TU Delft

Delft University of Technology

Early warnings of hazardous thunderstorms over Lake Victoria

Thiery, Wim; Gudmundsson, Lukas; Bedka, Kristopher; Semazzi, Fredrick H.M.; Lhermitte, Stef; Willems, Patrick; van Lipzig, Nicole P. M.; Seneviratne, Sonia I.

DOI
10.1088/1748-9326/aa7521

Publication date
2017

Document Version
Final published version

Published in
Environmental Research Letters

Citation (APA)
Thiery, W., Gudmundsson, L., Bedka, K., Semazzi, F. H. M., Lhermitte, S., Willems, P., van Lipzig, N. P. M., & Seneviratne, S. I. (2017). Early warnings of hazardous thunderstorms over Lake Victoria. *Environmental Research Letters*, *12*(7), [074012]. https://doi.org/10.1088/1748-9326/aa7521

Important note
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright
Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy
Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

This work is downloaded from Delft University of Technology.
For technical reasons the number of authors shown on this cover page is limited to a maximum of 10.

IOPscience iopscience.iop.org

Early warnings of hazardous thunderstorms over Lake Victoria

This content has been downloaded from IOPscience. Please scroll down to see the full text.

View the table of contents for this issue, or go to the journal homepage for more

Download details:

IP Address: 131.180.130.242
This content was downloaded on 03/08/2017 at 08:43

Please note that terms and conditions apply.

Environmental Research Letters

LETTER

Early warnings of hazardous thunderstorms over Lake Victoria

Wim Thiery[1,2,8], Lukas Gudmundsson[1], Kristopher Bedka[3], Fredrick H M Semazzi[4], Stef Lhermitte[5], Patrick Willems[2,6], Nicole P M van Lipzig[7] and Sonia I Seneviratne[1]

[1] Institute for Atmospheric and Climate Science, ETH Zurich, Universitaetstrasse 16, 8092 Zurich, Switzerland
[2] Department of Hydrology and Hydraulic Engineering, Vrije Universiteit Brussel, Pleinlaan 2, 1050 Brussels, Belgium
[3] Science Directorate, NASA Langley Research Center, 21 Langley Boulevard, Hampton, VA 23681, United States of America
[4] Department of Marine, Earth and Atmospheric Sciences, North Carolina State University, Raleigh, NC 27695, United States of America
[5] Department of Geoscience and Remote Sensing, Delft University of Technology, Stevinweg 1, 2600 GA Delft, The Netherlands
[6] Department of Civil Engineering, KU Leuven, Kasteelpark Arenberg 40, 3001 Leuven, Belgium
[7] Department of Earth and Environmental Sciences, KU Leuven, Celestijnenlaan 200E, 3001 Leuven, Belgium
[8] Author to whom any correspondence should be addressed.

E-mail: wim.thiery@env.ethz.ch

Keywords: Lake Victoria, early warning systems, extreme weather, vulnerability

Supplementary material for this article is available online

OPEN ACCESS

RECEIVED
1 November 2016

REVISED
18 May 2017

ACCEPTED FOR PUBLICATION
26 May 2017

PUBLISHED
6 July 2017

Original content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence.

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Abstract

Weather extremes have harmful impacts on communities around Lake Victoria in East Africa. Every year, intense nighttime thunderstorms cause numerous boating accidents on the lake, resulting in thousands of deaths among fishermen. Operational storm warning systems are therefore crucial. Here we complement ongoing early warning efforts based on numerical weather prediction, by presenting a new satellite data-driven storm prediction system, the prototype Lake Victoria Intense storm Early Warning System (VIEWS). VIEWS derives predictability from the correlation between afternoon land storm activity and nighttime storm intensity on Lake Victoria, and relies on logistic regression techniques to forecast extreme thunderstorms from satellite observations. Evaluation of the statistical model reveals that predictive power is high and independent of the type of input dataset. We then optimise the configuration and show that false alarms also contain valuable information. Our results suggest that regression-based models that are motivated through process understanding have the potential to reduce the vulnerability of local fishing communities around Lake Victoria. The experimental prediction system is publicly available under the MIT licence at github.com/wthiery/VIEWS.

1. Introduction

With a surface area of 68 800 km^2, Lake Victoria is the largest lake in Africa. The lake directly sustains the livelihood of 30 million people living near its coasts and its fishing industry is a critical natural resource for communities in East Africa (Song *et al* 2004, East African Community 2011).

However, severe thunderstorms and associated high waves represent a constant threat to the 200 000 fishermen operating on the lake (East African Community 2011). No reliable figures are available for the number of incidents in which people drown, but the International Federation of Red Cross and Red Crescent Societies (2014) assumes that 3000–5000 fishermen die every year on the lake, and boating accidents are often related to severe weather (East African Community 2011). Thunderstorms on Lake Victoria thereby substantially contribute to the global death toll from natural disasters. Also, these events have major implications for the regional economies, as each perished fisherman leaves on average eight relatives without an income (East African Community 2011). Rapid urbanisation along the lakefront (Seto *et al* 2012) will in the near-future likely lead to a sharp increase in exposure of local fishing communities to these natural hazards, whereas future climate projections indicate a strong increase in thunderstorm intensity especially over Lake Victoria (Thiery *et al* 2016). In particular, the projected future increase in extreme precipitation over Lake Victoria is about twice as large relative to surrounding land under a

© 2017 IOP Publishing Ltd

high-emission scenario, and consistently emerges from single-model, high-resolution simulations and coarser-scale ensemble projections.

Due to this unacceptable human cost, efforts have been ongoing to develop a well-functioning early warning system, which would prevent fishermen from taking risks when conditions are favourable for severe storm development. These efforts have aimed to reduce accidents via storm warnings derived from operational, high-resolution numerical weather prediction (NWP) systems. Notably, the meteorological service of the United Kingdom (Met Office, hereafter referred to as UKMO) has recently established a 4 km resolution limited-area NWP system for the larger Lake Victoria region and a first evaluation indicates better performance than persistence forecasts of 'today will be the same as yesterday' (Chamberlain *et al* 2014, Eagle *et al* 2015). In parallel, a 'Mobile Weather Alert' pilot was launched in 2011 by the World Meteorological Organization (WMO), providing Kenyan fishermen with free forecast and warning information via their cell phone (East African Community 2011, Chamberlain *et al* 2014). A similar effort is currently undertaken in Uganda by the Trans-African Hydro-Meteorological Observatory (TAHMO, http://tahmo.org/), while the Safe Water Foundation (SWF, https://forsafewaters.wordpress.com/) aims to integrate these efforts across the three countries bordering Lake Victoria (Uganda, Kenya and Tanzania). Finally, the Global Energy and Water Cycle Exchanges Project (GEWEX) has recently launched the Hydroclimate project for Lake Victoria (HyVic, www.gewex.org/hyvic/), which aims to provide scientific understanding of the climate of the region to improve weather prediction and climate projections (Semazzi *et al* 2014).

Thunderstorms and precipitation display a clear diurnal cycle over Lake Victoria. In contrast to the diurnal cycle observed over the surrounding land, convective activity over Lake Victoria peaks at night while being suppressed during daytime (figures 1(*a*)–(*c*); supplementary figure 1 stacks.iop.org/ERL/12/074012/mmedia). This distinct pattern arises from the lake/land breeze system which induces near-surface divergence during daytime and convergence at night, as well as from sustained evaporation over the lake surface and from anabatic/katabatic flows originating on the mountain slopes east of the lake (Song *et al* 2004, Anyah *et al* 2006, Williams *et al* 2015, Thiery *et al* 2015). Similar patterns are found for the other African Great Lakes, each time modulated by local orography (Thiery *et al* 2015).

A recent analysis of the controlling factors of extreme thunderstorms over Lake Victoria revealed a strong dependency of the nighttime over-lake storm intensity on the antecedent daytime land storm activity (Thiery *et al* 2016). Intense daytime land storms thereby modify the lake/land breeze system and associated moisture transport, in particular by inducing a moist anomaly in the lower layers of the atmosphere and by cooling the land surface. This cold anomaly in turn limits moisture divergence from the lake (weak lake breeze) while favouring nighttime near-surface convergence (strong land breeze). Overall this highlights the key importance of mesoscale circulation for understanding weather extremes in the region.

The afternoon control on nighttime storm activity also indicates an inherent predictability in the system which has not been exploited so far. Moreover, this analysis was based on a new proxy dataset for severe thunderstorm occurrence, suggesting that predictions might be derived from observational products. Finally, this proxy is derived from an operational weather satellite and can thus be made available in realtime. Altogether this presents an opportunity for developing a new, satellite-based short-term prediction system for severe thunderstorms over Lake Victoria.

The main goal of this study is therefore to explore the potential of satellite-based thunderstorm observations as a risk indicator for extreme storm occurrence over Lake Victoria. We propose an innovative yet simple approach to predict the occurrence of the 1% most extreme events, that is, the ~3–4 nights per year with the most intense nighttime storm activity. In particular, we develop a logistic regression model based on a 9 year severe thunderstorm dataset available for the region. The main advantages of this approach are the high skill, minimum computational cost and independence of existing forecast products. As such our data-driven approach complements and supports ongoing efforts from the NWP community (dynamical modelling) to eventually reduce the vulnerability of local communities around Lake Victoria.

In this paper, we first establish the proof of concept of observation-driven storm predictability by applying logistic regression to three different data products. We subsequently optimise the statistical model for one product through an objective calibration procedure, both at the lake and country scale. Finally, we outline the structure of the prototype prediction tool which is released into the public domain.

2. Data and Methodology

2.1. Overshooting top detections and rainfall data

Satellite observations enable the recognition of severe weather by detecting overshooting tops (OTs), which appear as dome-like protrusions atop a cumulonimbus anvil (Bedka *et al* 2010). OTs indicate the presence of deep convective events and are induced by intense updraughts through the tropopause into the lower stratosphere (Proud 2015). OT-producing convective thunderstorms frequently produce hazardous weather at the Earth's surface, like heavy rainfall, wind gusts, large hail and tornadoes (see Bedka *et al* (2010) and

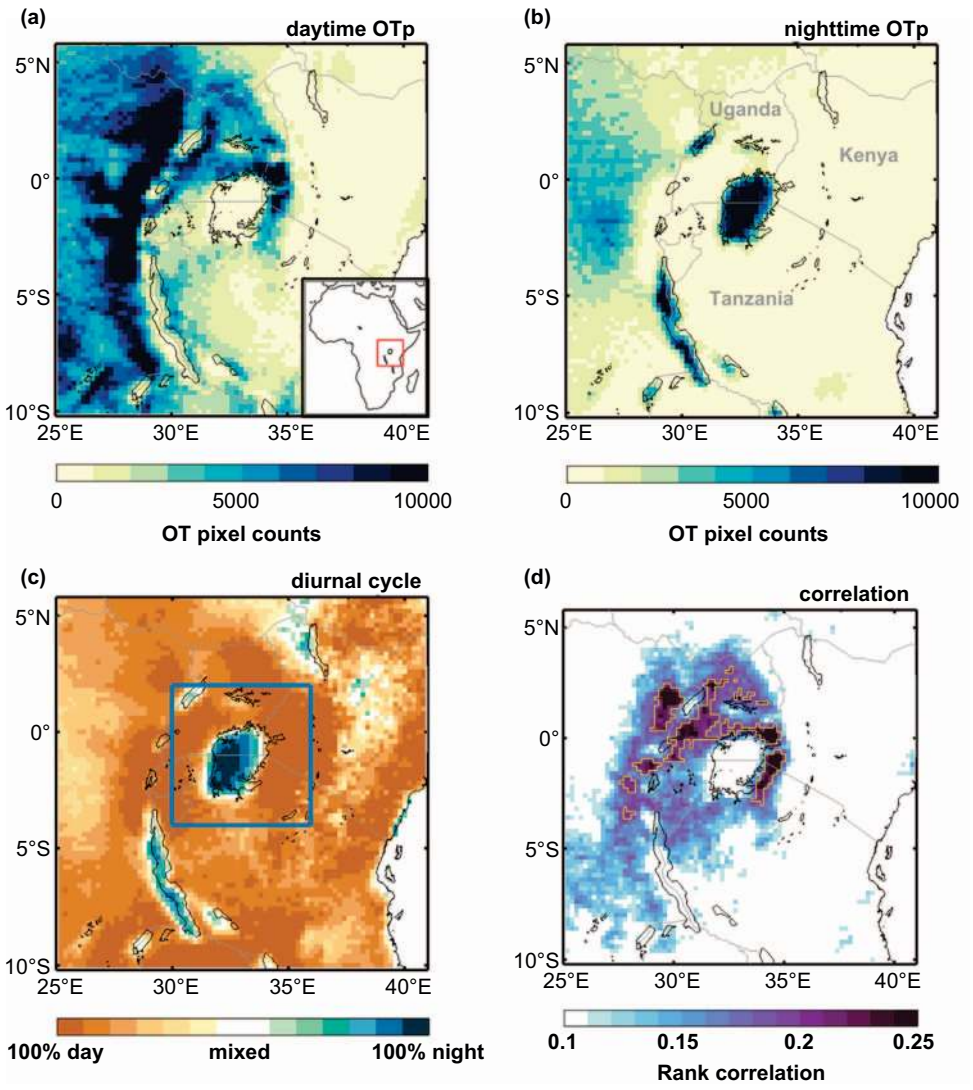

Figure 1. Lake imprint on severe thunderstorm occurrence in East Africa. (*a–b*), Satellite-based OT pixel detections during 2005–2013 from 12:00–18:00 EAT (daytime) and from 00:00 to 12:00 EAT (nighttime), respectively, as derived from the Spinning Enhanced Visible and Infrared Imager (SEVIRI) over equatorial East Africa (25 °E–41 °E, 10 °S–6 °N). (*c*), Fraction of OTp occurring during daytime and nighttime. The blue rectangle denotes land pixels selected to establish the proof on concept (section 3). (*d*), Temporal correlation of daytime land OTp (panel a) to nighttime OTp aggregated over Lake Victoria (panel b). As an illustration, all regions with rank correlation above 0.20 are marked by yellow polygons (section 4).

Dworak *et al* (2012) for an overview). The detection of OTs is therefore a relevant proxy for surface impacts of severe thunderstorms.

In this study we use a 9 year OT dataset for equatorial East Africa (25 °E–41 °E, 10 °S–6 °N, figure 1, Thiery *et al* (2016)) derived from the Spinning Enhanced Visible and Infrared Imager (SEVIRI) on board Meteosat Second Generation (MSG; Aminou (2002)). The OT detection algorithm is described in detail in Bedka *et al* (2010) and Bedka (2011); it builds on the premise that OTs are composed of a small region of very cold infrared brightness temperatures surrounded by a warmer cirrus anvil cloud (Wang 2007). The SEVIRI instrument originally provides images at 15 minute temporal and ~4-km spatial resolution over the Lake Victoria region. For our analysis the dataset was aggregated to a regular 0.2 ° × 0.2 ° grid, and from 15-min to hourly resolution, in both cases by summing all OT pixel detections in the high-resolution imagery. By reducing the size of the original data set, we increase the speed of the prediction system without affecting its predictive power. The dataset comprises more than 50 million OT pixels (hereafter referred to as OTp) from 2005–2013 over equatorial East Africa. We note however that a single OT is generally composed of multiple OT pixels (11 on average) and that it can persist for more than 15 minutes, in which case it will be recorded by consecutive satellite images. Sensitivity tests indicate that the treatment of occasionally missing data does not influence our results; we therefore assume that no OTp occur when a satellite image is missing.

The robustness of the prediction system is additionally tested against two precipitation products, which provide valuable information on past events but are not operationally available. We used satellite precipitation estimates from the Tropical Rainfall Measurement Mission product 3B42 (TRMM,

Kummerow *et al* (2000)), available at 0.25 ° spatial and 3 hourly temporal resolution from 1998 to 2013, and from a dynamical downscaling of the ERA-Interim reanalysis with the COSMO-CLM^2 regional climate model (Davin and Seneviratne 2012) from 1999–2008. The COSMO-CLM^2 simulation is described in Thiery *et al* (2015); it benefits from high spatial resolution (~7 km; Docquier *et al* (2016)), an advanced land surface representation (Akkermans *et al* 2014) and an interactive lake model (Thiery *et al* 2014a, Thiery *et al* 2014b). For the analysis the TRMM data was remapped to the 0.0625 ° resolution COSMO-CLM^2 grid using bilinear interpolation. Although TRMM generally outperforms other satellite precipitation products in Uganda and Kenya, the product underestimates extreme precipitation over East Africa (Maggioni *et al* 2016).

The selection of the three data sets is based on the following considerations: (i) product independence, (ii) coverage of multiple data sources (geostationary and polar-orbiting satellites and state-of-the-art climate modelling), (iii) different proxies for severe weather (OTp and extreme precipitation).

2.2. Statistical model setup

Here we aim to model the probability of extreme thunderstorm nights as a function of afternoon conditions over the surrounding land. We thereby rely on binomial logistic regression, and base our approach on that of Gudmundsson *et al* (2014) who estimated above-normal wildfire activity from meteorological drought. To start, we define extreme thunderstorm nights as nights during which the total number of OTp over Lake Victoria during 00:00–12:00 East African Time (EAT; 21:00–9:00 UTC) exceeds the 99th percentile (that is, 2236 OTp). This selection criterion was informed by an earlier analysis by Thiery *et al* (2016) suggesting a particularly strong dependency of this class of *OT* events on afternoon conditions. From this criterion we construct a binary series of extreme and non-extreme nights. The probability of an extreme night ($P(ex)$) is subsequently modelled as a function of the total number of OTp over the surrounding land during the preceding day (OT_{day}), such that:

$$\ln\left(\frac{P(ex)}{1-P(ex)}\right) = \beta_0 + \beta_1 OT_{\mathrm{day.}} \qquad (1)$$

Where β_0 and β_1 are the model parameters, derived using generalized linear regression (binomial distribution, logit transformation). β_0 is the intercept from the linear regression equation and sets the probability for an extreme thunderstorm night when there are no OTp recorded during daytime, whereas β_1 is the regression coefficient assigned to the explanatory variable OT_{day}. Here we define OT_{day} as the sum of all *OT* pixels detected between 12:00 and 18:00 EAT in an area enclosed by the blue rectangle in figure 1(*c*) but excluding Lake Victoria, thereby following Thiery *et al* (2016) (hereafter referred to as initial configuration).

By analogy, this setup can be used for forecasting extreme precipitation from TRMM and COSMO-CLM^2. In this case, the threshold criterion selecting the 1% most intense nighttime precipitation events are 2.96 mm h^{-1} and 3.01 mm h^{-1} for TRMM and COSMO-CLM^2, respectively. For each product we additionally construct the persistence forecast, that is, the logistic regression using conditions over Lake Victoria during the previous night (and in the corresponding product) as predictor.

As shown by equation 1, the logistic regression model does not predict the occurrence of an event, in this case an extreme thunderstorm night, but rather the probability of such an event given a certain precursor condition. Users are therefore faced with the challenge of deciding which probability is considered sufficiently large to issue a warning. Once such a threshold probability (θ) is selected, all warnings are automatically derived from the statistical model. By construction, the issued warnings will capture only a fraction of all actual extreme events. This fraction is known as the hit rate (H), and H will increase with decreasing threshold probability. Conversely, a false alarm occurs when a warning is issued without an extreme event actually occurring. The fraction of non-extreme events for which a warning is issued is known as the false alarm rate (F), and F increases with decreasing threshold probability. Increasing H will therefore always be at the expense of increasing F, and vice versa. Depending on the objective of the warning system, acceptable values of H and/or F can substantially vary. It is therefore not possible to present one unique recommendation regarding a most suitable threshold probability.

The trade-off between the hit rate and false alarm rate for different threshold probabilities is visualised in a receiver operating characteristic (ROC) curve. ROC curves that lie above and to the left of the 1:1 line indicate improved forecast skill relative to random guessing, and the better the forecasts, the closer the ROC curve approaches the upper-left corner of the diagram (Wilks 2011). One way to summarise ROC curves using a single scalar value is to compute the Area Under the ROC Curve (AUC), with AUC = 0.5 indicating random guessing and AUC = 1 representing a perfect forecasting system.

A ROC curve can subsequently be analysed to detect threshold probabilities that are relevant from a decision-making point of view. For instance, an 'optimal point' can be selected as the threshold probability that maximises the hit rate while minimizing the false alarm rate (i.e. it sets the highest value of $H - F$ along the ROC curve). Alternatively, false alarm rates for predefined, fixed hit rates can be easily retrieved from ROC curves, and vice versa. Examples of useful information which can be retrieved from ROC curves are listed in table 1.

Table 1. Model parameters and skill scores for the optimized configurations. β_0, β_1 denote the binomial logistic regression coefficients, PPV and NPV the positive and negative predictive value, respectively. OR, PPV and NPV are defined in the supplementary information.

	Lake Victoria	Sector Uganda	Sector Kenya	Sector Tanzania
Model parameters				
β_0	−6.7809	−6.2797	−5.3512	−6.5763
β_1	0.00026	0.00044	0.0011	0.00017
Nighttime (EAT)	00:00–12:00	2:00–8:00	17:00–23:00	4:00–10:00
Daytime (EAT)	6:00–21:00	5:00–20:00	3:00–14:00	6:00–21:00
Lead time (h)	3	6	3	7
Aggregation time (h)	14	14	10	14
r_{crit}	0.15	0.15	0.10	0.10
Model skill				
AUC	0.93	0.86	0.80	0.91
OR(H–F max)	36	18	11	34
H(H–F max)	0.85	0.82	0.76	0.85
F(H–F max)	0.13	0.20	0.23	0.14
F(H = 0.5)	0.04	0.05	0.11	0.05
F(H = 0.9)	0.21	0.42	0.43	0.20
F(H = 1)	0.30	0.99	0.97	0.67
PPV(H–F max)	0.06	0.04	0.03	0.06
NPV(H–F max)	1.00	1.00	1.00	1.00

To obtain an independent measure of storm predictability, we construct the ROC curves using leave-one-year-out cross-validation. During this procedure one year is removed from the time series and the model is fitted to the remaining data. The obtained model is then applied to generate storm predictions for the year which was left out. We subsequently repeat this procedure for all years in the dataset, that is, one-by-one each year is left out from the training data set and predictions are made for this left-out year. As such, we can compile a time series of extreme event predictions without the observed events in a given year contributing to the training of the model for that period. As such this procedure enables an unbiased assessment of model performance (Gudmundsson *et al* 2014).

2.3. Model optimisation and validation

In a next step we aim at optimising the skill of the forecasting system. Since, out of the three considered data sources, the OT dataset is the only one potentially available in realtime, and thus the only suitable candidate for an operational early warning system, we focus on this product from now onwards. First, we hypothesize that the window defining daytime hours influences predictive skill. Moreover, we expect that some regions contribute more to the predictor time series. This holds, for instance, for those regions characterised by strong orography, and in particular for the eastern lake shore, where intense convection is triggered when the afternoon lake breeze meets the steep mountain slopes and the westward synoptic flow (figures 1(*a*)–(*d*), see also Anyah *et al* (2006) and Ogwang *et al* (2014)).

We therefore try to optimise the skill by varying three parameters that shape the predictor time series OT_{day}: forecast lead time λ (h), predictor aggregation time μ (h) and a critical rank correlation threshold r_{crit} used for spatial selection (see below). For each pixel p, we first aggregate all observed OTp in time, such that:

$$OT_{p,\mathrm{day}} = \sum_{i=0}^{\mu} OT_{p,\lambda-\mu+i}. \qquad (2)$$

For example, given a lead time $\lambda = 6$ h and a predictor aggregation time (i.e. length of the daytime window) $\mu = 5$ h, we sum all OTp observed between 13:00 and 18:00 EAT to obtain a daytime OT time series per pixel (to be used for predicting nighttime OTp between 00:00 and 12:00 EAT). For each pixel we subsequently compute the Spearman rank correlation between the time series of daytime OTp and the time series of nighttime OTp over Lake Victoria. As a final step we select only those pixels with a correlation above the critical threshold r_{crit} (e.g. figure 1(*d*)), and calculate the OT_{day} time series as the sum of all daytime OTp over the retained pixels. Positive correlations between daytime OTp on land and nighttime OTp over the lake (figure 1(*d*)) are associated with the mesoscale circulation which triggers precipitation and extreme thunderstorms on Lake Victoria (section 1).

To test the model sensitivity, we vary λ, μ and r_{crit} over a range of plausible values (λ: 3 h to 11 h, μ: 2 h to 14 h, r_{crit}: 0.10 to 0.30). Note that we fix the minimal lead time to 3 h to account for warning transmission time in an operational context. Moreover, for high values of λ and μ the predictor time series extends into the previous night. As an optimisation criterion for selecting the optimal model configuration, we use the maximum AUC. In addition to optimizing the configuration for the whole lake, we also develop

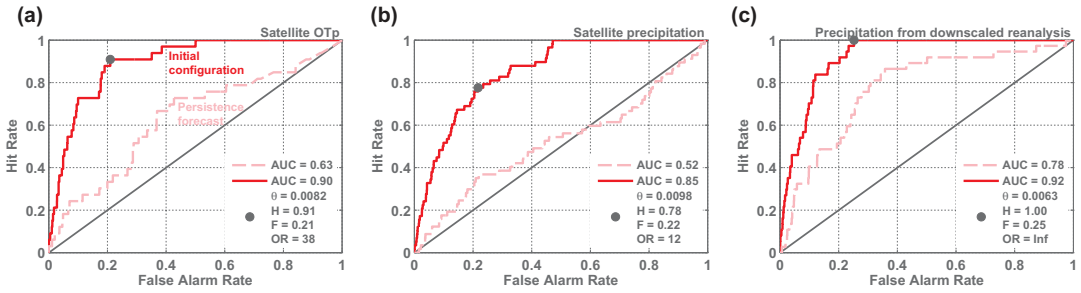

Figure 2. Proof of concept of storm predictability. Receiver operating characteristics (ROC) curves showing the trade-off between hit-rate and false-alarm rate for the predictions with difference threshold probabilities of the logistic regression model applied to (*a*) Satellite-based OT detections during 2005–2013, (*b*) Satellite-based precipitation observations during 1998–2013 from the Tropical Rainfall Measurement Mission (TRMM; 3B42 product) and (*c*) Precipitation during 1999–2008 as downscaled from ERA-interim by the regional climate model COSMO-CLM^2. Solid red lines indicate ROC curves using afternoon land OTp/precipitation as predictor (initial configuration, see section 2.2), whereas dashed light red lines denote ROC curves of the respective persistence forecast (nighttime lake OTp/precipitation from previous night as predictor). The ROC curve is estimated using leave-one-year-out-cross validation. Curves above the 1:1 line indicate that forecasts outperform random guessing. The black dots mark the location at which the difference between the hit rate and the false alarm rate is maximal. θ marks the threshold probability that was chosen to maximise this difference, H the hit rate, F the false alarm rate and OR the odds ratio at this point. The Area-Under-the-Curve AUC represents the dimensionless area under the ROC curve and is a measure for the overall skill of the regression model.

optimal configurations for the three lake sectors belonging to different countries (Uganda to the north, Kenya to the east and Tanzania to the south, figure 1).

3. Proof of concept

Figure 2 shows the ROC curves for the three considered data products under the initial configuration. This configuration generally displays high skill, with AUC values of 0.90, 0.85 and 0.92 for the OT, TRMM and COSMO-CLM^2 products, respectively. Overall there are significant links between extreme nighttime thunderstorms on Lake Victoria and afternoon storminess over the surrounding land, indicating that information on the latter is a suitable predictor for storm activity on the lake. This is confirmed by sensitivity experiments wherein we relax the definition of an extreme event to nights exceeding the 98th, 97th, 96th and 95th percentile, respectively: the model skill remains very close to the skill of the initial configuration.

Moreover, the initial configuration substantially outperforms the persistence forecast. For the observational products the persistence forecasts generally show only little added value compared to random guessing. In addition, the skill of the persistence forecast, if any, may partly arise from the seasonal cycle over the region, where wet seasons associated with the ITCZ overpass alternate with dry periods from June to September and January to February (Yang *et al* 2015). Only in COSMO-CLM^2 the persistence forecast attains appreciable skill. Finally, replacing afternoon over-land conditions by afternoon over-lake conditions as predictor also leads to a sharp decrease in predictive skill (not shown), highlighting the importance of mesoscale circulation for triggering extremes on Lake Victoria (Thiery *et al* 2016).

As an example, in the early hours of 16 May 2006, severe thunderstorms struck Lake Victoria (2436 OTp recorded and over 36 mm of rain observed in 9 h time over the entire lake). According to both the OT and TRMM products this night was as an extreme event, and all three model configurations issued a warning (optimal point). The consistent behaviour of all three data products generally underlines the potential of a data-driven prediction system. It also suggests a positive relationship between strong updrafts (OT detections) and increased precipitation: indeed statistically significant, positive rank correlations are found at night over Lake Victoria between OTp and precipitation from TRMM (0.78, $p < 0.001$, $n = 3287$) as well as from COSMO-CLM^2 (0.38, $p < 0.001$, $n = 1461$).

4. Improving forecast skill

In this section we aim to optimise the regression model configuration to improve forecast skill. The sensitivity of the AUC to variations in forecast lead time, predictor aggregation time and threshold correlation is shown in figures 3(*a*)–(*b*). The sensitivity diagrams indicate a clear tendency towards higher skill for shorter lead times, longer aggregation times and less stringent pixel selection. Interestingly, selecting a large number of land pixels is more important for the model skill than selecting pixels which are highly correlated to the conditions on the lake. Overall this suggests that using more information throughout the full extent of daytime hours to construct the predictor time series adds to the forecast skill. However, it is also clear that the sensitivity saturates, with only very limited added value of increasing the aggregation time beyond 10 hours, or of decreasing the threshold correlation below 0.15.

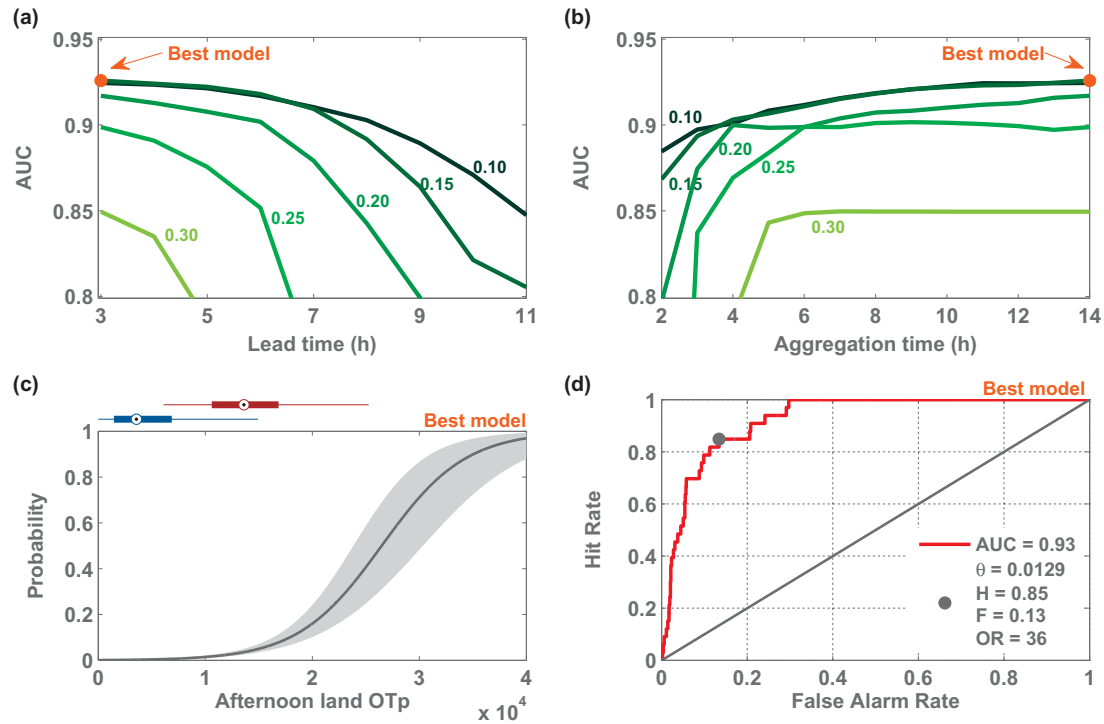

Figure 3. Optimizing the prediction system. (*a*) Area-Under-the-Curve AUC versus forecast lead time for various threshold correlations (predictor aggregation time = 14 h). (*b*) Area-Under-the-Curve AUC versus predictor aggregation time for various threshold correlations (lead time = 3 h). Rank correlation thresholds are indicated for each line. Orange dots in (*a*) and (*b*) indicate the best model, i.e. the model with the highest AUC. (*c*) Logistic regression with optimised lead time (3 h), predictor aggregation time (14 h) and rank correlation threshold (0.15), modelling the probability of extreme nighttime OT detections on Lake Victoria as a function of afternoon OTp over selected land pixels (line: best estimate, shaded area: 95% confidence interval). Boxplots indicate the distribution (median, interquartile range) of the afternoon land OTp associated with non-extreme (blue) and extreme (red) nights. Whiskers extend to the last value located within a distance of 1.5 times the interquartile range from the 25th and 75th quantile, respectively. (*d*) Receiver operating characteristics (ROC) curve associated with the optimised logistic regression model shown in (*c*) (compare to figure 2(*a*)).

In the optimised configuration, boxplots of afternoon conditions on land associated with extreme and non-extreme nights are clearly separated, and this feature is captured by the logistic regression (figure 3(*c*)). The best model has an AUC of 0.93 and is constructed using a lead time of 3 h, a predictor aggregation time of 14 h and a rank correlation of 0.15 (table 1). It represents a small yet noticeable increase in model skill relative to the initial configuration, in particular when considering low false alarm rates (compare ROC curves in figure 2(*a*) and figure 3(*d*)). Taking a threshold probability θ of 0.0129, for instance, enables the prediction of 28 out of a total 33 extreme events between 2005 and 2013 ($H = 85\%$), while having a false alarm rate of 13%. The associated odds ratio (OR) is 36, meaning that during days with $P(ex) > 0.0129$, the odds of an extreme night are 36 times higher than during other days. However, as the false alarm rate is still considerable in this case (a false alarm is issued almost once per week here), a user may prefer to pre-set a higher threshold probability. In that case it is, for instance, possible to forecast 50% of all extreme events while having a false alarm only about once per month (table 1).

Although false alarms do occur, they clearly tend to capture intense storm nights rather than calm nights (figure 4(*a*)). For instance, 30%, 50% and 70% of all false alarms correspond to nights with OTp above the 90th, 83th and 72th percentile, respectively (optimal point; figure 4(*b*): blue dots). The same conclusion can be made when choosing a different threshold probability. For instance, when choosing the threshold probability such that half of all extreme events are captured (i.e. $H = 0.5$), 30%, 50% and 70% of all false alarms lie above the 94th, 87th and 75th nighttime OT percentile (figure 4(*b*): red dots). Thus, while false alarms, per definition, miss the 1% most intense thunderstorm nights, they nonetheless often predict nights with strong thunderstorm activity. Overall this indicates that also false alarms contain valuable information for intense storm prediction. Here we note that a systematic recording of boating incidents would be very useful to further analyse the skill of our prediction system, and in particular the role of false alarms. However, such systematic reporting is currently still lacking.

As storms typically develop in the eastern part of the lake and intensify as they are advected westward along the trade winds (Thiery *et al* 2016), the diurnal thunderstorm cycle varies between the different lake sectors. In Sector Kenya (northeast), storm activity peaks in the late afternoon, whereas the diurnal cycle attains a maximum during early and late night in the Sector Uganda (north) and Sector Tanzania (south),

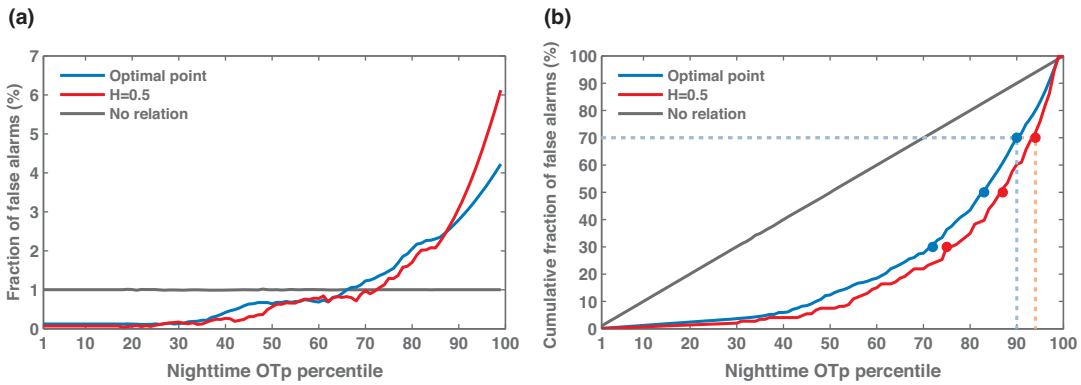

Figure 4. False alarm behaviour. (*a*) False alarms binned against nighttime OT pixel counts using a bin width of 1%. Blue and red lines indicate two different selection criteria (optimal point and hit rate fixed to 0.5, respectively), whereas the grey line denotes the behaviour in case there would be no relation between false alarms and nighttime storm intensity. Curves were smoothed using Savitzky-Golay filtering (order = 2, window = 27; Savitzky and Golay (1964)). (*b*) same as *a*, but now showing the cumulative fraction. As an example, the stippling lines indicates that 30% of all false alarms lie above the 90th and 94th nighttime OT percentile for the optimal point ans H = 0.5 cases, respectively.

respectively (figure 1(*b*); supplementary figure 1). Given these strong differences and the need to facilitate warnings at the country scale, it is appropriate to apply the optimisation procedure to each individual sector. The results overall indicate similar skill compared to the whole lake case, albeit a small reduction in skill owing to the reduced information content in the predictant time series and the imposed minimum lead time (supplementary figures 2–4 and table 1).

5. Towards operational warnings

Building on previous analyses, a software package was developed for Matlab and GNU Octave to enable automated extreme storm predictions over Lake Victoria in operational mode. Version 1.0 of the package, termed Lake Victoria Intense storm Early Warning System (VIEWS), is available at http://github.com/wthiery/VIEWS and is released under the MIT licence. At this stage the prediction system needs to be considered as a prototype; more research as well as input from the user community is needed to improve its skill, strengthen the links to societal losses (e.g. Semazzi and Mera (2006)), assess uncertainties (e.g. Lhermitte *et al* (2010)), and test its applicability to other tropical lakes. In particular, the African Great Lakes in East Africa and Lake Maracaibo in Venezuela experience similar thunderstorm dynamics (figures 1 (*a*)–(*b*); Albrecht *et al* (2016)). Thus, communities living around these lakes may eventually also benefit from satellite-based storm warning systems.

At forecast lead time, the software first reads in the OT images corresponding to the daytime hours. It subsequently computes the predictor value OT_{day} for each country and for the whole lake by performing the appropriate spatial and temporal selection (see equation 2 and table 1). The OT_{day} values then serve as input for the respective logistic regressions (see equation 1), yielding the probability for an extreme event. The operational statistical model employs the logistic regression coefficients derived for the optimal configuration for the whole lake and the individual lake sectors (see table 1 and section 4). Depending on the threshold probability defined by the user, the software will indicate whether or not a warning is to be issued for a specific lake sector or the whole lake.

6. Summary and discussion

In this study we present a new approach to predict hazardous thunderstorm activity over Lake Victoria. The prediction system, called VIEWS, relies on logistic regression to forecast the 1% most extreme thunderstorm nights based on observed afternoon land conditions, and is designed to complement and support ongoing efforts from the Numerical Weather Prediction (NWP) community in the region. VIEWS demonstrates substantial skill during the 2005–2013 hindcast period, especially relative to persistence forecasts. As it builds on predictability inherent to the lake-land breeze system, predictive skill is identified for different proxy variables for thunderstorm activity (Overshooting Top pixels (OTp) and extreme precipitation) as well as for different data sources (satellite products and dynamically downscaled reanalysis). Optimizing the OT configuration for the whole lake and individual sectors yields a small yet noticeable increase in skill.

This is a pilot study describing a new, experimental prediction system, and future research should aim at overcoming its current limitations. For instance, forecast skill may be further increased through the use of other environmental parameters, such as cloud cover, surface temperatures, wind velocities or atmospheric profiles. Those fields could be derived from remote sensing, but also from NWP output (e.g. Chamberlain *et al* (2014)) or in-situ measurements

(e.g. Jacobs *et al* (2016a), Jacobs *et al* (2016b)) resulting in hybrid forecast products. Enhanced predictive skill may also be achieved by accounting for large-scale teleconnections and their influence on inter-annual circulation variability in East Africa (e.g. Hawinkel *et al* (2016), Souverijns *et al* (2016)). Another option could be to increase the information content of the forecast by using other regression-based statistical tools that describe the full OT distribution (rather than predicting the probability of occurrence of an extreme event). In this case predictions can also be made on a continuous scale, or be separated into different categories of thunderstorm intensity (e.g. light, moderate, strong and extreme).

Finally, to implement and improve VIEWS as well as other warning systems for the region, it will be of key importance to collect experiences from the user community. Besides identifying impact-relevant parameters, users may also help to establish optimal operating points of scientific warning systems. Together with user input and high-resolution NWP, regression-based models have the potential to substantially reduce the vulnerability of local communities around Lake Victoria.

Acknowledgments

We acknowledge the CLM-community (clm-community.eu) for developing COSMO-CLM^2 and making the model code available, and Hans-Jürgen Panitz for providing the lateral boundary conditions. In addition, we are grateful to NASA and JAXA for developing the TRMM-3B42 dataset. WT was supported by an ETH Zurich postdoctoral fellowship (Fel-45 15-1). The Uniscientia Foundation and the ETH Zurich Foundation are thanked for their support to this research. The Belgian Science Policy Office (BELSPO) is acknowledged for the support through the research project EAGLES (CD/AR/02A). Computational resources and services used for the COSMO-CLM^2 simulations were provided by the VSC (Flemish Supercomputer Center), funded by the Hercules Foundation and the Flemish Government—department EWI. MSG SEVIRI data used to produce the OT detections were provided by the University of Wisconsin-Madison Space Science and Engineering Center. OT detection product development was supported by the GOES-R Aviation Algorithm Working Group and GOES-R Risk Reduction Research Program. All materials that have contributed to the reported results are available through GitHub or upon request. Correspondence and requests for materials should be addressed to WT (wim.thiery@env.ethz.ch).

References

Akkermans T, Thiery W and Van Lipzig Nicole P M 2014 *J. Clim.* **27** 2714–34

Albrecht R I *et al* 2016 *Bull. Am. Meteorol. Soc.* **1** 2051–68

Aminou D 2002 *ESA Bull.* **111** 15–7

Anyah R O, Semazzi F H M and Xie L 2006 *Mon. Weather Rev.* **134** 3588–609

Bedka K 2011 *Atmos. Res.* **99** 175–89

Bedka K, Brunner J, Dworak R, Feltz W, Otkin J and Greenwald T 2010 *J. Appl. Meteorol. Climatol.* **49** 181–202

Chamberlain J M, Bain C L, Boyd D F A, McCourt K, Butcher T and Palmer S 2014 *Meteorol. Appl.* **21** 419–30

Davin E L and Seneviratne S I 2012 *Biogeosciences* **9** 1695–707

Docquier D, Thiery W, Lhermitte S and van Lipzig N 2016 *Clim. Dyn.* **47** 3191–202

Dworak R, Bedka K, Brunner J and Feltz W 2012 *Weather Forecast.* **27** 684–99

Eagle C, Lean H and Webster S 2015 Convective Scale NWP Model congurations for the Lake Victoria Region *Technical report* (United Kingdom: Met Office Exeter)

East African Community 2011 Enhancing Safety of Navigation and Efficient Exploitation of Natural Resources over Lake Victoria and its Basin by Strengthening Meteorological Services on the Lake *Technical Report* (http://climlab02.meas.ncsu.edu/HYVIC/Final_Report_LVBC.pdf)

Gudmundsson L, Rego F C, Rocha M and Seneviratne S I 2014 *Environ. Res. Lett.* **9** 084008

Hawinkel P, Thiery W, Lhermitte S, Swinnen E, Verbist B, Van Orshoven J and Muys B 2016 *J. Geophys. Res.: Biogeosciences* **121** 2422–44

International Federation of Red Cross and Red Crescent Societies 2014 World Disasters Report 2014: Focus on culture and risk *Technical report* (Geneva) (www.ifrc.org/Global/Documents/Secretariat/201410/WDR%202014.pdf)

Jacobs L, Dewitte O, Poesen J, Delvaux D, Thiery W and Kervyn M 2016a *Landslides* **13** 519–36

Jacobs L, Maes J, Mertens K, Sekajugo J, Thiery W, van Lipzig N, Poesen J, Kervyn M and Dewitte O 2016b *Nat. Hazards* **84** 851–76

Kummerow C *et al* 2000 *J. Appl. Meteorol.* **39** 1965–82

Lhermitte S, Verbesselt J, Verstraeten W W and Coppin P 2010 *Photogramm. Eng. Remot. Sen.* **76** 673–82

Maggioni V, Meyers P C, Robinson M D, Maggioni V, Meyers P C and Robinson M D 2016 *J. Hydrometeorology* **17** 1101–17

Ogwang B A, Chen H, Li X and Gao C 2014 *Adv. Meteorol.* 143917

Proud S R 2015 *Q. J. R. Meteor. Soc.* **141** 909–15

Savitzky A and Golay M J E 1964 *Anal. Chem.* **36** 1627–39

Semazzi F H M *et al* 2014 HyVIC Science Plan *Technical report* North Carolina State University (www.gewex.org/hyvic/)

Semazzi F H M and Mera R J 2006 *J. Appl. Met. Clim.* **45** 1215–23

Seto K C, Güneralp B and Hutyra L R 2012 *Proc. Natl Acad. Sci. USA* **109** 16083–88

Song Y, Semazzi F H M, Xie L and Ogallo L J 2004 *Int. J. Climatol.* **24** 57–75

Souverijns N, Thiery W, Demuzere M and van Lipzig N P M 2016 *Environ. Res. Lett.* **11** 114011

Thiery W, Davin E L, Panitz H-J, Demuzere M, Lhermitte S and van Lipzig N P M 2015 *J. Clim.* **28** 4061–85

Thiery W, Davin E L, Seneviratne S I, Bedka K, Lhermitte S and van Lipzig N P M 2016 *Nat. Commun.* **7** 12786

Thiery W, Martynov A, Darchambeau F, Descy J-P, Plisnier P-D, Sushama L and van Lipzig N P M 2014a *Geosci. Model Dev.* **7** 317–37

Thiery W *et al* 2014b *Tellus* A **66** 21390

Wang P K 2007 *Atmos. Res.* **83** 254–62

Wilks D S 2011 *Statistical Methods in the Atmospheric Sciences* Vol 100 3rd edn (New York: Academic Press) (https://doi.org/10.1016/B978-0-12-385022-5.00008-7)

Williams K, Chamberlain J, Buontempo C and Bain C 2015 *Clim. Dyn.* **44** 1699–1713

Yang W, Seager R, Cane M A and Lyon B 2015 *J. Clim.* **28** 2385–404