Effect of El Niño–Southern Oscillation and local weather on Aedes vector activity from 2010 to 2018 in Kalutara district, Sri Lanka: a two-stage hierarchical analysis

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Summary

Background Dengue, transmitted by Aedes mosquitoes, is a major public health problem in Sri Lanka. Weather affects the abundance, feeding patterns, and longevity of Aedes vectors and hence the risk of dengue transmission. We aimed to quantify the effect of weather variability on dengue vector indices in ten Medical Officer of Health (MOH) divisions in Kalutara, Sri Lanka.

Methods Monthly weather variables (rainfall, temperature, and Oceanic Niño Index [ONI]) and Aedes larval indices in each division in Kalutara were obtained from 2010 to 2018. Using a distributed lag non-linear model and a two-stage hierarchical analysis, we estimated and compared division-level and overall relationships between weather and premise index, Breteau index, and container index.

Findings From Jan 1, 2010, to Dec 31, 2018, three El Niño events (2010, 2015–16, and 2018) occurred. Increasing monthly cumulative rainfall higher than 200 mm at a lag of 0 months, mean temperatures higher than 31·5°C at a lag of 1–2 months, and El Niño conditions (ie, ONI >0·5) at a lag of 6 months were associated with an increased relative risk of premise index and Breteau index. Container index was found to be less sensitive to temperature and ONI, and rainfall. The associations of rainfall and temperature were rather homogeneous across divisions.

Interpretation Both temperature and ONI have the potential to serve as predictors of vector activity at a lead time of 1–6 months, while the amount of rainfall could indicate the magnitude of vector prevalence in the same month. This information, along with the knowledge of the distribution of breeding sites, is useful for spatial risk prediction and implementation of effective Aedes control interventions.

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Introduction Mosquito-borne arboviral diseases, such as dengue, chikungunya, and Zika virus, are increasing in incidence and geographical range and causing frequent epidemics worldwide. The primary mosquito vectors of these diseases are Aedes aegypti and Ae albopictus. Because there are no effective vaccines or antiviral drugs, the control of dengue relies on vector control as the core intervention to reduce transmission. Although vaccine and drug development efforts appear to be promising, vector control is expected to remain important because integrated approaches targeting dengue vectors and viruses simultaneously are considered to be the most effective strategies to achieve sustainable and cost-effective disease control.

Of the Aedes borne diseases, dengue was the first to be serologically confirmed in Sri Lanka. Dengue was confirmed in 1962, followed by chikungunya virus disease in 1965. Zika virus disease has not been reported in the country at the time of writing. Dengue causes a large disease burden and exerts an enormous strain on health-care systems because the disease is hyperendemic with cocirculation of all four dengue serotypes. In 2017, the largest ever dengue epidemic with 185 000 suspected cases was reported in Sri Lanka; even districts with lowest dengue burden experienced large increases in incidence from 2013 to 2017. The chikungunya epidemic in 2006–08 was estimated to have affected about 80 000 people. Nearly 40% of total dengue cases were reported from the Colombo, Gampaha, and Kalutara districts located in the Western Province in which around 30% of the population of Sri Lanka resides (appendix p 6).

Dengue control efforts in Sri Lanka focus on integrated vector management, key to which is vector surveillance. This includes monitoring the spatiotemporal distribution of vectors for targeted and location-specific vector control. Vector surveillance data are generally compiled using vector indices. The three most commonly used indices in vector surveillance systems are the premise index, defined as the percentage of premises (eg, houses, multi-house compounds, and land units) infested with Aedes immatures (larvae and pupae), the container index, defined as the percentage of water-holding containers infested with immature Aedes; and the Breteau index, defined as the number of positive containers per 100 houses and premises.

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Evidence before this study
Dengue, transmitted by Aedes vectors, has become a major global public health problem because of its rapid and large epidemic potential. Surveillance of larval stages of mosquito vector populations is common in dengue-endemic countries worldwide. Although there is evidence of a relationship between climate variables, particularly temperature, rainfall, and El Niño–Southern Oscillation (ENSO), on dengue risk in Sri Lanka and other affected countries.21,22 However, the Southern Oscillation (ENSO), on dengue risk in Sri Lanka particularly temperature, rainfall, and El Niño–Southern Oscillation (ENSO), provides evidence of the influence of climate variables, and Oceanic Niño Index (ONI), and dengue risk, their influence on Aedes vector activity is poorly understood.

Added value of this study
We used systematically collected vector surveillance data for 9 years representing all study locations in Kalutara, Sri Lanka. We found a homogeneous and stable exposure-lag response association between weather variables and Aedes larval indices across ten different Medical Officer of Health divisions studied in a dengue-endemic district in Sri Lanka. Increasing temperatures and El Niño events were associated with future increases in Aedes vector activity with a 1–6 month lead time. A comparative evaluation of the three vector indices showed that premise index and Breteau index were more strongly correlated with each other and weather variables when compared with the container index. These findings, together with our earlier studies, quantified the full spectrum of association between weather and vector activity and dengue risk in Kalutara.

Implications of all the available evidence
Our findings have several important implications for vector control policies. The lags identified between climate and larval indices were shorter compared with those for climate and dengue incidence, which suggests that vector control needs to be implemented earlier than indicated by the previous studies to be effective. The amount of rainfall seems to indicate the magnitude of vector indices in the same month. Temperature and ONI have the potential to serve as predictors of vector activity with a lead time of 1–6 months. ONI has the added advantage of predicting the seasonal prevalence of Aedes vectors with a lead time of 6 months. This information is useful for spatial risk categorisation to prioritise areas for more intense vector control interventions. Knowledge of types and distribution of vector breeding sites in different geographical locations can help public health authorities to design and implement context-specific behavioural interventions for successful community mobilisation.

Methods

Study setting
Kalutara district is one of the most hyperendemic dengue districts in Sri Lanka.4 It is situated in the Western Province adjacent to the southern border of Colombo, the main metropolitan area in the country. The geographical boundaries of the district fall within the latitudes 6°19’ north–6°49’ north and longitudes 79°53’ east–80°22’ east (appendix p 6). Kalutara expands from the Laccadive sea on its western border to the edge of mountain ranges and rainforests on its eastern border. Altitude is less than 150 m above sea level in most parts of the district. It has a population of around 1 million inhabitants over a land area of about 1500 km².11 Administratively, the Kalutara district is divided into ten MOH divisions. The average population density is 662 people per km² (range 208–3352).11

Procedures

Vector surveillance is done in each district in the country by a team of public health officers under the technical supervision of a qualified entomologist according to the national guidelines on Aedes vector surveillance and control.19 During the study period surveillance was done in Kalutara district in prearranged and designated surveillance areas in each MOH division representing both urban and rural settings. In each area, a minimum of 100 premises were examined on a monthly basis. All potential vector breeding sites—located indoors, outdoors, and on or above ground level—were identified and characterised. Immature mosquitoes were collected...
and identified as *Ae albopictus* or *Ae aegypti*. Breteau index, premise index, and container index were calculated for *Ae albopictus* and *Ae aegypti* in combination—which is known as combined vector index—and for each vector alone. We used combined vector indices for the analysis.

Daily rainfall and temperature data were extracted from Jan 1, 2010, to Dec 31, 2018, at 18 rainfall and three temperature monitoring stations operated by the Department of Meteorology in Sri Lanka. These stations were scattered across the district representing each MOH division. We aggregated monthly cumulative rainfall and monthly means of maximum, minimum, and average temperature from daily data. The Oceanic Niño Index (ONI) data as a measure of ENSO activity in Niño 3.4 region was obtained from the National Oceanic Atmospheric Administration Centre for Weather and Climate Prediction. Accordingly, ONI values of 0·5 or higher indicate an El Niño event and ONI values –0·5 or lower indicate a La Niña event. A thorough description of the study setting, climate, and *Aedes* vector surveillance data collected at each MOH division is reported in the appendix (pp 3–6). All data were collected with the administrative approval of the Provincial Director of Health Service, Western Province, Sri Lanka.

**Statistical analysis**

We used a two-stage hierarchical procedure to assess the association between weather variables and dengue vector indices: premise index, Breteau index, and container index. In the first stage, non-linear exposure–lag response associations for each MOH division were calculated with Distributed Lag Non-Linear Models (DLNM) in the dlnm package (version number 2.4.6). A quasi-Poisson time series regression model was used to account for the over-dispersion of data and for the influence of time varying confounders. The DLNM method used the concept of creating flexible cross-basis function estimators to capture non-linear and delayed effect of exposure variables on the outcome.

The first stage division-specific model for rainfall and temperature was calculated as

\[
E(VI_i)_{i} = \beta + f(Rain_{ti}, vardf, lagdf) + f(Tmax_{ti}, vardf, lagdf) + s(T_{ti}, timedf)
\]

the first stage division-specific model for ONI was calculated as

\[
E(VI_i)_{i} = \beta + f(ONI_{ti}, vardf, lagdf) + s(T_{ti}, timedf)
\]

where \( E(VI_i) \) was the expected value for each vector index in each month \( t \) each MOH division \( i \). \( \beta \) was the intercept, \( f(Rain_{ti}, vardf, lagdf) \) was the cross-basis function for rainfall, \( f(Tmax_{ti}, vardf, lagdf) \) was the cross-basis function for maximum temperature, and \( f(ONI_{ti}, vardf, lagdf) \) was the cross-basis function for ONI in each MOH division with corresponding degrees of freedom for the climate variables (vardf) and their lag values (lagdf). \( s(T_{ti}, timedf) \) was the smoothing function of time with degree of freedom (timedf). Monthly vector indices were assumed to follow a quasi-Poisson distribution allowing for overdispersion. When evaluating the effect of rainfall and maximum temperature, we used the cross-basis functions of both variables in a single model to separate their effects on the outcome.

In the second stage, we pooled the division specific estimates to obtain joint estimates for the district using the mvmeta package (version number 1.0.3). In this process, we studied the heterogeneity in lagged associations across MOH divisions with a multivariate extension to the Cochran Q-test of heterogeneity by using the I² statistics. The statistical analysis was done using R (version 4.1.0). Models were evaluated with the quasi-Akaike information criterion (AIC). The model with the lowest quasi-AIC value was selected as the final model. A thorough description of the model selection procedure, definition of cross-basis functions, and model diagnostic procedure are reported in the appendix (pp 7–8, 17–23).

**Role of the funding source**

There was no funding source for this study.

**Results**

Between Jan 1, 2010, and Dec 31, 2018, three El Niño (2010, 2015–16, and 2018) and four La Niña events (2010–11, 2011–12, 2016, and 2018) occurred (figure 1). El Niño events were more intense as represented by ONI values ranging from 0·5 to 2·6 when compared with La Niña events (−0·5 to −1·6) for the study period.

![Figure 1: Temporal associations between climate variables and dengue vector indices](https://www.thelancet.com/planetary-health_VOL6_JULY2022_e579)

**Figure 1: Temporal associations between climate variables and dengue vector indices**

Data are from January, 2010, to December, 2018, in all ten MOH divisions, Kalutara, Sri Lanka. The ONI exceeding the two grey horizontal dashed lines of +0·5 (above) marks El Niño and −0·5 (below) marks La Niña events. MOH=Medical Officer of Health. ONI=Oceanic Niño Index.
Concomitantly, the highest mean temperature (31.8°C) was recorded at the monitoring station in Rathmalana, which is located close to the coast. A descriptive analysis of the distribution of rainfall and temperature across all MOH divisions is given in the appendix (pp 3–5).

Of the three vector indices, premise index had the lowest and container index had the highest mean value across all ten MOH divisions. The mean values ranged from 6.7 (Panadura) to 10.5 (Agalawatta and Bandaragama) for premise index; from 8.4 (Panadura) to 15.2 (Ingiriya) for Breteau index; and from 19.7 (Ingiriya) to 28.7 (Palindanuwara) for container index. Premise index and Breteau index were highly correlated (r 0.75); however, these indices were not individually correlated with container index (Breteau index r 0.39; premise index r 0.38; appendix pp 4–5).

The main vector breeding sites were discarded receptacles (eg, plastic containers, tins, clay pots, coconut shells, damaged ceramic items) which accounted for 41904 (39%) of 108 000 breeding sites examined. Data are averaged across all Medical Officer of Health divisions in Kalutara, Sri Lanka, from 2010 to 2018. MOH=Medical Officer of Health.

Increasing rainfall above 200 mm per month was associated with increased risk of higher vector indices in the same month (lag of 0 months; figure 3A). The maximum relative risks were estimated to be 1.55 (95% CI 1.03–2.14) for premise index and 1.48 (1.03–2.12) for Breteau index for a rainfall value of 1000 mm per month. However, the associations were less prominent for container index having a statistically significant association between rainfall values ranging from 270 to 670 with the maximum relative risk of 1.17 (1.03–1.49) at 500 mm per month. When lag advanced from 1 month to 3 months, the association was less prominent and not significant.

(figure 1). A previous analysis done in Kalutara district, Sri Lanka between 2009 and 2013 found that rainfall and temperature were correlated with El Niño conditions (ONI >0.5), with lags of 1 to 6 months for rainfall and 1 to 4 months for temperature.10 Concomitantly, the highest average monthly rainfall (884.6 mm) and average maximum temperature (33.6°C) events were recorded following the major—so-called Godzilla—El Niño from October, 2014, to March, 2016. The highest monthly rainfalls during the 2014–16 El Niño were reported at the monitoring stations in Palindanuwara (1203.0 mm), Bulathsinhala (1138.9 mm), and Agalawatta (1089.0 mm) MOH divisions. The highest temperature (34.3°C) was recorded at the monitoring station in Agalawatta. The other two El Niño events in 2010 and 2018 were also associated with relatively high rainfall and temperature (754.2 mm and 33.4°C in 2010; 759.9 mm and 33.2°C in 2018). Across the whole study period, the highest average rainfall was reported in Palindanuwara. Panadura, which is close to the coast, received the lowest amount of rainfall (208.9 mm per month). Of the three temperature monitoring stations, the highest mean temperature (31.8°C) was recorded at the monitoring station in Rathmalana, which is located close to the coast.

### Figure 2: The potential vector breeding sites and prevalence of pupae by breeding site

(A) Proportion of potential breeding site at which Aedes larvae were detected. (B) The number of pupae per 100 breeding sites examined. Data are averaged across all Medical Officer of Health divisions in Kalutara, Sri Lanka, from 2010 to 2018. MOH=Medical Officer of Health.

| Breeding sites                                      | MOH divisions | MOH divisions | MOH divisions | MOH divisions | MOH divisions |
|-----------------------------------------------------|---------------|---------------|---------------|---------------|---------------|
| Discarded receptacles                               | 39            | 139           | 139           | 139           | 139           |
| Temporarily removed                                 | 15            | 15            | 15            | 15            | 15            |
| Covering items                                      | 11            | 11            | 11            | 11            | 11            |
| Water storage                                       | 8             | 8             | 8             | 8             | 8             |
| Tyres                                               | 6             | 6             | 6             | 6             | 6             |
| Refrigerator trays                                  | 6             | 6             | 6             | 6             | 6             |
| Other                                               | 4             | 4             | 4             | 4             | 4             |
| Natural                                             | 4             | 4             | 4             | 4             | 4             |
| Roof gutters                                        | 1             | 1             | 1             | 1             | 1             |
| Pet feeders                                         | 1             | 1             | 1             | 1             | 1             |
| Ornamental                                          | 1             | 1             | 1             | 1             | 1             |

| Proportion of breeding site at which pupae were detected (%) |
|--------------------------------------------------------------|
| 0                | 10             | 20             | 30             | 40             | 50             | 60             | 70             | 80             | 90             | 100            | Average |
| 0                | 1              | 2              | 3              | 4              | 5              | 6              | 7              | 8              | 9              | 10             | 11             |

| Pupae per 100 containers |
|--------------------------|
| 0                | 1              | 2              | 3              | 4              | 5              | 6              | 7              | 8              | 9              | 10             |
| 0                | 1              | 2              | 3              | 4              | 5              | 6              | 7              | 8              | 9              | 10             |

The main vector breeding sites were discarded receptacles (eg, plastic containers, tins, clay pots, coconut shells, damaged ceramic items) which accounted for 41904 (39%) of 108 000 breeding sites examined. Data are averaged across all Medical Officer of Health divisions in Kalutara, Sri Lanka, from 2010 to 2018. MOH=Medical Officer of Health.
(appendix pp 7–10). The divisional heterogeneity, defined by the Cochran Q-test, for the observed rainfall-index associations at a lag of 0 months was not statistically significant (p>0·05) for Breteau index and container index, but was significant for premise index with a Cochran Q-test of 37 (p=0·024; appendix p 17).

Monthly means of daily maximum temperature had the lowest quasi-AIC value suggesting a better fit to the data when compared with mean and minimum temperature (appendix p 7). The relative risk of vector indices seemed to increase with increasing maximum temperatures above 31·5°C. The highest relative risk was observed with the premise index and Breteau index at a maximum temperature of 34°C after a 2 month lag (figure 3B), which subsequently subsided 1 month later (appendix pp 11–13). The relative risks of all three vector

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**Figure 3:** Relative risk of dengue vector activity by rainfall, maximum temperature, and ONI

Relative risk of dengue vector activity by rainfall at a lag of 0 months (A), maximum temperature at a lag of 2 months (B), and ONI at a lag of 6 months (C).

The exposure-response functions at each lag were predicted from the pooled exposure-response function obtained from the meta-analysis for all ten Medical Officer of Health divisions in Kalutara, Sri Lanka, 2010–18. Shaded areas are 95% CIs. Relative risks were calculated with reference to the risk at a rainfall value of 0 mm per month, a temperature value of 31·5°C, and an ONI value of 0. The most important lags for each exposure variable were selected for presentation. The full spectrum of exposure-lag response associations is given in the appendix (pp 8–16). ONI=Oceanic Niño Index.
indices increased with increasing maximum temperature above 31.5°C starting with a lag of 1 month (appendix pp 12–14); however, at a lag of 1 month, the exposure-response association was significant only for premise index (appendix pp 12–14). At a lag of 2 months, the maximum relative risk was estimated to be 1.35 (95% CI 1.16–1.57) for premise index, 1.26 (1.07–1.49) for Breteau index, and 1.14 (0.99–1.31) for container index. Although maximum relative risk appeared to increase up to a lag of 2 months, the exposure-response association between temperature and container index was not statistically significant. The divisional heterogeneity for the observed temperature-index associations were not significant (p value >0.05) for any of the vector indices (appendix p 17).

All three vector indices were significantly associated with ONI with pronounced increases in relative risk during El Niño events starting at a lag of 5 months and a maximum at a lag of 6 months (figure 3C; appendix pp 14–16). At the 6 month lag, the maximum relative risk observed at ONI of 2 was 1.54 (95% CI 1.25–1.90) for premise index, 1.53 (1.25–1.88) for Breteau index, and 1.29 (1.11–1.51) for container index. The divisional heterogeneity for the observed ONI–vector index associations were significant for premise index (Q-test 61.4; p=0.01) and Breteau index (Q test 53.9; p=0.03), but not for container index (Q test 27.8; p=0.83) (appendix p 17). To a lesser extent, the La Niña events were also associated with increased relative risk of premise and Breteau indices from lag of 2 to 5 months. The full spectrum of relationships from lag values of 1 month to 6 months are reported in the appendix (pp 14–17). Here we found that the relative risk of the three vector indices decreased for the early lags of 2 months and 3 months, but less so compared with the overall increased risk observed at a lag of 6 months.

Discussion

We analysed Aedes vector activity patterns for nine years in ten administrative subdistricts in Kalutara, Sri Lanka. We observed robust associations between rainfall, temperature, and ONI, and three vector indices at different time lags. These associations were reasonably homogeneous across all MOH divisions. The relative risk of premise index, Breteau index, and container index increased in the same month (ie, lag 0) with increasing rainfall. With increasing maximum temperatures above 31.5°C, the relative risk of all three vector indices increases up to 34°C with a delay of 1–2 months. During El Niño conditions with increasing ONI above 0.5, relative risk increases linearly in all three vector indices at a lag of 5–6 months. In a previous study we evaluated how ONI was associated with dengue risk at a lag of 5–6 months. In a previous study we evaluated how ONI was associated with dengue risk at a lag of 5–6 months. In a previous study we evaluated how ONI was associated with dengue risk at a lag of 5–6 months. These findings, together with the results of this study quantify the full spectrum of the exposure–lag-response association between weather (rainfall, temperature, and ONI), Aedes vector activity, and dengue risk in Kalutara, Sri Lanka.

Monthly rainfall of more than 200 mm seems to significantly affect vector indices and cause outdoor discarded receptacles to be filled with sufficient water to sustain the aquatic phase of mosquito development, which lasts 7–10 days. The larval stages can be identified as early as within 2 days of egg hatching through vector surveillance, which is within the temporal scale of a 0 month lag, before pupae emerge into adults. In the adult stage, vector survival and longevity are affected by temperature. Given an average survival rate of 89% per day, eggs, larvae, and pupae in containers are a product of the reproduction rate of previous generations of mosquitoes that were exposed to temperatures during a time frame before sample collection. The mean duration of the gonotrophic cycle (the time duration between a blood meal and oviposition) is shortened with increasing temperature (from 7 days at 24°C to 5 days at 30°C). Therefore, recurrent exposure to temperatures higher than 31.5°C over 1–2 months would increase the number of adult ovipositing female mosquitoes and increase the relative risk of high larval indices. The slight increase in the relative risk of Breteau index could be observed at low temperatures even after adjusting for the effect of rainfall. However, this observation was not statistically significant and might be associated with non-climate driven factors, such as presence of indoor mosquito breeding places.

ENSO is the strongest interannual climate cycle on Earth and affects the climate of Sri Lanka. During El Niño events, the western parts of the island receive lower than normal rainfall during the southwest monsoon season (May–September) and higher than normal rainfall during the second intermonsoon season (October–November). Temperature is higher in all seasons during El Niño years. Our observation of increased relative risk of all vector indices at around 6 months lag with increasing ONI over 0–5 is compatible with climatological phenomena of shifting rainfall patterns for 1–4 months and higher temperatures during El Niño events. This shifting of rainfall could explain the reduced risk of vector indices observed with increasing ONI values in the early lags as a result of reduced rainfall in earlier months. Climate and dengue associations identified in the same setting and elsewhere show that more than 200 mm rainfall per month were associated with increased dengue risk over a 2–3 month lag. Similarly, temperatures higher than 29.9°C were associated with increased dengue risk over a 1–3 month lag. The long-term influence of ONI appeared to be stable for both vector and dengue risk, with the highest relative risk around 6 months. Compared with heterogeneous associations found previously between climate and dengue, the climate-vector associations we identified appear to be relatively homogeneous across all ten MOH divisions, as demonstrated by the non–significant Cochran test of heterogeneity (p=0.05) mainly for rainfall
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and temperature. This observation suggests the presence of a stable relationship between the environment and vectors, whereas a more diverse relationship exists between the environment and dengue transmission risk across locations.²¹⁻²³ A potential reason for this is the higher complexity and variability of the processes linking climate to dengue and the intermediate role of vectors in transmission dynamics. An example would be the varying immunity between people because of periodic exposure to different dengue serotypes. Lags were shorter for climate and vector indices compared with climate and dengue incidence in the same setting.²² The difference is 2–3 months for rainfall and 1–2 months for temperature. A 1–3 month lag between climate–vector and climate–dengue relationships would include the necessary time for adult vectors to become infected with the virus through blood feeding, the extrinsic incubation period in the mosquito, refeeding, and the intrinsic incubation period in the host and the time for a patient attending a health facility to be notified as a dengue case.

Associations between meteorological variables and *Aedes* vector indices have been analysed in only a few previous studies. A study in Nepal found that rainfall and temperature increased the vector indices from 2015 to 2016 in two different geographical regions.⁵ However, a lagged relationship was not shown in the study. A modelling study in Réunion established a positive association between weather variables and Breteau index using a process-based modelling approach and evaluated the capacity of the climate information in predicting *Aedes* vector activities with a lead time up to 4 weeks.⁶ A study in the Gampaha, Western Province, Sri Lanka, using data for 1 year, found a statistically significant increase only for ovitrap index and not for the vector indices during the two monsoonal periods.⁷ Similarly, a study in Hong Kong showed that ovitrap indices were positively correlated with the mean air temperature with a lag up to 22 days and total rainfall with a lag up to 15 days before the ovitrap measurement.⁸ This finding is compatible with the time lag of 1 month and same month observed between monthly vector indices and temperature and rainfall in our study. Several other mosquito sampling methods, such as adult sticky traps, have also been used in studies and been found to have a statistically significant association with weather variables.⁹ The *Aedes* vector indices used in our analysis are easy to calculate and less resource demanding; therefore, the inferences can more easily be translated to the operational vector control interventions in resource-constrained settings. Our study quantified the associations between meteorological factors and specifically included ENSO, which requires longitudinal *Aedes* vector surveillance data for a long period of time. Our findings are informative because they describe the lagged relationship of the metrological variables over their full range of values.

Overall, we observed that *Ae albopictus* was the dominant vector in Kalutara, which is a well established dengue vector in Sri Lanka and other countries.²⁶⁻²⁹ Vector ecology and behaviour are different for *Ae albopictus* and *Ae aegypti* and should be taken into consideration when extrapolating the findings of this study.⁰ For example, *Ae aegypti* might be less affected by local weather conditions because it often breeds and feeds indoors, whereas *Ae albopictus* is considered a species related to more natural environments and is more exposed to rainfall and ambient temperature.¹ Of the three vector indices, container index appeared to be less sensitive to weather variables and did not correlate well with the other two. Container index was only poorly associated with rainfall when compared with the other two indices at any lag period. This might be because the index includes the number of wet containers. For example, during the rainy season an abundance of available wet containers caused less competition for containers to breed in that could give rise to lower index values. Breteau index varies widely globally¹⁰ and depends on vector surveillance and sampling protocols.¹¹ Therefore, future studies should investigate how vector prevalence relates to species composition, surveillance capacity, and socioecological factors (eg, housing conditions, water management practices, human behaviours, and the wider ecological context).

We found that the Breteau index had a statistically significant relationship with La Niña events (ONI less than –0.5) to some extent. This observation was more prominent earlier at a 2 months lag for both premise index and Breteau index. Negative ONI values might cause dry and hot conditions in Sri Lanka.¹²⁻¹³ The resultant human behavioural adaptation could be increased water storage practices leading to increased availability of mosquito breeding places. The three vector indices have slightly different inferences regarding the distribution of mosquito breeding in a setting. Breteau index measures the number of mosquito larvae positive containers per 100 houses examined, and it is more closely related to the behavioural adaptation of the community and resultant distribution of mosquito breeding places. By contrast, the premise index only accounts for the absence or presence of mosquito breeding places in a premise (or a house); it is a cruder measure of the distribution mosquito breeding places. The container index measures the proportion of mosquito larvae positive containers, and it does not necessarily relate mosquito breeding in relation to human dwellings. Therefore, we can assume that the Breteau index is superior in capturing behavioural responses of the community for the environmental conditions. However, this assumption needs validation by closely examining the environmental factors and the resultant distribution of mosquito breeding places during La Niña conditions.

El Niño conditions were prominent and more intense compared with La Niña conditions during the study. We consider this as a limitation because we were unable to
capture La Niña induced environmental conditions fully. The prevalence of *Ae albopictus* in Kalutara was a limitation for analysing the individual influence of the weather variables on each species. However, the two species might thrive together in different environmental conditions observed in our study setting. We could not evaluate the effect of relative humidity, which might be another important factor affecting the survival and longevity of *Aedes* vectors, due to a scarcity of data at the time of analysis. Furthermore, the effect of relative humidity might partly be explained by rainfall and temperature combined because dengue modelling studies suggest that a substantial proportion of the residual deviation associated with relative humidity could be explained by their combination. We could not show the effect of extreme temperature on *Aedes* vector activity. Temperatures higher than 34°C predicted in future climate change scenarios might alter the linear increase in the risk observed in our study due to increased mortality of *Aedes* mosquitoes at higher temperatures.

Our findings have several implications for vector control policies. The amount of rainfall seems to provide an indication of the magnitude of vector prevalence in the same month. Higher vector prevalence could be anticipated during months with higher rainfall. Temperature and ONI serve as predictors of vector activity with lead times of 1–6 months. ONI has the added advantage of predicting seasonal prevalence of *Aedes* vectors with a lead time of 6 months. This information is useful for developing early warnings and spatial risk categorisation to prioritise areas for more intensive vector control interventions. Furthermore, when coupled with medium-range seasonal climate data, predictions could provide opportunities to issue early warnings on *Aedes* vector prevalence from the start of the year for the entire dengue season. Models have been developed predicting seasonal dengue risk using ENSO. Our findings on the association of climate and *Aedes* vector indices would be a step forward in the process due to the ability to quantify the risk of occurrence of *Aedes* vectors before the emergence of dengue epidemics. Dengue vector control is challenging and requires planning and meticulous resource allocation. Knowledge of types and distribution of vector breeding sites in different subdistrict locations along with the early warnings on seasonal vector prevalence issued at the beginning of the year would allow public health authorities to determine context-specific behavioural objectives and facilitate community mobilisation towards cost-effective source reduction interventions. Extending the analysis to cover all districts and climate zones in Sri Lanka would create opportunities to capture the ENSO driven differential effects on weather and *Aedes* vectors around the country with sufficient lead time for planning source reduction interventions and area-specific prioritisation of resources.

Our findings are relevant for understanding the consequences of climatic variability on vector activity and broadly on all *Aedes*-borne diseases, including chikungunya and Zika, in Sri Lanka and other tropical countries. Although dengue transmission is expected to intensify due to climate change, its extent needs to be assessed using local and global climate projections and scenarios. The evidence of the association between *Aedes* vector indices and climate would enable policy makers to set up medium-term and long-term targets to control dengue and other *Aedes*-borne diseases. In addition to temperature and rainfall variability, longer-term climate change can influence water management, land use, irrigation practices, and population movements. All such phenomena will determine the influence of climate variability and change on dengue and the potential to use climate and weather information in the context of vector and disease surveillance and early warning systems.

**Declaration of interests**
We declare no competing interests.

**Data sharing**
Climate data collected for the study is available upon request from the Data Processing and Archival Division, Department of Meteorology, Sri Lanka. Subdistrict level data on *Aedes* larval indices can be made available upon request to the Regional Director of Health Services, Kalutara, Sri Lanka and the Director, National Dengue Control Unit, Ministry of Health, Sri Lanka.

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We refer you to the references listed at the end of the article for further information on the subjects discussed.

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