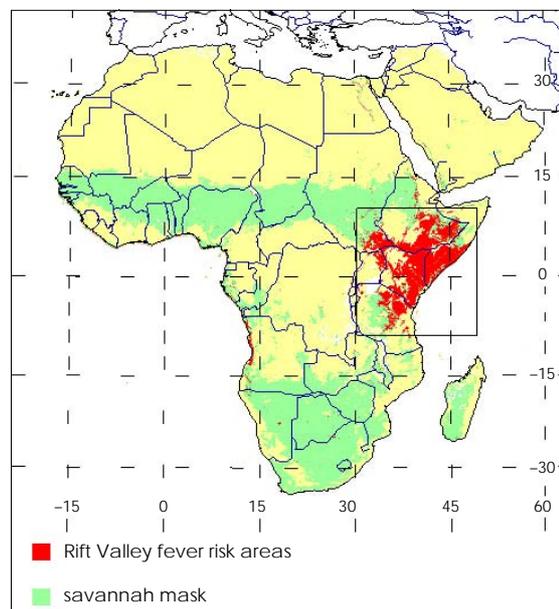

Figure 4
Rift Valley fever risk map, December 1997 to February 1998
Elevated RVF risk is depicted in red for much of East Africa
The largest RVF outbreak in the last 20 years occurred during this period covering a large geographic area (1 280 000 km²) of East Africa
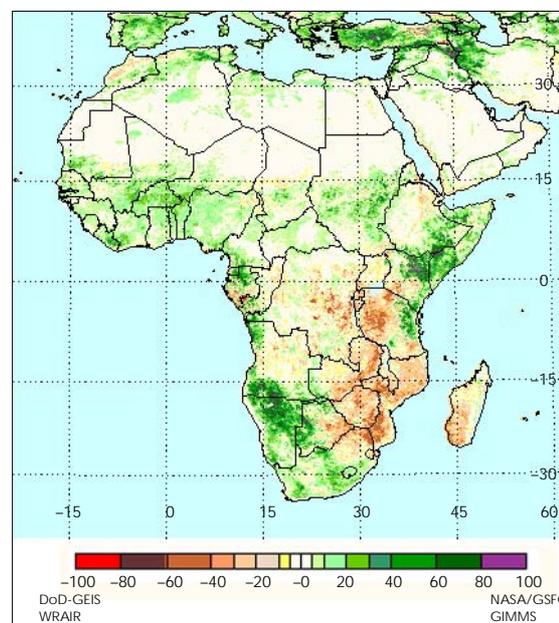

Figure 5
Normalized difference vegetation index anomalies for November 2006 depicting favourable ecological conditions for mosquito breeding, associated with elevated rainfall in much of East Africa

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The RVF risk model uses population dynamics of mosquito vectors and eco-climatic indicators to reconstruct likely historical patterns of RVF outbreaks and monitor eco-climatic conditions associated with disease outbreaks over large areas with satellite measurements (2). Disease mapping might provide public health authorities with information with which to target disease surveillance and control teams. Targeted response increases efficacy and minimises the cost of surveillance over large areas.
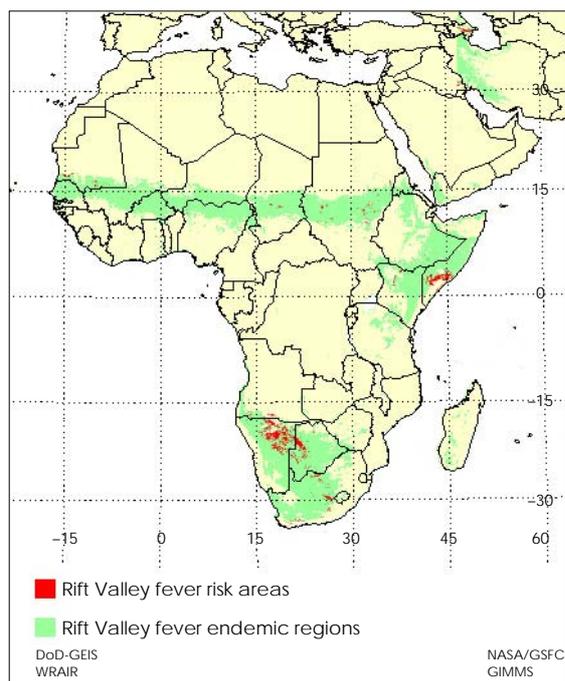

Figure 6
Rift Valley fever risk potential map, November 2006
Elevated RVF risk is depicted in red in Somalia, northern Kenya and Namibia, Botswana and South Africa

Development of a risk assessment system for potential introduction of Rift Valley fever into the United States

The documented expansion on RVF range beyond sub-Saharan Africa into Egypt in 1977 (17) and, more recently, the emergence of the disease in Saudi Arabia and Yemen in 2000 (6) makes RVF a possible candidate for further globalisation. Similar to the introduction of West Nile virus (WNV) into the United States in 1999, an introduction of RVF into the United

States would pose a substantial risk to humans, domestic animals and wildlife populations. RVF would also present significant effects on the agricultural and public health communities. The effect on the United States economy, including livestock feed suppliers, health care insurance, the food-service industry and loss of confidence in the food supply, would be substantial. The bovine spongiform encephalopathy (BSE) outbreak in the United Kingdom in 1986 cost the European Union more than US$100 billion. The United States had beef-related exports in 2003 of US$5.7 billion. Additionally, the World Organisation for Animal Health (OIE: Office International des Épizooties) imposes a four-year trade ban on any country with confirmed RVF transmission and the ban is lifted only after a country is disease-free for six months. It is important to now consider methods for adapting the RVF risk mapping methodologies developed for Africa to other regions of the world. Below we describe the process being developed in the United States.

The United States early warning system for potential mosquito vectors of Rift Valley fever

The rapid spread of WNV showed how rapidly an exotic arbovirus could establish in the United States, yet demonstrated our capacity to respond with improved public health, vector/virus surveillance and control, agency coordination and public education. However, there is more that can be done with respect to mosquito vector surveillance in the United States and we are developing a GIS-based early warning system for potential vectors of RVF. In Africa, remotely sensed climate data are routinely and successfully used to flag areas at high risk of vector outbreaks and thus identify RVF epizootics at their earliest stage (1, 3, 13). We are developing a companion approach in the United States, but RVF is not present in the United States and there is no historical climate precedent for RVF outbreaks. We are instead looking at the predictive power of climate to inform us of population dynamics of potential RVF mosquito vectors. Population dynamics, such

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as the timing, distribution and abundance of competent mosquito vectors, are critical factors in the risk of spread of an introduced mosquito-borne pathogen like RVF. Risk is compounded with biogeographic interactions of the pathogen, its vectors and susceptible human, livestock and wildlife populations.

Our ability to predict the distribution, timing and abundance of a vector population hinges on unique biogeographic linkages between the species and its environment. A mosquito species in the United States, such as *Aedes vexans*, has an overall range estimated by a maximum polygon enclosing all observation points derived from field collections (8). This polygon is not an optimal representation of the environment's temporal and spatial patchiness that drives distributions of organisms. The actual range is in fact a mosaic of patches environmentally appropriate for that species. The species can be thought of as divided into populations occupying these patches. The relationship between a mosquito species and its environment – based on snapshot measurements – are frequently used to provide a habitat suitability index from which predictions of future distributions can be made (9, 11, 21). However, analysis of long-term climate-species relationships may be more powerful. The relative success of a mosquito population over a long-term period of climate variation will give a better picture of the full range of climate conditions in which a species may survive (4, 7, 10, 16). We are looking at this relationship with long-term mosquito population data and long-term climate data.

Mosquito population data

We have compiled long-term population data from mosquito surveillance records gathered from mosquito and vector control districts (MVCDs) and state public health agencies throughout the United States. This database is a record of historical patterns of mosquito species abundance. Although mosquito population samples are collected from an array of trap types which may sample different elements of mosquito communities, traps are often placed in consistent locations and many have produced data for periods of years to decades to half centuries. Population data for a species are normalized in a monthly index of the mean number of females collected per trap per night, since MVCDs may trap over different time spans in a month. In the GIS, plotted trap location points are linked via attribute tables to the long-term mosquito surveillance database. For the species of interest, data are combined from all traps to create a unique distribution map for a given period of time. The majority of trap data we are evaluating are from Florida, but we have compiled data from several regions around the United States to represent a variety of ecological regions: the north-west (Washington, Oregon, Montana), north-central (Minnesota, Michigan), the north-east (Connecticut, New Jersey), and the south-east (Florida, Georgia, Louisiana). We have also included data gathered from mosquito surveillance across continental United States (CONUS) military bases by the United States Army Center for Health Promotion and Preventive Medicine (USACHPPM). Military bases may be ecological islands amid rapidly changing landscapes and may provide unique insight into climate-mosquito population dynamics, particularly when compared to adjacent civilian trap data. For instance, an outbreak of RVF could easily spread into neighbouring urban or rural areas from military installations and it will be a strategic advantage to have an understanding of mosquito population dynamics in either environment.

Climate data

For more than 25 years, NOAA has maintained satellites that gather United States climate data, providing information on climate for the entire life span of the majority of mosquito traps in the United States. NOAA climate data, such as NDVI gathered by AVHRR satellites (18, 19, 23), provide detailed global coverage in georeferenced raster format suitable for GIS. NDVI is particularly useful for landscape level study of populations since the index captures the combined effects of temperature, humidity, insolation, elevation, soils and precipitation. Figure 7 depicts NDVI values for North America in June 2005. Extensive greening of

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most of North America is observed. The coupling of climate and vegetation dynamics enables a single 'greenness' index to be used
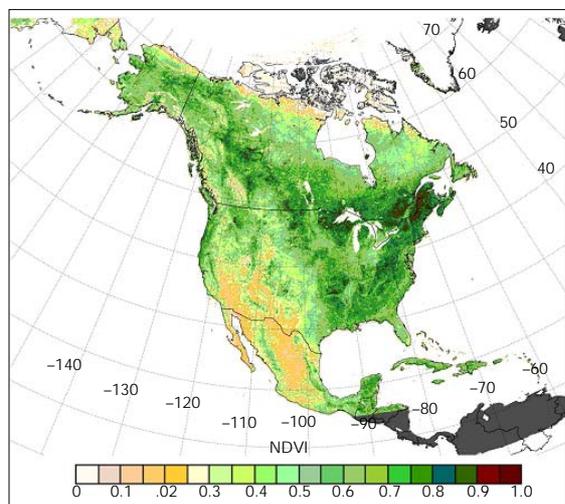

Figure 7
Normalized difference vegetation index for North America, June 2005 showing the increased green coverage of vegetation over the continent during early summer

for multiple analyses between populations and component parameters which otherwise may on their own be misleading. By examining monthly NDVI anomalies compared to 25 year means, we can quantitatively describe the greenness of the landscape and the probability of mosquito populations surviving. Figure 8 depicts NDVI anomalies for North America in June 2005. Positive vegetation anomalies are observed in northern Nevada and in a band extending from New Mexico to Canada just east of the continental divide. The 8 km² NDVI raster cells blur some landscape heterogeneity and mosquito traps sample small areas within those cells. However, if climate-population associations emerge from coarse analyses we will use them as a guide to pursue climate-population relationships at progressively finer scales. In addition, since species are sampled at multiple locations, and NDVI anomaly values vary among locations, we have the opportunity to examine population-NDVI relationships within a time period, as well as at single locations across multiple time periods. NOAA has also cultivated a terrestrial nationwide network of cooperative climate

reporting stations with data up to 100 years old. We may interpolate precipitation or temperature data from terrestrial stations to estimate climate at trap sites where pre-satellite era mosquito population data exist, and in many cases MVCDs capture their own rainfall data at trap sites.
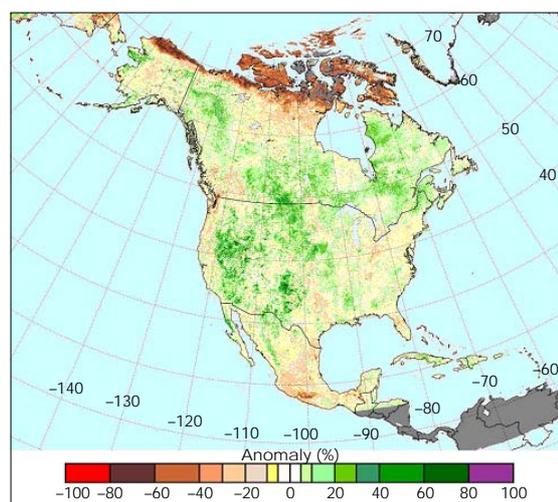

Figure 8
Normalized difference vegetation index anomalies in North America for June 2005 showing above normal vegetation conditions over western United States
Anomalies are computed with respect to the 1981-2003 mean period

Approach

Our first task is to link changes in environmental parameters with changes in vector populations subject to those parameters. Using geographic information technology we are looking for these links at two spatial scales. The first analysis looks at coarse, regional associations between population changes and a single climate parameter measured by satellite remote sensing; the second analysis examines fine scale associations between temporal variation of populations at sample locations and environmental parameters at those locations. Both analyses are facilitated by using a GIS computerised mapping platform for storage, editing, display and temporal-spatial statistical analysis of all population and environmental data. By looking at long-term historical relationships between changes in climate and changes in mosquito populations, we will identify environmental factors such as

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temperature and precipitation that can be used to predict the population dynamics of a mosquito species. Specifically, our objective is to build a model that predicts when and where environmental conditions are favourable for the emergence of unusually large mosquito populations. Given that more mosquitoes can increase the risk of dispersal of mosquito-borne pathogens like RVF in humans, livestock and wildlife, these environmentally-based spatial and temporal predictions will drive disease risk maps. If particular climate patterns precede mosquito population changes, an automated GIS and remote sensing system may track climate and provide early warning of areas at risk. This system is the vector early warning GIS (VEW-GIS).

Coarse-scale climate-population analyses

For a vector species of interest, data are pulled up from all traps to create a unique distribution-density map for a given month in the GIS. The GIS is used to calculate mean NDVI values for that month across all sample points from a population, and we plot those NDVI values with population densities. In tandem with NDVI values, we calculate anomaly NDVI values to provide a measure of positive or negative deviation from the 25-year mean value for that month. What follows is a simple qualitative analysis or a simple regression analysis of monthly climate-population relationships spanning several years to determine whether relationships exist between increases in populations and increases in greenness or greenness anomalies. Alternatively, plots of population densities and NDVI anomalies could reveal patterns of lag between climate actions and population responses. If relationships do exist, we will examine finer scales of climate and habitat to pinpoint key features that best predict increases or decreases in a population. NDVI may be sufficient to flag areas at risk of elevated vector populations at a scale usable by mosquito control districts or national preparedness agencies. Alternatively, we may find little or no relationships with NDVI. In this case, other global climate indicators, such as the ENSO or finer detail indicators such as

land use change, mosquito control practices, or even major land-falling hurricanes, could be examined.

Fine-scale climate-population analyses

We will use an ecological niche mapping approach to look at fine scale relationships between population sample locations, the species found there (type and abundance), and the unique set of environmental attributes that define that location using DesktopGARP (20) (genetic algorithm for rule-set production). With GARP we will create a temporal series of niche models for each species and with an iterative approach test whether the niche derived at one time period matches that derived at another. The greater number of temporal matches, the greater the confidence that a certain habitat niche – which includes climate as well as an array of landscape features – is greatly predictive of the presence (or possible presence) of a mosquito vector of concern. Niche models developed using long-term analyses can be tested against randomly excluded data, or by restricting model parameters to conditions early in the data period to predict later known values, assessing our ability to tag areas at risk of elevated populations. Also by monitoring the landscape and flagging areas which evolve to possess the features of a species' niche, we can identify areas that may potentially harbour invasive species or vectors that were previously rare or unrecorded. Future GIS analyses will also include climatic factors such as air temperature and degree-day statistics which can affect vector competence and vectorial capacity of potential mosquito vectors of RVF depending on the time and place of introduction of RVF in the United States.

Spatial information product: how will the climate-population analyses be used?

There are two components for strategic implementation of VEW-GIS in minimising the risk of RVF in the United States.

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Component I, Prevention

Effective prevention depends on monitoring the constellation of favourable conditions needed for RVF to enter the United States, as follows:

- the climate and consequent magnitude of RVF activity in Africa
- reports of RVF activity in Africa and worldwide, and trade and movement of people between the United States and Africa
- the status of candidate vectors, as modelled by VEW-GIS
- the status of likely vertebrate reservoirs at nodes of projected arrival pathways of RVF.

Component II, Preparation

Preparation is nested within preventive efforts. Effective preparation for response, should RVF be detected in the United States despite prevention, depends on the status of vectors *when* and *where* introduction takes place. The status of candidate RVF mosquito vectors can be assessed by a combination of current surveillance data from mosquito control districts and risk maps produced by VEW-GIS. By developing predictive risk models of where vectors could be at any given time in the United States, we can more efficiently target, mobilise and implement control and containment strategies should RVF actually be detected in the United States.

At its core, the VEW-GIS automated system simply flags regions susceptible to unusually high densities of mosquito vectors. Ideally the products of the VEW-GIS should be part of larger surveillance systems, such as those outlined in the prevention and preparation components. But the VEW-GIS is operational on its own as a clearinghouse of United States mosquito vector data. Mosquito and vector control agencies already integrate data from mosquito population surveillance into daily activities at a local level, but our goal is to synthesise these data at a national level The VEW-GIS predictive index can be integrated into existing surveillance/control measures by MVCDs, or can alert public health communities or other stakeholders (e.g. cattle and sheep producers or wildlife health agencies) that they should take extra measures to protect themselves and their interests. Many

states may not perform mosquito surveillance or typically be exposed to elevated populations of pathogen-carrying mosquitoes, but climate can change and new vectors and new pathogens may arrive. Spatially-specific recommendations allow limited resources to be distributed more effectively, for instance freeing some areas from unnecessary blanket precautions by spatially targeting vector control, distribution of vaccines and diagnostics and dissemination of information to stakeholders based on the status of mosquito populations. Since climate in the United States is linked to phenomena such as the ENSO, climate activity elsewhere in the world could be used to estimate risk indices months into the future and provide ample time for preparation and prevention across the United States.

Conclusion

Our current monitoring and risk mapping system – based on NDVI and SST data from AVHRR instruments on polar orbiting NOAA satellites – is effective in assessing the potential spatial and temporal distribution of RVF transmission in Africa, as demonstrated by having predicted the recent RVF outbreak. However, RVF has expanded its distribution beyond the African continent. To prepare for a potential introduction into the United States, we are developing a GIS/remotely sensed early warning system for RVF vectors in the United States using mosquito surveillance data collected by mosquito control and public health agencies, and climate data measured by satellites and terrestrial weather stations. The GIS predicts disease transmission patterns based on the quantitative relationship between mosquito activity and patterns of local and global climate. Linkages between climate and mosquito densities are evaluated with spatial and temporal statistics, generating risk maps to inform vector control agencies. Mosquito prediction information will be disseminated throughout the United States, providing several months warning before conditions are suitable for elevated mosquito populations, permitting targeted implementation of mosquito control, animal quarantine and

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vaccine strategies in time to reduce or prevent animal and human disease. Many of the systems we develop in preparation for RVF can be laterally transferred to inform strategies against other mosquito-borne disease threats. Additionally, the methodologies that we are developing for RVF surveillance could be adapted for use in neighbouring countries in North America and elsewhere.

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