Empirical Dynamic Modelling Identifies different Responses of *Aedes Polynesiensis* Subpopulations to Natural Environmental Variables

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To control mosquito populations for managing vector-borne diseases, a critical need is to identify and predict their response to causal environmental variables. However, most existing attempts rely on linear approaches based on correlation, which cannot apply in complex, nonlinear natural systems, because correlation is neither a necessary nor sufficient condition for causation. Applying empirical dynamic modelling that acknowledges nonlinear dynamics on nine subpopulations of tiger mosquitoes from three neighbouring reef islets of the Raiatea atoll, we identified temperature, precipitation, dew point, air pressure, and mean tide level as causal environmental variables. Interestingly, responses of subpopulations in close proximity (100–500 m) differed with respect to their causal environmental variables and the time delay of effect, highlighting complexity in mosquito-environment causality network. Moreover, we demonstrated how to explore the effects of changing environmental variables on number and strength of mosquito outbreaks, providing a new framework for pest control and disease vector ecology.

Mosquito-borne diseases contribute significantly to human mortality causing more than 1 billion cases and over 1 million deaths every year¹. A case in point are mosquitoes of the genus *Aedes* being the main vector of dengue fever. For predicting disease outbreaks, population dynamics of mosquitoes are important concern. A critical need is therefore to understand and predict how environmental change may impact on fluctuation of mosquito populations².

There are two main strains of research aiming to examine how mosquito populations respond to climate changes. On the one hand, lab experiments are conducted to detect causal environmental drivers of mosquito survival, larval developmental time and other fitness parameters (e.g.³⁴). However, whether the findings in lab experiments can be generalized to natural systems remain unclear. On the other hand, time series data of mosquito abundance in natural systems are analysed for statistical associations with climate variables. For example, population abundance of the yellow fever mosquito *Ae. aegypti* was found to correlate with temperature, humidity, and precipitation⁵–⁹. However, majority of the studies linking natural mosquito abundances with climate variables employed linear correlation analyses. While, correlation does not necessarily imply causation, lack of correlation does not imply lack of causation either¹⁰¹¹. Applying linear methods to time series data generated from nonlinear processes bears the risk to detect mirage correlations, which may lead to wrong and misleading conclusions¹⁰¹²¹³.

Indeed, mirage correlation (or non-stationary relationship) between mosquito populations and climate variables were often found in nature⁷¹⁴. Mirage correlation is commonly found, as a result of a fundamental property of nonlinear dynamical systems, known as state dependency¹⁰¹⁵. State dependency means that the relationships among interacting variables change with different states of the dynamical system¹⁵. The following example illustrates state-dependence in mosquitoes. It was shown experimentally that *Ae. aegyptii* females...
have lower vector competence for dengue virus in lower temperature environments only when the temperature is fluctuating; in comparison, without such a specific temperature combination (i.e. mosquitoes living in the environment of high temperature or constant temperature), the females have higher vector competence\textsuperscript{41,37}. For *Aedes* mosquitoes, evidence abounds suggesting that nonlinear population dynamics are common. For example, experimental studies show that larval survival depends on larval density\textsuperscript{18}, temperature\textsuperscript{4}, and the mosquito’s genomic background and microbiome\textsuperscript{19} in a complex, nonlinear way. In addition, abundance data of lab and field populations are best described by nonlinear mathematical models\textsuperscript{19–21}. All these studies suggest that, in general, mosquito–environment interactions are complex, nonlinear, and inter-dependent; as such, linear methods are not adequate for these questions.

Here, we aim at disentangling the causality network between climate variables and mosquito populations and predict how environmental change may impact on the populations. To overcome the limitation of linear approaches, we use the empirical dynamical modelling (EDM) framework, which is specifically designed for analysing time series data with underlying nonlinear dynamics\textsuperscript{11,13,15}. To demonstrate the efficacy of EDM framework for disease vectors, we analysed a unique longitudinal data set of the Polynesian tiger mosquito, *Aedes polynesiensis*, which is an important vector for lymphatic filariasis and dengue fever in the South Pacific\textsuperscript{22,23} (see Supplementary Material for more information on *Ae. polynesiensis*). The data consist of biweekly (14-day interval) mosquito counts over two years at nine sampling points on three motu islands\textsuperscript{24} (Figs S1, S2). The motus have similar climate, but differ in vegetation and human activity as well as in larval competition and average body size of adult mosquitoes. This exceptionally high temporal and spatial resolution gives unique opportunities for studying population dynamics of mosquitoes. In particular, it allows investigating to what extent the local habitat drives mosquito dynamics and how neighbouring population in a meta-population are interconnected. Our objectives are (1) to identify the critical environmental variables that causally affect mosquito populations using convergent cross mapping (CCM) (Methods), (2) to test for causal interactions between mosquito subpopulations, and (3) to explore scenarios how change in a causal environmental variable may affect mosquito abundance as well as number and strength of mosquito outbreaks.

**Results**

**Causality between environment and mosquito abundance.** Comparing the results based on CCM versus correlation demonstrates the efficacy of using EDM in our data. Indeed, correlation does not imply causation (Fig S3), while lack of correlation does not imply lack of causation (Fig S4). Moreover, correlation can change sign, depending on ecosystem context, known as mirage correlation (Fig S5). These examples from our data highlight the need to employ correct methods for studying causality in complex nonlinear systems.

When analysing the mosquito dynamics for each of the nine sampling sites separately using CCM, we found that temperature, precipitation, dew point, air pressure, and mean tide level are causal variables for the mosquito populations (Fig 1; Supplementary Table S2). Remarkably, the forcing environmental variables varied substantially among the nine sampling sites (Fig 1). For example, we found that sampling site S7 at Toamaro island is affected by four climate variables (temperature, dew point, precipitation, mean tide level), site S8 by only one (air pressure), and site S9 by none. Similarly strong differences between sampling sites were found for the other two islands. However, when repeating the same analysis for each of the three islands (sum of the three sites within the same island) and for the whole meta-population (i.e., sum of the nine sampling sites), we found no climatic effect on mosquito abundance from any variable that we analysed here. The spatial scale dependence is remarkable, given the small sizes of the islands (100–500 m length) and short distance between sites (a maximum distance between two sampling sites of less than 5 km).

Moreover, the causal forcing variables showed large variation in time lag, from zero day to more than five weeks even for the same environmental variables. For example, the mean tide level affects the mosquito dynamics at S6 with a time lag of 0–4 days, but the lag is 27–30 days at S7; time lags for air pressure are 14–17 days at S1, but 34–39 days at S8. In other words, the causal effect of climate on the mosquito dynamics has strong temporal scale dependence.

A striking spatial pattern emerges when the three islands are compared with respect to the number of causally forcing variables and the time lag of the causal effect. For Horea, we found only the mean tide level and the air pressure to be causal drivers. The associated time lags are 7–9 and 14–17 days, respectively (Fig 1). For Tiano and Toamaro, on the other side, we detected four and five causally forcing variables, respectively, and the associated time lags range from 0 to 35 days for Tiano and 9 to 39 days for Toamaro (Fig 1). These results suggest that mosquito–environment interactions are more complex on Tiano and Toamaro than on Horea.

**Causality between mosquito populations.** We tested for causal interactions between all pairs of the nine subpopulations, and found bidirectional causality in one case (S8 → S9) and unidirectional causality in four cases (S1 → S3, S2 → S3, S2 → S7, S7 → S8) (Fig 1, black arrows; Supplementary Table S3). A clear spatial pattern emerges. All causality links start and end at Horea or Toamaro, but none at Tiano. Further, five of the six links appear within motu (either Horea or Toamaro), with no time lag. Between-motu interaction among subpopulations was only found in one case, from Horea (S2) to Toamaro (S7), with a time lag of 14 days. This case is surprising because Horea and Toamaro are not neighbouring motus, but separated by Tiano (cf. Fig 1). The lack of connectivity between the subpopulations of Tiano and the other two motus may be explained by the fact that Tiano has the lowest mosquito abundances due to intensive pest control management\textsuperscript{24}.

**Scenario Exploration.** After identifying the critical forcing environmental variables, we then explored the scenarios how changes of these causally forcing variables may affect mosquito abundance (Methods). The key idea is to predict mosquito abundances for scenarios, in which a climate variable is increased or decreased at each time point, and then compare the predicted abundances with the original values. Take site S7 as an example, Fig 2
shows the observed abundances of *Ae. polynesiensis* and the predicted abundances for a scenario with increased mean tide level. We found that the predicted abundances are higher than the observed for 28 time points but lower for the other 19. Note that increasing tide level does not always result in reduced or elevated mosquito abundance; rather, the response depends on the state of population (e.g. the abundance of mosquitos in combination of other environmental variables at a given sampling interval). We conducted a large-scale screen for all causality links between climate variables and mosquito abundance. The results suggest that state dependence is a common feature of the *Ae. polynesiensis* population dynamics (Supplementary Fig. S7).

Finally, using the same approach, we also explored how environmental change affects the number and strength of mosquito outbreaks. Here, mosquito outbreak is defined as mosquito abundance that is five standard deviations larger than the median abundance of a given time series. This analysis focuses on mosquito peak abundances but not averages because the former are of particular importance for pest control and disease prevention. For example in S6, changes in the mean tide level may have substantial effect on mosquito outbreaks (Fig. 3). Increased mean tide level is predicted to increase the number of mosquito outbreaks from 12 up to 17 (Fig. 3A,C) and the outbreak strength by up to a factor of 1.5 (Fig. 3A,C,D). However, the predicted effect depends on the specific time lag under consideration. For instance, a moderate reduction in MTL is predicted to reduce the number of outbreak for \(d = 0\) (Fig. 3A), but to increase outbreak for \(d = 1\) (Fig. 3B). General predictions for the mean tide level are difficult to make because our methodology does not allow evaluating the joined effect of all time lags.

Figure 1. Causality network of the Polynesian tiger mosquito (*Ae. polynesiensis*). Upper graph: Field site in Raiatea (French Polynesia). Lower graph: Causal interactions within the mosquito meta-population (black arrows) and between climate variables and mosquito abundances (coloured arrows). Causality was evaluated using convergent cross mapping. Only significant results are shown (see Methods, Supplementary Tables S2, S3 for details). Numbers next to arrows indicate the time lag \(d\) (in days), for which causality was detected. Symbols S1 to S9 denote the different sampling sites.
brackish water due to their high tolerance to salinity 27,28. Considering that tide is likely to affect both the water
pressure on mosquito survival has been suggested from lab experiments, although for a different species (e.g.4), whereas studies using longitudinal field data employed mostly linear statistical
methods such as correlation analysis5,9,26 that are not appropriate for the nonlinear mosquito dynamics. Here, our
causality analysis confirms the experimental predictions that, however, hitherto have not been confirmed at the
population level in the natural environment.

At S7, changes in three climate variables were found to significantly alter number and/or strength of mosquito
outbreaks (Fig. 3E,F), including the dew point with a lag of 22 days, the mean tide level with a lag of 28 days, and
precipitation with a lag of 9 days.

Discussion

Causality between environment and mosquito abundance. We applied for the first time the cau-
sality test using CCM to a longitudinal mosquito data set and found that temperature, precipitation, dew point,
air pressure, and mean tide level are forcing climate variables. Our analyses confirm the common belief that
temperature and precipitation causally affect mosquito abundance; in particular, container breeder mosquitoes,
such as Ae. polynesiensis and Ae. aegypti, critically rely on rainfall and moderate temperatures for their larval
development25. However, previous rigorous tests for causal effects of environmental factors on mosquitoes stem
only from lab experiments (e.g.4), whereas studies using longitudinal field data employed mostly linear statistical
methods such as correlation analysis5,9,26 that are not appropriate for the nonlinear mosquito dynamics. Here, our
causality analysis confirms the experimental predictions that, however, hitherto have not been confirmed at the
population level in the natural environment.

Surprisingly, we found that the mean tide level, an environmental factor that was rarely discussed in the lit-
erature, is the most influential environmental variable (quantified by the number of significant tests) in affecting
mosquito populations in French Polynesia (Fig. 1). We suggest the effect of tide may be related with the special
life style of Ae. polynesiensis. Specifically, larvae of Ae. polynesiensis can develop in breeding containers filled with
brackish water due to their high tolerance to salinity27,28. Considering that tide is likely to affect both the water
level and the degree of salinity in the breeding containers, tide potentially has an impact on the number and
quality of breeding sites, which may cause changes of oviposition, larval density, larval survival and subsequently
mosquito population dynamics. Our finding may have important management implications because the tide level
is mainly determined by lunar cycles and therefore bears a high long-term predictability. This is in stark contrast
to the other climate variables, which have comparatively low long-term predictability. An interesting question
for future research is whether the long-term predictability of the tides may be used for improving forecast of Ae.
polynesiensis outbreaks.

We additionally found that the air pressure is a forcing variable of Ae. polynesiensis. While the effect of air
pressure on mosquito survival has been suggested from lab experiments, although for a different species (Ae.
aegypti), the empirical evidence for natural mosquito populations has never been found. A possible explanation
is that mosquitoes use decreasing air pressure as an indicator for adverse weather conditions and modify their
behaviour (e.g. mating) to reduce the risk of injury or death. Such changes in behaviour were previously reported
for Drosophila melanogaster29 as well as for beetles, moths, and aphids30.

Our results on the dew point suggest that evaporation and condensation of water are causal drivers of the
mosquito dynamics. Evaporation reduces water level and increases salinity in breeding containers, whereas con-
densation has the opposite effect. A previous study showed a positive correlation between the dew point and the
percentage of containers holding water versus number of Ae. aegypti larvae31.

Temporal scale dependence of mosquito-climate interactions. The mosquito-climate interactions
exhibited temporal scale dependence. This may be associated with the mosquito life cycle that consists of 5–10
days larval development including pupation, and a total life span of up to four weeks. Our causality analysis
revealed short time-lag effects of 0–9 days for temperature, precipitation, dew point, and mean tide level, which
may reflect a causal effect of the climate variable on adult mortality, larval developmental time or mortality at
late larval stages. Intermediate time-lag effects were found for temperature, precipitation, mean tide level, and air
pressure, which may reflect an effect on larval mortality, larval competition or larval developmental time. Long
time-lag effects were found for temperature, dew point, and mean tide level, which may indicate an effect of the climate variables on female fecundity or host availability (e.g., human, bird, rat, dog). Very long time-lag effects of 30–39 days were found for dew point, mean tide level, and air pressure, which may reflect an effect on the availability of breeding habitats such as broken coconuts or crab holes. We remark that the causal effect may be direct, e.g., temperature may directly affect larval survival due to stress, or indirect, e.g., temperature may alter behaviour of larval predators. In addition, indirect causality may involve human activity, e.g., temperature dependent behaviour of pesticide usage. Importantly, the same climate variable may affect the mosquito at different life stages with different time lags. This may even occur at the same population; e.g., S4 is affected by temperature with delays of 8 days and 20–23 days.

Spatial variation in mosquito-climate interactions. The causality network displays strong spatial scale dependence with respect to mosquito-environment interactions. Causal interactions were only detected at the smallest spatial scale of a single sampling site, but neither at the level of a motu nor at the whole meta-population. Similar patterns were previously reported for the dynamics of measles, which showed signatures of nonlinearity and predictability only at the city-by-city scale, but not at the larger country-wide scale. In both cases, signatures for nonlinearity are lost by summation of subpopulation dynamics. This may seem counter-intuitive, but is actually to be expected for a nonlinear dynamical system, in which subpopulations are affected by different forcing variables or the forcing is non-synchronized, as was found in this study (Fig. 1).

The causality analysis revealed substantial heterogeneity in terms of causal environmental variables and time-lagged effects between neighbouring populations even on the same motu (Fig. 1). How are such differences at a very small spatial scale determined? A possible explanation is that populations in close proximity respond differently to the climate, due to difference in microhabitat such as canopy cover, water availability, salinity and availability of breeding sites even if the distance is less than 100 m. When interpreting the results, however, it should be kept in mind that the climate data were not directly collected at the mosquito sampling points (Methods). Climate data with spatial resolution are necessary to evaluate whether Ae. polynesiensis is really affected by its microhabitat.

An interesting finding was that mosquito-environment interactions are more complex on Toamaro and Tiano than on Horea (Fig. 1). This difference in complexity may, to some extent, be explained by differences in mosquito body size. In a previous study on Ae. polynesiensis using the same mosquito samples, Mercer et al. reported that female body size is significantly smaller on Toamaro motu than on Horea. The authors explain this finding by higher larval densities and longer larval developmental times on Toamaro. We hypothesize that either (i) the longer developmental times and the smaller adult body sizes make mosquitoes on Toamaro more sensitive to environmental fluctuations, and that this causes the complex mosquito-climate interactions found for this motu.
or (ii) the climatic variables influence the larval stage which leads to longer development time, smaller adult body size, and the complex dynamics. The hypotheses could be tested using longitudinal data that include both adult and larval stages.

**Causality between mosquito populations.** An interesting finding was the detection of causality between subpopulations (Fig. 1). There is a clear spatial pattern with five out of six links connecting neighbouring populations, and only one link connecting two motus. A possible explanation is that female mosquitoes disperse by prevailing winds. When interpreting the results, however, it is important to keep in mind that the lack of identified causal coupling could be due to data limitation, e.g. time series may not be long enough to fully decipher the system attractor. Longer time series data may reveal a more complex network of causal couplings between the populations, and the strength of coupling may vary over time.

Our results demonstrate that CCM allows identifying interactions within a meta-population. Meta-population dynamics and structure are important determinants of ecological and evolutionary processes. Meta-population dynamics and structure were typically studied by directly measuring migration and dispersal, e.g., by mark-release-recapture experiments, or indirectly reconstructed by estimating gene flow between populations, e.g. using microsatellite data. Here for the first time, we demonstrated that CCM may provide an alternative solution, which may be of wide applicability. For example, one may study how climate variables, community composition, and population density causally affect the migration behaviour of a focal species. This analysis provides information of the interconnectedness in a meta-population. CCM and scenario exploration allow further investigating whether the meta-population structure itself is context-dependent and how changes of climate variables alter the interconnectedness in the meta-population. Such research questions are difficult to study with the existing methods.

**Effect of pest control strategies.** While the three motus were chosen as study sites because they have similar climate, they actually differ with respect to vegetation and human impacts. In Tiano, pest control is intense and canopy cover and mosquito abundances are low; in Horea, canopy cover is high, pest control happens on irregular basis and mosquito abundances are intermediate; in Toamaro, canopy cover is high, pest control is mostly absent, and mosquito abundance is high. Among the three motus, Toamaro suffered the least human effects, while the mosquito populations on this motu are characterized by the most complex interactions between the climate variables and mosquito abundances and high connectivity between the subpopulations (Fig. 1). A comparison with the two other islands reveals an interesting pattern. There are only two causal climate drivers on Horea, but strong connectivity between subpopulations, and four causal climate variables on Tiano, but no connectivity between subpopulations. This suggests that pest control strategies may not only reduce mosquito abundance but also alter the complexity of mosquito-climate interdependencies. This may be a relevant aspect in pest control. We hypothesize that regular and intense pest control reduces coupling between subpopulations while irregular pest control reduces causal effect of climate on mosquitoes.

**Multiple testing and false positives.** The whole analysis involved 2079 single tests for causality. There are 1935 tests for climate effects on mosquito populations (9 populations, 5 climate variables, 43 time lags), and 144 tests for mosquito-mosquito interactions (9 × 8 ordered pairs of sampling sites, 2 time lags). An important question is therefore how often false positives occur and whether the results are artifacts of multiple testing. In order to estimate the number of false positives, we conducted additional causality tests with climate data collected in Münster (Germany), a place distant enough to have no causal effect on the mosquito populations (Methods, Fig. S8, Table S4.). This analysis suggests that false positives occur in 1 to 1.5 out of 1000 tests. However, we identified 46 causal interactions in 2079 tests (Fig. 1, Tables S2, S3). This is in strong contrast to the expected 2–3 false positives, suggesting that the results are no artifact of multiple testing.

**Scenario Explorations.** We used the scenario exploration technique to predict how environmental change affects mosquito abundance. Our analysis revealed strong state dependent responses (Fig. 2, Supplementary Fig. S7). This result is expected given the various empirical evidences for complex and nonlinear mosquito-environment interactions. Here, we tailored scenario exploration to the specific needs of disease vector control, and investigated how environmental change affects mosquito outbreaks. This analysis suggests that climate change may substantially alter the number and strength of outbreaks, but that the outcome critically depends on the local environmental conditions and may differ even between populations in short distance of less than 200 m (Fig. 3).

We propose using scenario exploration as a new framework to predict environmental change effects on mosquito abundances and disease outbreaks. The main difference to previous forecasting methods is that realistic, nonlinear mosquito-climate interdependencies are fully acknowledged. We believe that this offers new opportunities for mosquito forecasting. As the skill of EDM forecasting depends crucially on the quality of data, there is a critical need for long-term mosquito monitoring. We suggest to collect time series data of mosquito abundances on a regular base of 1–2 weeks, and to combine them with climate information from data logger and case reports of transmitted diseases at local hospitals. Scenario exploration may then be used to (1) predict when outbreaks of mosquitoes or mosquito-borne diseases happen, and to (2) simulate different pest control strategies and explore how they depend on climate conditions. In that sense, we hope that this study sets a first step towards a new direction of pest control and disease prevention strategies.

An important question is how far in the future we can predict using this new approach. For dynamical systems (as are the mosquito populations that we analysed here), due to the chaotic behaviour, the prediction horizon is necessary short-term. More specifically, the response of mosquito population to decrease/increase of a specific causal variable is context-dependent at a specific time point (Fig. 2); thus, for precise forecasting, continuous time
series data are needed (as we illustrated using scenario of exploration). Nevertheless, the general tendency of the effects of a specific variable can still be found in some variables (Fig. 3). In such a case, long-term prediction for future climate can be possible; however, the precision is context-dependent.

In conclusion, we deciphered the causality network of a mosquito meta-population with climate variables (temperature, precipitation, dew point, air pressure, mean tide level) using EDM (Fig. 1) that was otherwise difficult to discern using linear methods. The findings that the responses of subpopulations in close proximity (100–500 m) differed substantially with respect to their causal environmental drivers and that no causal climate variables were found for the motu scale and whole meta-population scale highlights the importance of spatial scale dependency in complex systems. Moreover, we found strong temporal scale dependence of the causality with time lags ranging from zero up to five weeks, suggesting that climate acts on the different life stages of the mosquito and that the interdependencies of mosquito–climate interactions have a high degree of complexity. More importantly, albeit with the complexity, we presented a new framework based on EDM to predict how environmental change may affect the number and strength of mosquito outbreaks. These results bear profound management implications for disease vector ecology and pest control.

Methods
Mosquito field site. Adult *Aedes polynesiensis* mosquitoes were collected on three neighboring motu islands, Horea, Tiano, and Toamaro, on the western coast of Raiatea24 (see also Fig. 1). Mosquito data are shown in Supplementary Fig. S1.

The linear distance between the shoreline of Raiatea and the motus is approximately 500–700 m. Horea, the smallest among the three, is a publically held circular island of an area of 1.41 ha, with vegetation consisting of 60–80% canopy cover. This motu is semi permanently inhabited, and insecticides and wood smoke are used for mosquito control. Mosquito larvae on this motu develop in artificial containers, coconuts, spathes, phytotemata, and burrows made by the terrestrial crab *Cardisoma carnifex*. Blood meals of mosquitoes are from humans, dogs, rats, and birds including chicken.

Tiano, the largest among the three, is privately owned and has a size of 6.34 ha. The vegetation has an open canopy in the center (<20% cover) and 80–90% canopy around the edge. Mosquitoes are controlled by pesticide usage and breeding site reduction. Mosquito larvae on this motu develop in cryptic tree holes, crab burrows, and a pool that is temporarily filled with water. Blood meals are from dogs, rats, birds, and humans.

Toamaro is a privately owned motu with an area of 4.06 ha. The vegetation consists of 70–95% canopy and has greater stratification with herbaceous and shrub layers than Horea and Tiano. This island is occasionally managed by vegetation clearing. Insecticides are used for mosquito control during periods of coconut collection. Mosquito larvae on this motu develop in artificial containers, broken coconuts, phytotemata, and crab burrows. Blood meals are from rats, birds, and occasionally dogs, cats, and human.

Time series data. *Ae. polynesiensis* population data were previously presented by Mercer et al.24. Adult mosquitoes were collected on three neighboring motu islands, Horea, Tiano, and Toamaro, on the western coast of Raiatea (Society Archipelago, French Polynesia; 16°49.4′S, 159°29.2′W) from 1 February 2008 to 3 December 2009 (Fig. 1). On each motu, there were three sampling sites, and mosquitoes were collected at a 14-day interval using Biogent Sentinel traps (data shown in Supplementary Fig. S1). Sampling sites are numbered serially from north to south and denoted by S1 to S9. All collected mosquitoes were species identified, sex determined, and counted for each time interval. In the present study, we focused on female *Ae. polynesiensis*, which comprised about 99% of the caught mosquitoes. For further details see Mercer et al.24.

Climate data were downloaded from the National Oceanic and Atmospheric Administration (http://www.noaa.gov/). From Bora Bora airport (16°26.4′S, 151°45.1′W; approx. 50 km distance to the sampling sites at Raiatea), we obtained daily records of mean temperature (T), dew point (DEW), precipitation (PREC), and air pressure (mean atmospheric sea level pressure, SLP). From Pago Pago (American Samoa; 14°16.6′S, 170°41.3′W), we obtained hourly tide data, from which we calculated the daily average mean tide levels (MTL). Pago Pago has a distance of approximately 2000 km to Raiatea and was the nearest weather station providing tide data. Note that Raiatea and Pago Pago have similar latitude. We remark that the mean tide level is mainly driven by the lunar cycle and therefore highly correlated among pacific islands of the same latitude. This justifies the usage of the American Samoa data for tide level. All climate data were recorded daily for the period from 7 December 2007 to 3 December 2009 (Supplementary Fig. S2). This period is eight weeks longer than mosquito sampling and thus allows investigating possible time-lag effects of climate variables.

Data analysis. Convergent cross mapping. Causal effects between mosquito populations, and from environmental variables to mosquito populations were tested using convergent cross mapping (CCM)10. CCM tests whether two variables, each given as a time series, are coupled in the same dynamical system. Variable X is said to be causally affected by Y if the underlying dynamic of X is a function of Y. This method, based on Takens’ theory for dynamical systems11, tests for causation by measuring the extent to which the causal variable has left an imprint in the time series of the affected10. The method is rooted in state space reconstruction by shadow manifold by lagged coordinate embedding, and the essential ideas are summarized in the following animations: tinyurl.com/EDM-intro. In this study, the embedding dimension (Eb) for each causal link (e.g. from Y(t) to X(t)) in CCM analysis was determined by testing values of Eb from 2 to 10 dimensions that optimizes the cross-mapping ρ in which X(t) is used to predict Y(t).

The causation, Y causes X, can be confirmed if and only if SSRXY cross-mapping SSRYX converges, meaning that the cross-mapping skill ρ(L) improves with increasing library lengths (L) of X10. The direction of cross-mapping (X maps Y) is opposite to the direction of causation (Y causes X) because only Y can leave footprints on X and makes the backward cross-mapping from X possible. Note that in this study, we also explored the causations with lag response24. Specifically, for investigating effects of climate variables on mosquitoes, we tested
for time lags ranging from $d = 0$ to 42 days, while 14-day arithmetic means of the climate variables were used such that the climate time series match the mosquito-sampling interval. To investigate causal effect among mosquito populations, we conducted CCM between paired populations. Potential lag effects were evaluated for $d = 0$, 14 and 28 days.

To determine the convergence in cross-mapping, three statistical criteria were applied. First, Kendall’s $\tau$ test was used to examine whether the cross-map skill $\rho$ increases monotonously as a function of library size $L$. Results are considered as significant if $\tau > 0$ and $P < 0.01$. Second, Fisher’s $Z$ test was used to examine whether the predictability under maximum library size, $\rho(I_{\text{max}})$, is significantly higher than the predictability under minimum library size, $\rho(I_{\text{min}})$. The threshold was set to $P < 0.05$. Third, we tested whether $\rho(I_{\text{max}})$ of the observed time series is significant different from a null model, using the surrogate time series test. 100 surrogates were generated, following 39, by randomly reshuffling phases, while preserving the mean, variation and power spectrum. The results are deemed significant if $\rho(I_{\text{max}})$ of the original data is larger than the 95% upper bound of the surrogates ($P < 0.05$) 12,34. To account for multiple testing, however, we reduced the level of significance to $P < 0.01$ when testing for causal climate effects.

**Scenario exploration.** To evaluate how change in a climate variable (the causal variable identified by CCM) affect mosquito abundances of a given subpopulation, we used multivariate simplex projection following 12. Specifically, we conducted scenario explorations with an extended shadow manifold that has $E_0 + 1$ dimensions 12 (Supplementary Fig. S6). The first $E_0$ dimensions contain the time-delayed embeddings of the mosquito abundances, as described above. Then, to explore potential effects of changing environment, an additional coordinate axis of either the time series of a climate variable or another mosquito population was appended, resulting in $E_0 + 1$ dimensions in state space. It is this extra variable that we aim to “manipulate” to achieve scenario exploration. Specifically, we purposely increase or decrease that forcing variable by multiples of its standard deviation and then forecast the resultant mosquito abundance one step (in our case, 14 days) into the future for every time point.

The scenario exploration approach allows us to investigate how change in a climate variable affects the number and strength of mosquito outbreaks for each mosquito time series. Here, mosquito outbreaks are defined as mosquito abundances that are five standard deviations larger than the median abundance. The outbreak strength is defined as the arithmetic mean of the five highest abundances. For each mosquito time series, we compared the number and strength of mosquito outbreaks as predicted under a “scenario” versus those in the original data. To quantify the effect of a scenario of changing a climate variable, we calculated the relative outbreak strength, which is defined as the arithmetic mean of the five highest population abundances under scenario exploration divided by that of the original data.

**Estimation of false positives.** To account for multiple tests, we estimated the number of expected false positives by applying the aforementioned CCM analyses to climate data of Münster, Germany (51°57′N 7°37′E). Daily records of mean temperature and precipitation were downloaded from the National Oceanic and Atmospheric Administration (http://www.noaa.gov/) for the period from 7 December 2007 to 3 December 2009 (Fig. S8). This is the same time interval as analyzed above. Münster was chosen because of its distance to the mosquito sampling sites in French Polynesia (>15.000 km). A causal affect of temperature and precipitation on the mosquito populations is impossible. Münster is also the place where this manuscript was written.

We tested for causal interactions of the Münster climate on the Polynesian tiger mosquito by conducting the CCM analysis for the nine populations, the two climate variables, and time lags ranging from zero to 42 days. Within these $9 \times 2 \times 43 = 774$ tests, we found only one significant result (Table S4). In conclusion, the number of false positives is estimated to be one out of 774, and the probability for false positives in a single test to be 0.13%.

**Further details of data analysis.** Time series analysis was conducted using the rEDM package (version 0.2.4) of the programming language R 40. To minimize autocorrelation and heteroscedasticity, all time series were first differenced and normalized to zero mean and unit variance 41,42. Due to the paucity of observation points, we performed leave-one-out cross-validation 43.

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Author Contributions
Design of study: A.T., C.H., F.G.; data analysis: F.G. supervised by C.H. and A.T.; interpretation of results: F.G., J.F.S., C.H., A.T.; writing of manuscript: F.G., J.F.S., C.H., A.T. All authors gave final approval for publication.

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